

**DEVELOPMENT OF ARTIFICIAL INTELLIGENCE
DRIVEN CULTIVATION FRAMEWORKS FOR
PRECISION AGRICULTURE**

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Electronics and Communication Engineering

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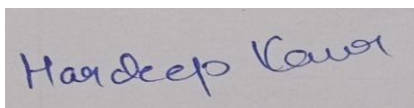


LOVELY PROFESSIONAL UNIVERSITY, PUNJAB

2026

DECLARATION

I, Hardeep Kaur, bearing Registration No. 42300178, hereby declare that the research work embodied in the Ph.D. thesis titled "**Development of Artificial Intelligence Driven Cultivation Frameworks for Precision Agriculture**" submitted to Lovely Professional University, Punjab, India is the original and bonafide work carried out by me under the supervision of **Dr. Bhanu Priya**, Assistant Professor, School of Electronics and Electrical Engineering, Lovely Professional University, Punjab, India. I further declare that the work presented in this thesis is an original contribution to the field of research and is based on investigations carried out during the period of my doctoral study. The research has been conducted in accordance with the academic and ethical standards prescribed by the University, with due acknowledgement and appropriate references provided for all sources and contributions of others. I further declare that this thesis has not been submitted, either in part or in full, to any other university or institution for the award of any degree or diploma.



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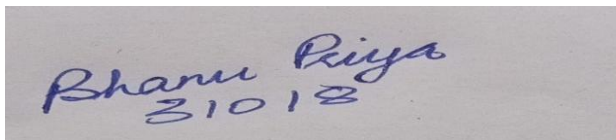
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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled “**Development of Artificial Intelligence Driven Cultivation Frameworks for Precision Agriculture**” submitted in fulfillment of the requirement for the award of degree of Doctor of Philosophy (Ph.D.) in the School of Electronics and Electrical Engineering, is a research work carried out by **Hardeep Kaur, 42300178**, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.



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ABSTRACT

The advent of Precision Agriculture has laid the foundation for modern agricultural frameworks, which are likely to support global food security and optimal resource utilisation. The efficient algorithms embraced by these frameworks and the advanced applications enable precision agriculture to be more dynamic and complex. These challenges motivated the adoption of Artificial Intelligence techniques in precision agriculture smart frameworks. Intelligent agricultural frameworks employ image processing techniques to enhance practices. However, the non-trivial constraints that obstruct the deployment of smart frameworks include the accuracy of capturing complex patterns in leaves, underlying soil factors, and water intake. Ensuring this challenge in mind, the dissertation proposes smart precision agricultural frameworks that improve yield through data-driven strategies, enhancing crop health and resource management.

The analysis of visual attributes of leaves is an indispensable aspect of highly efficient techniques in smart frameworks to curb various parameters that harm crop yield. To achieve the set objectives of addressing the precision agriculture framework problem, the dissertation presents an explicit scientometric analysis. The proposed analysis classifies a literature selection strategy relying on crops, approaches, and crop management factors. The scientometric analysis identifies the extensively studied staple crops, leading countries, global research coordination among institutions to promote joint research, pioneer journals, and key topics related to agriculture. Based on these attributes, an extensive literature review of prominent farming methods has been conducted. The detailed literature review emphasises the fundamental techniques and inherent limitations of existing approaches in crop health monitoring. In addition, it has been highlighted that insufficient research has been conducted apart from the major staple crops such as wheat, rice, and maize. Considering the above, a cash crop, specifically bananas, has been undertaken for study, which is economically significant for farmers, food security, and intelligent AI-based agriculture systems.

Precision agriculture is a breakthrough, upgrading conventional methods, improving crop health, and ultimately production. One of the major challenges in developing

disease detection methodologies is the severity of the disease. Therefore, an intelligent framework has been developed to find out the severity of the disease. The proposed framework classifies fungal infections, such as Cordana, Pestalotiopsis, and Sigatoka of banana. Four different Convolutional Neural Network (CNN) architectures have been proposed, labelled CNN1 through CNN4, with varying layer depths and hyperparameters to extract distinctive features from diseased leaf images. The empirical evaluation has demonstrated that the 5-layer CNN2 architecture, achieving the best classification accuracy of 96.86%, outperforms other CNN variants in multiple parameters, including sensitivity, specificity, precision, and F1 score. Further, classification is followed by color thresholding to determine the severity grade. HSV and Lab color spaces have been employed to segment the affected area. The analytical results are validated through an extensive simulation that indicates the severity percentage for each image. Accordingly, appropriate volumes of fungicides have been recommended.

In cash crops such as bananas, nutrient deficiencies reduce the plant's resistance against pathogen attacks. Stunted growth, chlorosis, and necrosis are visible symptoms that manifest micronutrient and macronutrient deficiencies. Nutrients such as boron, potassium, and zinc significantly affect fruit size, the ultimate attribute for their market value. Existing strategies are ineffective in handling these deficiencies, even with modern techniques such as Transfer Learning. Subsequently, an integral framework has been proposed that concatenates pretrained models such as MobileNetv2, DenseNet169, and ResNet50. The hybrid DenseNet169 + MobileNetv2 has achieved 93.21% accuracy, followed by quantification of the severity based on color and contour thresholding. Segmentation based on HSV has been performed to identify the damaged leaf area, which has been further validated by Intersection over Union (IoU). IoU for boron is 0.87, indicating strong agreement between the ground and predicted value. In addition, soil features such as soil pH, electrical conductivity, and organic carbon have been fused with the hybrid model's categorization to recommend fertilizer amounts for the fields based on severity.

The emergence of novel and diverse applications to increase yield in smart approaches has emphasized the optimum utilization of resources. However, the existing techniques

minimise water consumption in the field at the cost of yield. Therefore, an automated irrigation framework has been presented that helps farmers to take appropriate action after final decisions from AI models that consider satellite-based weather data along with sensor data. The reinforcement learning-based algorithm Proximal Policy Optimization (PPO) has been trained to automate irrigation by considering environmental parameters, such as evapotranspiration, growth factor, that is the crop coefficient, and soil moisture. The agent is rewarded based on soil moisture in a desired range, rainfall utilization, crop stress, and irrigation actions. Experimentally, the proposed scheme has been evaluated and achieved a root-mean-square-error of 0.110 for soil moisture. The proposed algorithm is also compared with fixed and rule-based irrigation, outperforming them in terms of yield and stress days for the crop.

Thus, a comprehensive approach has been proposed to revolutionize agricultural practices with advanced techniques that can be generalized for a variety of crops and could serve as a reference for farmers and researchers.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
DL	Deep Learning
DOI	Digital Object Identifier
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
ENN	Edited Nearest Neighbors
GAP	Global Average Pooling
HSV	Hue, Saturation, Value
ISV	Intermediate Severity Value
IoT	Internet of Things
IoU	Intersection over Union
KNN	K-Nearest Neighbour
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multi-Layer Perceptron
NN	Neural Network
ReLU	Rectified Linear Unit
RF	Random Forest
RGB	Red, Green, Blue
RL	Reinforcement Learning
ROC	Receiver Operating Characteristics
RNN	Recurrent Neural Network
SI	Severity Index
SMOTE-ENN	Synthetic Minority Over-sampling Technique-Edited Nearest Neighbors
STEM	Science, Technology, Engineering, and Mathematics
SVM	Support Vector Machine
TL	Transfer Learning
UAV	Unmanned Aerial Vehicle
UMA	University of Western Australia
WoS	Web of Science

Chapter 1

Introduction

1.1 Overview

The exponentially rising population, along with depleting natural resources, poses a major challenge to fulfilling the food needs of the world's masses. This concern directs the increase in efficient crop production. At the same time, conventional methods in agriculture are still practiced, including manual inspection, uniform input application, and experience-based decisions, which are inadequate to meet current production quantity and reduce agricultural input wastage. Variation in the soil fertility, environmental resources availability, weather, and the crop condition [1] are the factors that must be addressed to achieve agricultural growth. The current alarming situation highlights the need to upgrade farming approaches through technical interventions based on analytics-driven frameworks to utilize resources efficiently.

This chapter highlights the motivation behind the study reported in this dissertation. The traditional farming procedures, along with their related disadvantages, have been discussed first. Furthermore, the revolutionary change brought by precision agriculture, through efficient resource utilization, has been focused. Subsequently, the significance of smart decision support systems with integrated data analytics algorithms has been presented next in the section. The identified research gaps helped delineate the objectives of the proposed research. Ultimately, the chapter underscores the key contributions in the field of agriculture and the organization of the dissertation.

1.2 Motivation

The current agricultural ecosystem requires us to advance swiftly towards using only the necessary resources and proper timing to obtain optimal yield. The world population would rise to over 9.1 billion by 2050, compared to 8 billion currently [2]. Other statistics state that between 713 million and 757 million people remained undernourished in 2023 [3]. Evidently, insufficient food and inadequate nutrition are prominent issues that pose serious challenges to the current agricultural system. This

demonstrates a great need to expand production in addition to improving the crop quality.

Meanwhile, deteriorating natural resources, including water availability and soil fertility, global warming, and extreme weather conditions, are putting consistent stress on sustainable agricultural growth. According to a United Nations report, melting glaciers and unforeseen variations in water availability pose threats to countries that depend on irrigation from these water supplies. More than 2 billion people [4] are at potential risk of encountering a shortage of food and water due to declining water reservoirs. Ultimately, the production gets directly affected by these fluctuations, thereby posing a major threat to food security. The above studies highlight an urgent need for an innovative approach to food security, considering population, dietary concerns, and climate uncertainty. Therefore, advanced frameworks with inherent sensors, data-trained algorithms, and decision support systems are required to overcome the outlined challenges of present agricultural systems.

Furthermore, evolving from traditional to industrial agriculture, conventional agricultural practices [5] are still operational in most of the regions of the world. The procedures for crop growth rely on visual inspection, flooded irrigation, manual harvesting, heavy machinery, and uniform application of fertilizers, pesticides, and fungicides. Consequently, these input systems lead to the accumulation of chemicals, degradation of organic matter in soil, and water pollution.

Figure 1.1 illustrates techniques that have been common in traditional farming. Detection of pest attacks, disease outbreaks, and crop growth analysis have been performed manually, which may be inaccurate or delayed. Thereafter, agricultural inputs such as pesticides, fungicides, and weedicides [6] have been uniformly applied to all crops without evaluating the specific needs of individual crops. This is harmful to the environment and human health, since chemicals accumulate in the atmosphere and enter the food chain. It is also an inefficient way for diverse agricultural settings with wide variations in soil nutrients, soil type, temperature, seasons, water pH, and air content. These variables highly influence production to evaluate the suitability of atmospheric parameters for a particular crop. Further, water requirement is mostly met through surface irrigation [7] from canals, rivers, reservoirs, and even from the ground with furrows or basins. However, this is the oldest method to supply water to fields due

to its convenience; it causes significant water loss. Run-off due to overwatering, evapotranspiration from fields, soil erosion, and increasing soil salinity are common issues associated with flood irrigation. In addition, harvesting is one of the most labour-intensive processes, which involves heavy machinery and ultimately a high price. These activities, taken together, are laborious, time-consuming, and not cost-effective to attain future needs.

Hence, numerous challenges are being encountered by conventional farming. Environmental degradation in terms of water pollution, degradation in soil quality, increased stress on land, and the economic challenges faced by farmers are the main concerns. Therefore, it is high time to revolutionize the approach towards farming. In view of this, integration of technology is accepted to simplify procedures and expedite while taking into consideration the necessary inputs to the fields and maximizing production.

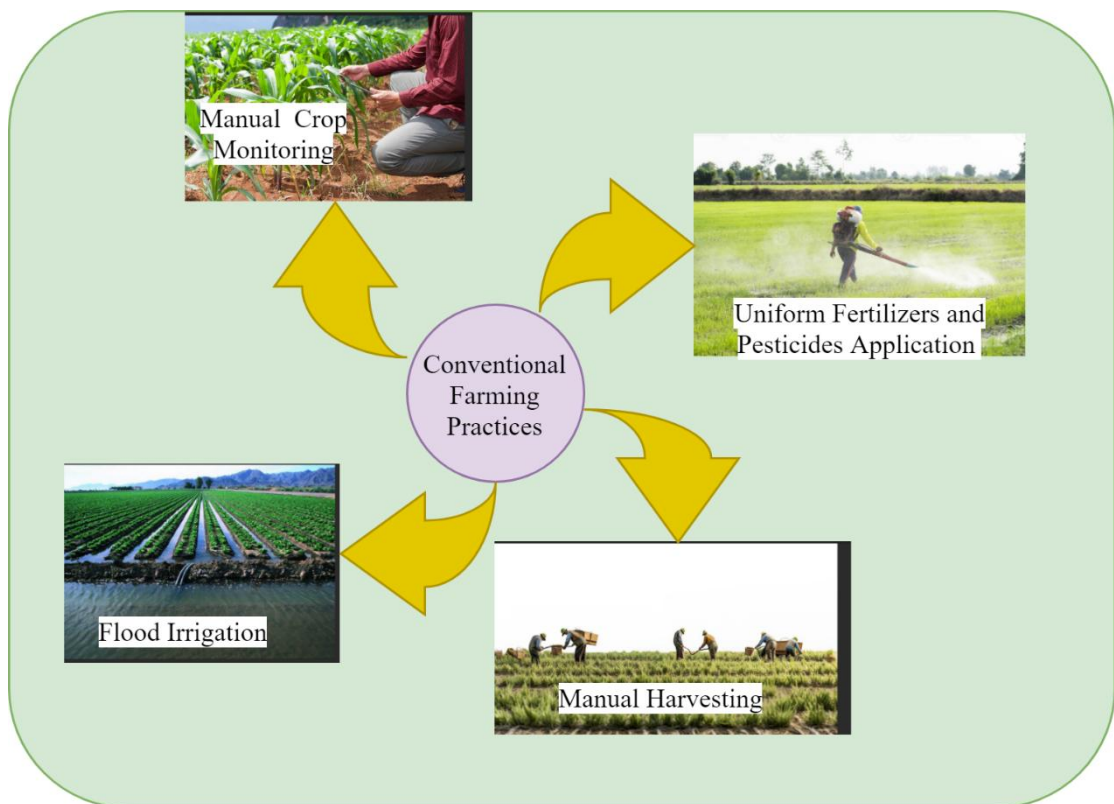


Figure 1.1: Overview of Conventional Farming Practices

To reduce excessive chemical use and inefficient water use, precision agriculture offers a viable solution. This study provides precise and timely input to crops, depending on crop stage and growth. In addition, weather parameters and geographical factors are considered in the resources to be provided.

This section outlined the study's motivation and the need for it. Later in this section, the basic concept of precision agriculture and its advantages are discussed.

1.3 Precision Agriculture

Precision Agriculture [8] is a transformative approach to enhance production by minimizing resource intake and reducing manual intervention. Farmers and researchers widely adopt precision practices to maintain long-term land productivity while achieving sustainability. Primarily, in precision agriculture, data is collected by a network of devices connected to the Internet of Things (IoT) ecosystem or from satellites. IoT network integration with wireless networks such as 5G, Wi-Fi, and Unmanned Aerial Vehicle (UAV) is crucial for remote sensing. Field moisture, soil pH, organic matter, and weather parameters such as temperature, pressure, rainfall, and more are collected through numerous on-field sensors. Meanwhile, UAVs have enabled faster aerial data acquisition from large areas while giving deeper insights into the field. The Global Positioning System (GPS) further provides accurate location information with environmental parameter values. The collected data is transferred via wired or wireless mode to data analytics to aid farmers in making decisions. Information is further analysed with big data algorithms after evaluating patterns and their outcomes. By evaluating the information, including crop and land features, actuators, and wireless networks, the IoT ecosystem can also take proper action.

At the outset, precision agriculture was employed to spray chemicals at specific locations, based on crop health, atmospheric parameters, and soil conditions. It prevents harmful effects on the surroundings by limiting the release of unnecessary chemicals. Currently, precision farming is not limited to variable-rate fertilizers, pesticides, or weedicides; it supports numerous applications. Automated machines and robotics utilize location data and sensors to perform seeding, weed control, and harvesting. Even carbon emissions are reduced by avoiding unnecessary tractor movement. Irrigation hours are scheduled based on soil moisture, crop stage, and environmental parameters

to prevent water overflow and underflow. Thus, precision agriculture proposes self-operating farms with minimum resources, and they can be monitored for yield and better profit margins.

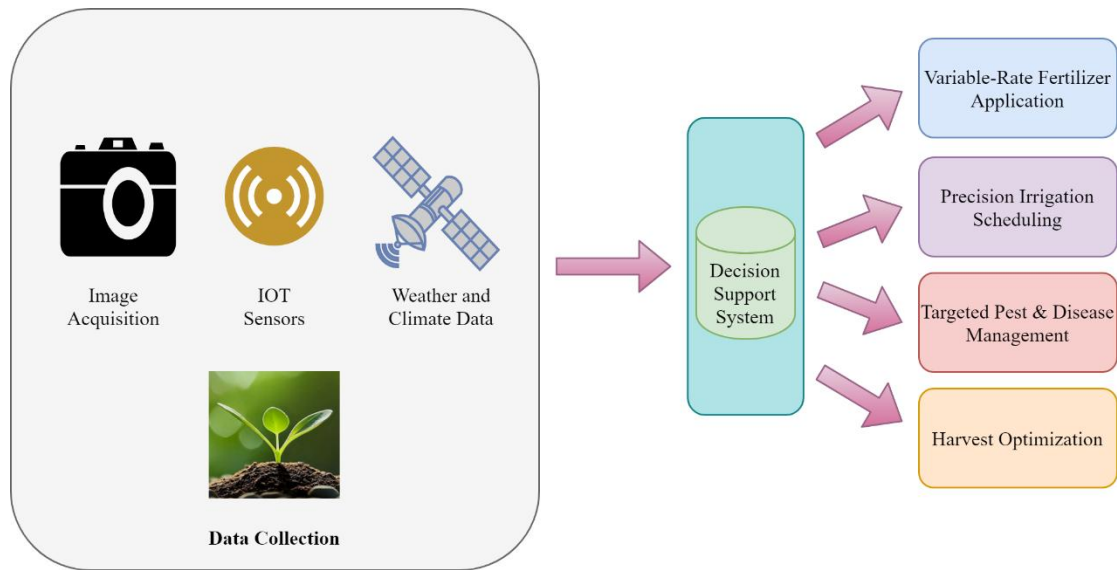


Figure 1.2: Abstract of Precision Agriculture

The data has been acquired from deployed sensors in the field, weather satellites, and images taken by drones or manually through cameras, as depicted in Figure 1.2. The integrated data is then evaluated to support prompt actions in fields, based on pre-defined thresholds or rules. Artificial Intelligence-driven models and knowledge-based and data-driven decisions support the farms' actions. Considering time and location variability, site-specific operations are performed, such as applying the required chemicals to targeted pests, insects, and weeds. Providing the right volume of water to crops, necessary nutrients to plants, and harvesting crops at their maximum ripeness and maximum yield is achieved. Thus, precision farming lowers production costs, reduces resources, and protects the earth. The integration of sensors, data analytics tools, and intelligent decision-making algorithms leads to efficient management of agricultural fields.

Precision agriculture is a breakthrough that not only protects the environment but also adopts sustainable practices [9] by minimizing resources. The following are the features of precision agriculture:

1. Aided decisions using data analysis

Apart from prior knowledge and experiences, decisions [10] are supported by the data analyzed by advanced technologies. Hyperspectral images provide information beyond what can be visually perceived. Geographical information systems provide information about environmental conditions with ease and remote access.

2. Appropriate usage of agricultural inputs

Efficient utilization of resources has been achieved by applying suitable agrochemical nutrient supplements, water, and planting of seedlings [11] in accordance with the season and location.

3. Increase in crop yield

By consistently tracking the status of the crop, assessing environmental parameters, monitoring soil conditions, and accordingly taking correct action, boost the quantity and quality of the end product [12] by large amounts.

4. Reduced input costs

Inputs to the fields are applied wisely to reduce waste and cut production costs.

5. Improvement in soil health

By reducing excessive chemical content, soil contamination is decreased, and the soil's organic matter is preserved.

6. Efficient water management

With the help of technology and advanced designs, pumps operate automatically, and sprinklers provide the required amount of water only to the plants' roots. Water is largely conserved; it is the most precious resource for life on Earth.

7. Protection of the environment

By fulfilling the tailored requirements of the crops, chemical runoff to nearby water bodies, groundwater, and excessive penetration into the soil have been largely reduced. Thus, harmful impacts on the surroundings can be mitigated.

8. Early control of risk

By observing early plant features, diseases, and nutrient deficiencies are identified, enabling agriculturists to act at the earliest.

9. Self-Operating Farms

Robots and self-driving machines have decreased manual work and increased the speed at which tasks are completed. Nowadays, robots do harvest, pumps irrigate fields automatically, tractors operate themselves, and much more.

10. Adaptation of farming practices to a changing climate

Farmers are not only able to select crops based on climate forecasting but also take necessary steps in advance to protect them to the greatest extent by acting swiftly.

At the core of precision agriculture exists artificial intelligence, which analyses large volumes of data to facilitate timely and precise farm management decisions.

1.4 Need for Artificial Intelligence

Artificial Intelligence (AI) can be defined as the capability of systems to replicate cognitive behaviour to perform activities like humans. Learning from patterns, unpredictable situations, and outcomes, developing logic, analytical skills, and finally making decisions are operations accomplished by machines with AI [13]. Algorithms and methodologies are gradually upgraded to provide more efficient solutions than conventional computational systems that depend on predefined tools. AI systems adapt to the changing environment by analysing data, interacting with their surroundings, and optimizing results. Now, intelligent machines have taken over intensive labour work and mentally exhaustive tasks. Recognizing the potential of AI, several algorithms and models have been developed, including neural networks, transformer networks, and generative models.

The basic architecture of AI [14] consists of various layers as illustrated in Figure 1.3. Firstly, the AI backbone comprises high-intensity data centres that store massive amounts of data and a repository of information, crucial for confidentiality. Also, it contains the underlying network algorithms that extract the features from the inputs. Next, the input layer, the perception layer that collects the raw data from various sensors, images, videos, audio, trends, and logs. It may be in real-time or offline data. Succeeding this layer is the cognitive layer, where information is processed. It is a network of interconnected elements that deduces the relationships between intricate patterns. The network gets trained to recognize different patterns to perform classification for various purposes. The decision support layer provides the final output.

All these layers operate in accordance with the specific application. After model evaluation, the proposed structure is deployed for the application.

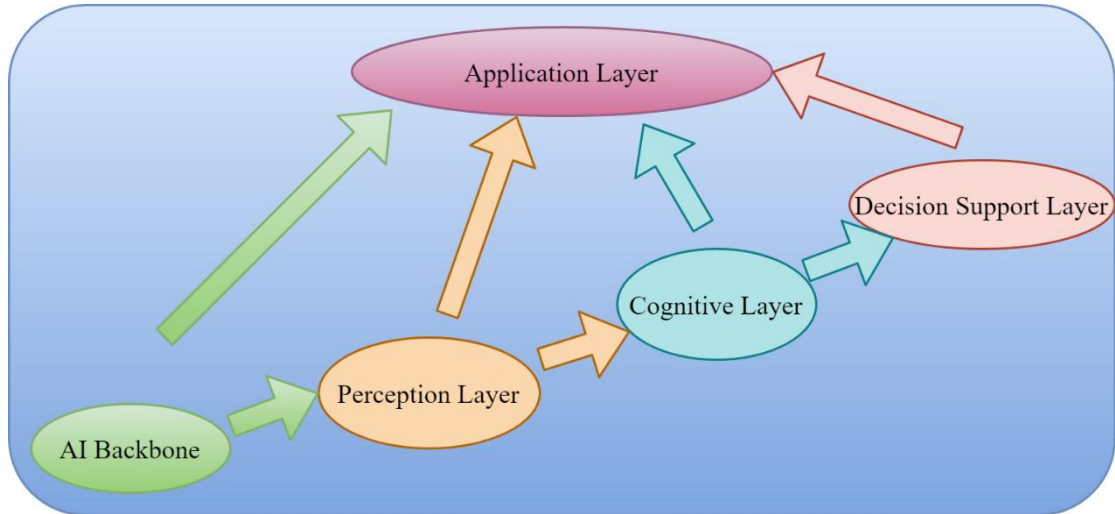


Figure 1.3: Architecture of Artificial Intelligence

With the remarkable advances in AI, it has a revolutionary influence across a wide range of areas. AI has emerged as a boon to agriculture by increasing yield in recent years. Early detection of crop diseases, nutrient deficiencies, and consistent monitoring of crop health [15], and providing appropriate inputs as per requirement are elements of AI in farming. Intensive manual work has been drastically reduced, and decisions taken by automated machines or agriculturists are now more accurate with the aid of AI.

The framework of integrated AI algorithms in a real-time agricultural field is presented in Figure 1.4. AI models can be machine learning algorithms such as K-Nearest Neighbour, Random Forest, Decision Tree, and deep learning algorithms such as Convolutional Neural Network, Transfer Learning, and Reinforcement Learning based on Q-learning or policy-based. All form the core component of the framework. It is their performance accuracy that makes the model successful in the field. It has been illustrated that in an automated network, real-time data is acquired by sensors, remote access by UAVs, observation by on-field robots, and meteorological information by satellites. AI models make better decisions for farms and predict yield using statistics-driven models in the cloud layer on personal devices. Such a framework paves the way for automated fields in the future while accomplishing sustainable farming practices.

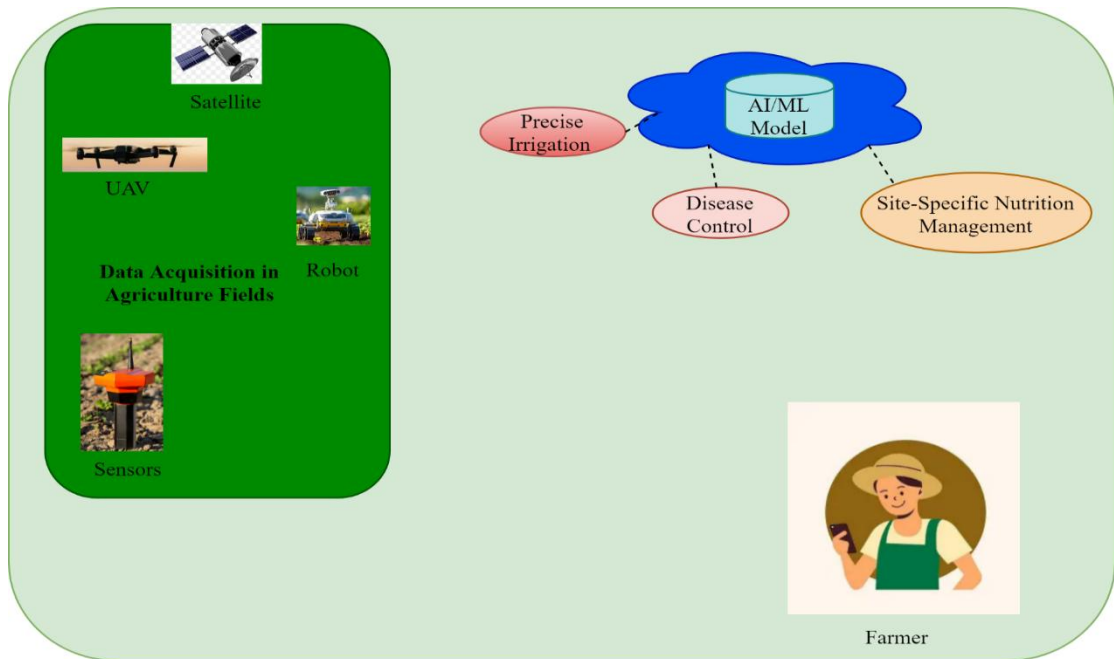


Figure 1.4: Proposed AI-enabled precision agriculture framework

AI plays a substantial role in precision farming by facilitating each practice at every step. Its role becomes more prominent when considered more deeply at every stage in the plant's lifecycle. Initially, with the first phase of farming, AI-assisted technologies provide guidance even before transplanting and putting seeds in the soil. Sowing of seeds at the proper location and at the correct time of the season are also under its supervision. Planning with respect to the distance between plants and the levelling of soil are also directed during the sowing of seeds. Nutrients are properly provided at the earliest to avoid any deficiency in crops, as per the stage of the crop. Diseases, weeds, and pests are removed efficiently to protect the plants. Also, irrigation is scheduled to manage water efficiently. Harvested crop quality inspection and sorting can be done automatically. It is supported by robots and automatic machines depending on the ripening of crops. Sensors in a warehouse can predict which food needs to be sold early depending on its condition. Also, the price of produce in the grain market, demand for crops, and their yield information can be utilized for the next crop selection. Figure 1.5 shows the holistic picture of AI assistance at each stage of the crop.

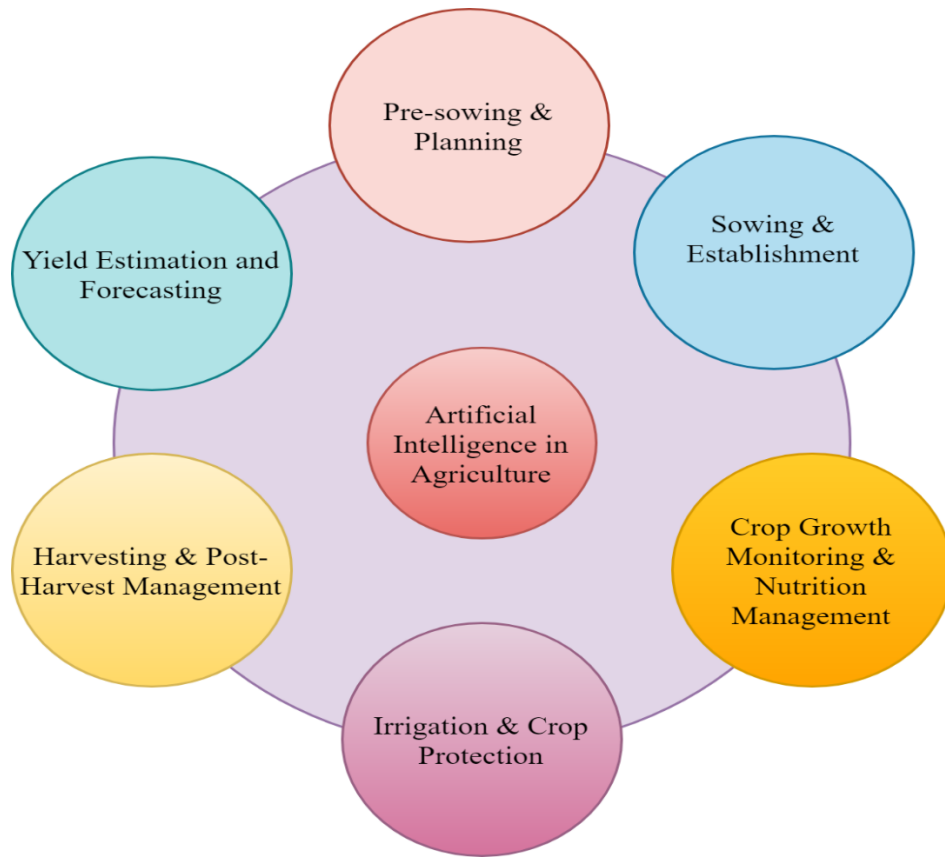


Figure 1.5: AI applications across the agricultural lifecycle

Contemporary agricultural systems use artificial intelligence for strategic analysis, but their success depends largely on the underlying technologies. These technologies are at the core of AI-powered agricultural solutions. Therefore, it is essential to understand the technologies to implement AI realistically in agricultural fields.

1.5 Enabling AI Technologies for Precision Agriculture

Along with data and infrastructure, advanced algorithms have a crucial role in extracting patterns from complex farm data. Deep learning techniques are required to process massive data and extract features. However, pre-trained models can be leveraged for other kinds of applications without any need to train the model again, that is, transfer learning. Reinforcement learning achieves outstanding performance in an uncertain environment. Optimizes the result by continuously interacting with the surroundings.

Convolutional Neural Network: Convolutional Neural Network (CNN) [16] is a class of deep learning models primarily used for image analysis. It has the potential to extract

features for high-dimensional images, audio, and video. It leverages the convolution operation by considering two functions and analysing how the input varies with respect to the second function. In CNNs, filters or kernels slide over the input image to determine low-level features such as edges, corners, shapes, and textures. Afterwards, high-level features are built on it, for instance, faces and objects. Filters are generated automatically and fill an output feature map. From the determined patterns, tiny details are removed to make faster calculations. The CNN has an edge over neural networks; it considers local regions at once, not the whole image. It repeats the same kernels on the image with no manual intervention to create filters. Another indispensable feature of CNN is that layers can be modified as per the application. Figure 1.6 illustrates the inherent layers of a deep convolutional neural network. The following are the intrinsic layers of the CNN models:

- a. Convolution layer- Convolutional layers compute distinctive characteristics from images with the use of filters [17].
- b. Pooling layer – Pooling layers are essential components of CNN. The main aim is to down-sample the extracted features of the convolution layer. This reduces both spatial dimensions and the amount of computing power to process images. Additionally, there are two types of pooling: maximum and average. Average pooling yields the mean value of each image part, whereas maximum pooling yields the maximum value of each image.
- c. Dropout layer-To prevent overfitting, neural networks use a dropout layer as a regularization technique. During training, it works by randomly "dropping out" several neurons. This prevents the model from relying extensively on neurons and compels it to develop more robust patterns.
- d. Flatten layer- The basic purpose of the flatten layer in neural networks is to transform the output of a preceding layer into a one-dimensional vector.
- e. Dense layer- Dense layer, also referred to as a fully connected layer, where each neuron in the layer has connections to every other neuron in the layer above it. This type of layer finalizes the results by multiplying each input by the appropriate weight, then summing an activation function. This layer is important for the final classification of extracted images. Since the final classification or regression tasks are carried out by fully connected layers that

combine the retrieved feature representations. Non-linear activation functions are used across the network to help CNNs model complex decision boundaries. Gradient-oriented learning methods are commonly used for model optimization.

Further, CNN architectures have evolved into increasingly deep and efficient models, including AlexNet, VGG, Inception, ResNet, and EfficientNet. Deep networks, residual links, and multi-dimensional feature extraction have greatly enhanced learning capacity and generalized performance. CNNs are being used as central spatial feature extractors in multimodal learning frameworks, where they are combined with complementary learning modules to manage diverse input sources.

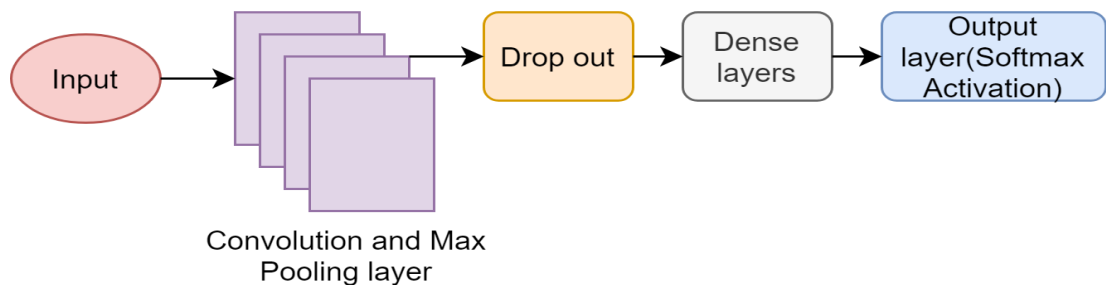


Figure 1.6: Pictorial representation of a Convolutional Neural Network

Transfer Learning: Transfer learning [18] is a deep learning strategy that facilitates learning by reusing knowledge from a source activity to enhance learning performance on a related target task. This is also known as a pre-trained convolutional neural network. Since the early layers extract the same visual patterns, these are frozen layers. The final layers are tuned, modified, and trained on a new dataset to make a classification. This approach saves time, GPUs/CPU, and data, and provides better performance. The following are the Common CNN Models Used in Transfer Learning, which have been tested on massive data and transferred to new tasks:

- Visual Geometry Group (VGG): Strong baseline feature representations are provided by VGG models, which are characterized by deep and uniform architectures using small convolutional filters, but at a greater computational cost.

- ResNet: Enhances gradient flow and model stability by introducing residual connections that allow very deep networks to be trained effectively.
- Inception: Efficiently captures a variety of spatial characteristics by using concurrent convolutional procedures at various scales.
- MobileNet: Designed for computational efficiency with depth-wise separable convolutions, it is appropriate for resource-constrained and real-time applications.
- DenseNet: Dense connectivity between layers promotes feature reuse and strengthens information flow, which is useful for fine-grained feature discrimination.
- EfficientNet: Achieves better accuracy with less computing complexity by balancing the scaling of network depth, width, and resolution.
- Xception: Extends the Inception architecture with depth-wise separable convolutions, allowing for more efficient learning with fewer parameters.

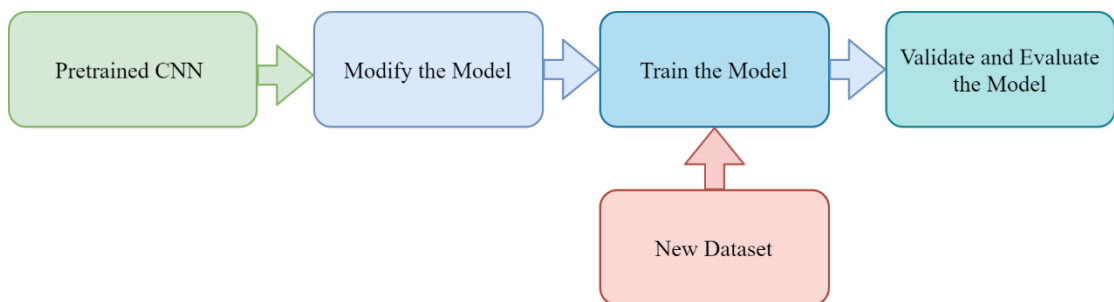


Figure 1.7: Overview of Transfer Learning Method

Figure 1.7 depicts the four stages of the transfer learning process: selecting a suitable pre-trained model, modifying the network architecture to suit the target task, training with task-specific data, and then performance validation. The pre-trained models can be selected first and downloaded to suit an application. Thereafter, initial layers can be kept fixed for feature extraction, such as edges, corners, and shapes. The last layers get modified by varying the number of neurons in the final dense layer, optimizers, loss function, epochs, and batch size to get the best accuracy.

Deep learning such as CNN classifies objects efficiently, but they also need to interact with changing environments, and decisions can be made according to desired results.

Whereas, transfer learning methods like reinforcement is the next level in AI technologies, executing actions in its surroundings by analysing results and taking appropriate actions.

Reinforcement Learning: A reinforcement learning (RL), teaches an agent how to behave optimally through constant contact with its surroundings. As shown in Figure 1.8, the agent examines the environment's present state and chooses an action. The environment then transitions to a new state and sends a reward signal that assesses how successful the previous action was. The agent's decision-making policy is iteratively refined using trial-and-error learning in this feedback-driven process. RL [19] is especially useful for sequential decision-making and control issues that call for long-term performance optimization since it does not rely on labelled input-output pairings, in contrast to supervised learning.

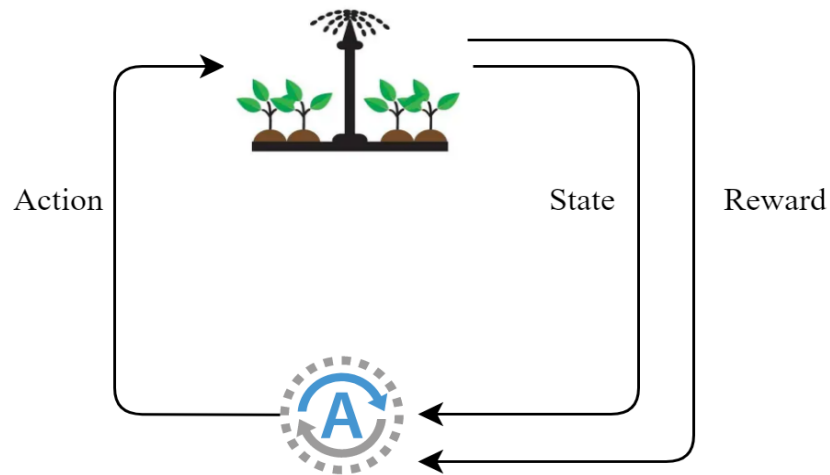


Figure 1.8: The abstract model of Reinforcement Learning

RL Types: RL is widely categorized [20] into the following classes based on its learning strategy and policy representation:

- **Value-Based RL:** These techniques acquire a value function that calculates the expected return of states or pairs of states and actions. Value maximization is the indirect source of action selection. Q-learning and Deep Q-Networks (DQN) are traditional examples. Value-based approaches have drawbacks in continuous control issues, notwithstanding their effectiveness in discrete action spaces.

- **Policy-Based RL:** By explicitly learning a parameterized policy that associates states with actions, policy-based methods facilitate the efficient management of continuous action spaces. These strategies use gradient-ascent techniques to maximize predicted rewards to optimize the policy. The basis for many contemporary RL algorithms is policy gradient approaches.
- **Actor–Critic Methods:** Actor-critic algorithms merge the features of value-based and policy-based approaches by learning a policy (actor) as well as a value function (critic). Especially in complicated situations, this structure increases sampling efficiency and learning stability. Proximal Policy Optimization (PPO) belongs to this category with consistent training convergence.
- **Deep Reinforcement Learning (DRL):** DRL integrates deep neural networks with reinforcement learning to regulate high-dimensional state spaces. DRL has greatly increased RL's applicability to real-world issues, including resource management, autonomous systems, and robotics.
- **Single-Agent and Multi-Agent Reinforcement Learning:** Single-agent RL interacts with the environment through a single decision-making entity, whereas multi-agent reinforcement learning (MARL) involves numerous agents who may cooperate or compete. Agricultural decisions, such as scheduling irrigation, are frequently modelled with single-agent RL frameworks.

1.6 Scope of the Work

The purpose of this study is to design and evaluate AI-driven frameworks to facilitate precision agriculture, such as crop disease management, nutrient deficiency assessment, and irrigation scheduling. Although smart agriculture can be considered for numerous disparate use cases, services, and scenarios, accounting for all of them in the present study is beyond the scope of this work. Therefore, the scope of the presented research work is limited to the major services associated with these application domains. The emphasis of this research is on applying AI technologies to make agriculture a sustainable livelihood for farmers. It is an effort to mitigate farmers' problems with accessible modern tools.

The study commences with a scientometric analysis of agriculture, staple crops, and their production constraint. This investigation further dives into the evolution of innovative techniques and the bibliographic data extracted from the Scopus database. Global research trends, collaboration among top countries, institutions, and authors have been examined. Emerging research topics have been identified, helping to select AI techniques to investigate further to increase the yield. Furthermore, a disease detection and management framework is proposed with the evolution of the CNN architecture. Apart from disease identification, the disease severity is determined, and the intensity has been given a grade. Based on the severity grade, fungicides are recommended. Subsequently, nutrient deficiency and its management framework are presented with pre-trained CNN networks. Feature concatenation models have been evaluated to determine nutrient deficiencies, and the severity is calculated. Fertilizer application is modified to avoid unnecessary spread to the surroundings. Finally, resource management is addressed by scheduling water to the fields through reinforcement learning. By considering unforeseen weather, soil, and crop stage, water use is optimized.

It is vital to emphasize that the disease, nutrition, and irrigation modules are designed and validated as separate but complementary decision-support components. The integration of these modules into a single unified real-time farm management system is beyond the scope of this study; it is indicated as a viable area for future research.

Collectively, the scope of this work is restricted to AI to usage to facilitate precision agriculture practices through data-driven diagnosis, severity assessment, and input optimization.

1.7 Research Gaps and Research Questions

The machine vision for crops has shifted from classical image processing algorithms to deep learning methods with the development of artificial intelligence technology. These methods have solved challenging problems, but this technology offers development potential and application value. However, the typical challenges for the selection of deep learning methods, as identified from the existing literature, are:

1. Disease diagnosis- Most deep learning-based plant disease detection techniques now in use are based on supervised learning. Therefore, other learning methods need to be investigated so that they can be considered.
2. Health Monitoring-Most of the research ignores the intricate relationships between several nutrients in favour of concentrating on specific nutritional deficits. It is essential to realize these relationships and their effect on crop health to design predictive models.
3. Data-driven cultivation-With traditional methods, obtaining agricultural data like soil properties, environmental parameters, water requirements, and fertilizers recommendations required a large amount of labour and time-consuming manual testing. Consequently, there is a need to develop strategies that integrate diverse data sources, including reliable weather data, soil information, and historical crop performance data, to enhance decision-making capabilities.

Considering the foregoing, the scope of this study has been reduced to the following research questions:

- RQ1: What is the significance of Artificial Intelligence in Precision Agriculture?
- RQ2: How to design an intelligent framework for precision farming?
- RQ3: How to optimize the practices for smart agriculture?

1.8 Research Objectives

From the rigorous literature review, research gaps have been meticulously identified. Further, to fill the research gaps, the following objectives have been formulated to develop frameworks to facilitate precision agriculture.

1. To investigate the pertinent artificial intelligence-driven frameworks related to crop health analysis and cultivation practices in precision agriculture.
2. To propose an intelligent diagnostic framework for the detection of crop diseases in smart agriculture.
3. To develop a plant health monitoring framework for automated detection of nutritional deficiency in crops.
4. To design a data-driven framework to facilitate cultivation practices for precision agriculture

1.9 Specific Contribution of the Work

This thesis provides the following distinctive and unique contributions to the realm of AI-driven precision agriculture:

1. A thorough scientometric analysis covering the significance of artificial intelligence research in agriculture has been conducted to identify dominant fields, advancing research trends, prominent authors, and upcoming application areas, resulting in a structured research foundation for AI-driven agricultural studies.
2. A convolutional neural network (CNN)-based disease detection framework has been developed to identify agricultural illnesses from leaf images. It also includes disease severity estimation for stage-wise disease evaluation and fungicide recommendations.
3. A transfer learning-based nutrient deficiency identification model has been proposed, in which pre-trained deep learning architectures are fine-tuned for agricultural images and coupled via feature concatenation to improve classification performance and allow severity-aware fertilizer suggestion.
4. Proximal Policy Optimization has been employed to train an agent to irrigate the fields to optimise crop production while maintaining the appropriate soil moisture for banana fields. An adaptive irrigation policy has been designed for different seasons, crop stages, soil parameters, and environmental conditions.
5. The proposed research together contributes to precision farming with AI-driven support systems. The crop management practices reduce intensive human labour and improve resource utilization.

1.10 Thesis Organization

The thesis is divided into six chapters to describe the research work thoroughly and its outcomes. The following is an outline of the contents of each chapter:

Chapter 1: Introduction

This chapter motivates Artificial Intelligence-driven frameworks for diversified and advanced applications in agriculture. After presenting a detailed overview of conventional agriculture and its evolution to precision farming, distinct AI-enabled application domains have been discussed. Furthermore, it presents the significance of

AI in agriculture, followed by a thorough discussion on various enabling technologies that are significant to precision farming. Afterwards, research questions have been formulated, corresponding to which research objectives have been defined. Subsequently, the scope of the work has been discussed. Finally, this chapter presents the research contributions and an outline of the thesis.

Chapter 2: A Comprehensive Scientometric Analysis and Literature Review

This chapter presents a well-structured methodology for scientometric analysis and a comprehensive literature survey on the existing techniques and research trends in the field of farming. The introduced taxonomy classifies crop selection strategies based on their growth management. Finally, an extensive survey has been conducted on retrieved data, classified by the taxonomy to derive a comprehensive overview of the present study's selection areas.

Chapter 3: Smart CNN Models for Efficient Banana Disease Detection and Severity Estimation

This chapter proposes a disease identification framework in the banana crop based on the CNN model. It presents the quantitative analysis of the proposed model through performance evaluation. Subsequently, the severity level has been computed based on colour thresholding. Finally, fungicides are recommended based on severity grade.

Chapter 4: An AI-Based Intelligent Framework for Banana Nutrient Deficiency Diagnosis and Severity Estimation

This chapter presents a framework for nutrient deficiency detection and precise fertilizer recommendation that ensures resource optimization. The proposed framework and the concerned system model have been thoroughly discussed. Finally, the effectiveness of the proposed scheme has been validated through comparison with other conventional schemes based on convergence analysis, paired t-test, intersection over union, and dice coefficient.

Chapter 5: Adaptive Irrigation for Yield Stability and Stress Minimization for Banana Cultivation

This chapter proposes an intelligent irrigation framework to ensure optimal resource utilization. A detailed discussion of the proposed framework is provided, followed by a description of a reinforcement learning–based approach. To ascertain the validity of the proposed scheme, its performance has been compared with other conventional schemes, considering the convergence analysis.

Chapter 6: Conclusion and Future Prospects

This chapter summarizes the conclusions drawn from the research presented in the preceding chapters, along with the discussion on recommendations and future extensions.

Chapter 2

A Comprehensive Scientometric Analysis and Literature Review

In many nations worldwide, agriculture is the main source of income. The UN projects that by 2050, there will be 9.7 billion people on the planet, with an upsurge in population from 7.5 billion [2], raising the demand for land. However, the expansion of cultivable land is expected to be minimal, with only a 4% increase anticipated by 2050. Consequently, farmers will face the challenge of maximising productivity with limited resources. Additionally, to address the pressing global challenges of zero hunger and malnutrition, as envisioned by the United Nations, it is essential to focus on the mass production of staple foods, which form a significant portion of the human diet. Staple crops such as rice, wheat, and maize are the primary sources of calories and vital nutrients for billions of people worldwide [1], [21], [22], [23].

These factors drive the exploration of innovative methods that can boost production and minimize resource waste. In this context, AI has progressively become integral to the technological advancement of the agricultural sector. AI-driven solutions promise not only to enhance operational efficiencies for farmers but also to elevate sustainable agricultural practices. Artificial Intelligence has evolved as a disruptive technology in agriculture, taking agricultural practices such as disease detection and nutritional deficiency monitoring [24], irrigation scheduling, and soil content sensing [25], [26] to different levels. These agricultural practices empowered by AI have gained popularity, which can be confirmed by the number of publications shown in Figures 2.1 and 2.2.

Diseases are one of the major reasons that lead to reduced crop production. However, the adoption of innovative technology like Deep Learning (DL) and Machine Learning (ML) has helped to overcome these obstacles by early disease detection and effective crop management, leading to sustainable agriculture [27]. Numerous AI-based solutions have contributed [28] to the research for efficient disease detection to curb the spread of the disease. For disease detection, the advanced AI algorithms either learn the intricate patterns and features from images or analyse the time-series data collected from sensors to track the disease progression over time [17].

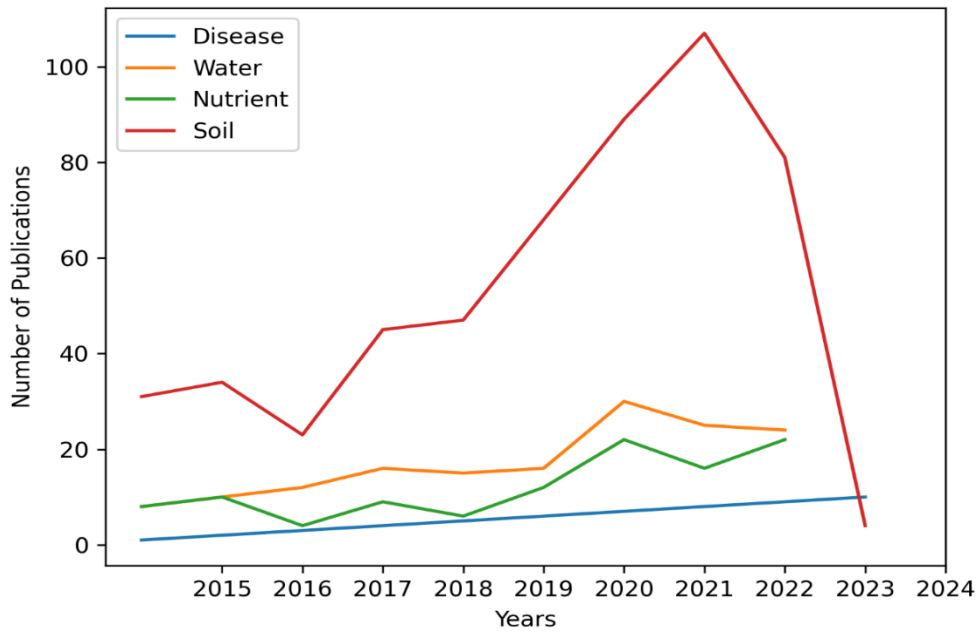


Figure 2.1: The number of publications concerned with key agricultural practices elevated by the usage of Artificial Intelligence

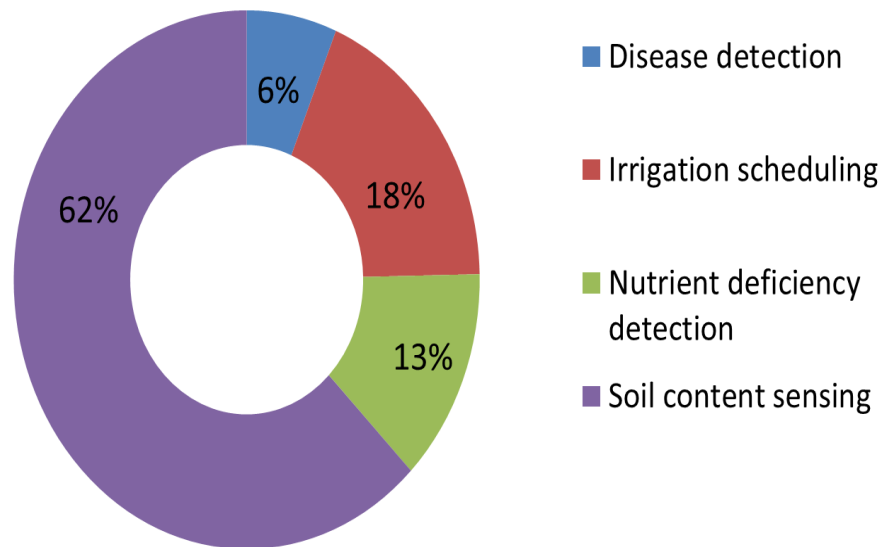


Figure 2.2 Percentage distribution of publications

Furthermore, crop production issues are often caused by nutrient imbalance. The plant leaves frequently exhibit symptoms of malnutrition [29]. As a result, AI supports autonomous image processing based on computer vision to identify dietary deficits. AI

algorithms have been proposed to analyse the multivariate dataset [30] to identify the indicative patterns of nutritional deficiency and the factors affecting plant health [31].

In addition to the discussion, the unequal distribution and climate change-induced uncertainties pose a significant barrier to agricultural development, hindering sustainable farming practices. Therefore, AI can play a crucial role in the prediction and mitigation of climate change on water resources. AI-powered intelligent irrigation systems [32] command accurate water delivery to crops, thereby reducing waste and increasing efficiency. AI algorithms [33] incorporate information from multiple sources, including satellite imaging, drones, IoT sensors, and weather stations. Predictive analytics and ML models can foresee the shifts in weather patterns, which can further help to adopt proactive measures to conserve and manage water efficiently [34]. The advanced AI algorithms enable optimized irrigation schedules by interacting with the agricultural environment and maximizing rewards by choosing appropriate actions, for instance, water usage. Neural network (NN) models [35], [36] are one of the AI approaches used in irrigation planning that forecast soil moisture and schedule irrigation based on environmental inputs such as soil characteristics and climatic data. Moreover, by evaluating crop requirements, weather forecasts, and real-time field data, advanced techniques like deep reinforcement learning and deep Q-learning (DQN) [37], [38] optimize irrigation to save water and sustain yields effectively. Thus, the discussed agricultural practices constitute precision agriculture.

Similarly, AI algorithms [39], [40] are employed to examine data acquired from diverse sensors and sources to evaluate soil attributes [41], [42] like pH, texture, compaction, moisture content, and nutrient levels. Scientists optimize crop development conditions with high accuracy by using AI approaches [43], [44], [45] like ensemble learning (e.g., XGBoost and LightGBM) [46] to forecast soil parameters [47], [48] based on nutrient and environmental data. Precision agriculture is aided by ML models like Gaussian Process Regression and Random Forest, which use soil photos and remote sensing data to forecast soil water content and organic carbon distribution. These algorithms assist farmers in making well-informed choices on crop selection, fertilization, and irrigation techniques for managing their soil. The algorithms can evaluate changes in soil

conditions over time or forecast future soil moisture levels by analysing temporal data from weather stations or through soil images [49], [50].

The state and development of AI in agriculture have not yet been quantitatively examined, despite several noteworthy publications on the subject. The scientometric analysis reported in the presented work allows quantitative evaluation of articles [51], [52] revealing the advancements in research in the above-stated area for a decade, i.e., 2015-2024, with the following contributions:

1. Scholarly literature trends concerned with the latest ML techniques in the various subcategories of agriculture have been analysed.
2. An elaborated citation analysis of articles, journals, and publications has been carried out in the presented work.
3. Characteristic patterns and relations of the social framework for scientific research across the world have been highlighted in the presented work.
4. A quantitative and qualitative analysis of the pertinent literature has been carried out to reinforce further research in this direction.

The remainder of the chapter's structure has been established as follows: In Section 2.1, the information regarding the related work carried out by the researchers is investigated. Section 2.2 illustrates the methodology adopted to carry out the scientometric analysis along with the various analyses. Section 2.3 depicts the criteria being followed to extract the literature from the database. Section 2.4 explains the thorough procedure of the analysis carried out. Section 2.5 sheds light on the significance of developing more advanced algorithms for underexplored crops. Finally, Section 2.6 delineates a succinct conclusion regarding the presented study to carry out further research.

2.1 Background

With the increase in research centred on AI-driven agricultural research practices, it is critical to adopt a methodical approach to identify the sources related to the most influential studies. Therefore, a scientometric analysis has been presented in this work,

which allows a systematic review of the related research papers. The analysis covers citation structure analyses, top papers ranked by citation count, study subjects, highly prolific journals, well-known authors, co-citations between writers, institutional involvement, geographic contribution, bibliographic coupling between writers, nations, institutions, and journals, among other things [53]. This study would establish a benchmark of recent scientific papers, which would serve as a reference for researchers from a variety of fields, institutions, and geographic locations that are convergent in this field. Such analyses have been carried out on a variety of domains, such as a publication and citation structure analysis tailored to a certain journal.

While searching the literature related to scientometric analysis focused on the significance of AI in agriculture, only a few documents were found in the Scopus database, as discussed next.

A scientometric analysis comprising keyword co-occurrence and clustering analyses related to the application of AI in post-harvest agriculture [54], [55] has already been implemented. The study examined 586 articles published between 1994 and September 2022 that discussed the use of AI in postharvest agriculture research and were obtained from the Scopus database. Bibliometric and review assessments of geographic analysis and AI in agriculture [56] have been widely analysed. The authors utilised the Scopus database to study thousands of documents published between 1992 and 2021. The presented study offers details regarding the relationships among agriculture, geospatial analysis, and artificial intelligence. Garcia et al. presented a scientometric analysis centred on the application of information technologies and AI [57] in agriculture from 1939 to 2021. The study comprises the top ten journals, affiliations with the highest participation, top ten authors, and most cited papers. Nonetheless, the existing literature turned out to be incompetent in addressing various aspects such as publication growth, share of AI, and keyword co-occurrence. Consequently, an extensive scientometric analysis has been conducted, which comprises the (i) publication growth, (ii) share of AI, (iii) geographical distribution, (iv) citation analysis, (v) keyword co-occurrence, (vi) author analysis, and (vii) institution analysis. The methodology adopted for the same has been delineated in the next section.

2.2 Methodology

This section highlights the methodology adopted for the scientometric analysis concerned with the application of AI in agricultural practices. The methodology consists of the selection of the database, followed by the search strategy and literature selection. After retrieving the relevant literature, the duplicates are removed using unique DOI (Digital Object Identifier) and EID (Scopus ID) to avoid any kind of discrepancy in analysis. Subsequently, the analysis in terms of publication growth, keyword co-occurrence, citation analysis, geographical distribution, and institution analysis [58] has been carried out. The same has been highlighted in Figure 2.3 and discussed in the subsequent subsections.

2.2.1 Database Selection

The three most widely used bibliographic databases are Google Scholar, Web of Science (WoS), and Scopus. Clarivate Analytics' Web of Science database enjoyed considerable popularity between 1973 and 2004. However, in comparison to Google Scholar and Web of Science, the Scopus database which offers more current and comprehensive data on high-quality articles, making it a popular option [59], [60].

2.2.2 Tool Selection

Utilizing data analysis along with visualization technologies is essential in scientometric investigations to create a graphical representation of the bibliographic data and identify related patterns. For data analysis and visualization in quantitative research, a vast array of tools and software is accessible. The most popular packages include the Bibliometrix R package, Citespace, HistCite, Gephi, and VOSViewer. In this work, research documents are quantitatively analyzed using the Bibliometrix R package and VOSViewer[61], also known as Visualization of Similarities. Both are open-source platforms that offer useful quantitative analysis capabilities and a necessary graphical user interface, respectively [62], [63]. VOSviewer is [64] an open-source, Java-based software designed for bibliometric analysis [65] and network data mapping. It processes large datasets to generate, visualize, and explore network maps using input files or API-retrieved data. VOSviewer [66] offers three visualization modes: network, overlay, and density, enabling users to map and cluster data such as keywords, geographic affiliations, and user-defined metrics. Its clustering approach,

based on the VOS mapping technique [67], provides an alternative to traditional multidimensional scaling methods, offering clear and insightful representations of scientific knowledge and relationships.

Biblioshiny, an open-source visualization [68] software based on RStudio proposes robust tools for literature analysis, including index computation, network analysis, and knowledge mapping. It supports data import from Web of Science (WoS) and Scopus, enabling functions like co-citation analysis, coupling, and scientific collaboration analysis. With simple commands, `install.packages ("bibliometrics")`, `library ("bibliometrix")`, `biblioshiny()`, users can access Biblioshiny to process data from major databases, creating structured matrices for deeper insights into field development, existing knowledge, thematic trends, and future predictions, aiding research planning, and progression.

2.3 Procedure for Selecting Literature

As this procedure demands the gathering of multiple documents, a methodical search strategy has been developed. This strategy focuses on searching for documents focused on the implementation of Artificial Intelligence in agricultural practices. The search has been conducted in November 2023 using the following criteria: first, search terms containing the Agricultural keyword, i.e. in the search following is included: “Agriculture” AND “Machine learning” OR “Artificial Intelligence” OR “Wheat” OR “Rice” OR “Maize” OR “Crop” AND “Disease Detection” AND “Soil” AND “Irrigation” AND “Nutritional Deficiency” within the publication year limited to 2015 to 2024, excluding documents written in languages other than English since it is the predominant language of scientific communication, and many researchers write in this specific language only to reach a broader audience and improve citation visibility. Furthermore, to ensure high-quality data, filters for document types such as books, journals, and conference proceedings [69] have been included. Even articles, reviews, and conference papers have been given precedence.

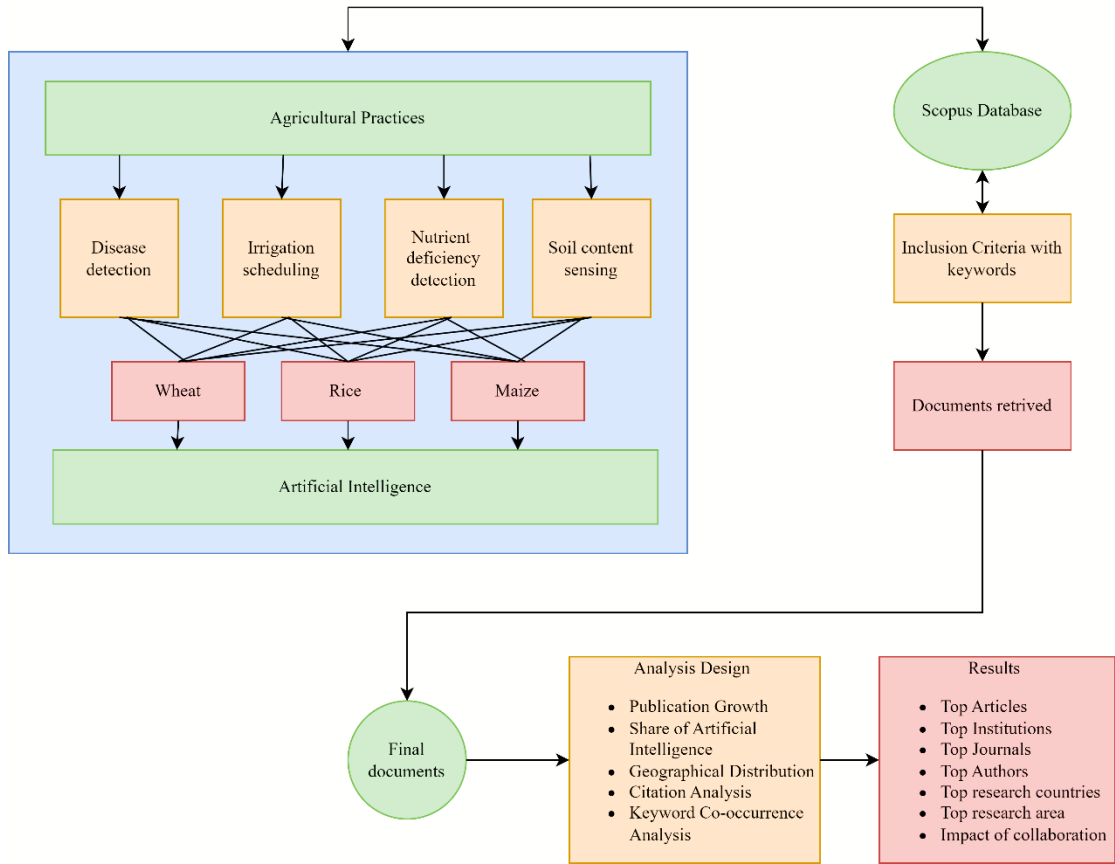


Figure 2.3: Methodology adopted for the scientometric analysis of the significance of AI in agriculture

2.4 Analysis Design

Based on the selected literature as discussed in the previous section, a detailed analysis has been carried out as discussed in the subsequent section.

2.4.1 Increase in Publications

The total number of filtered AI papers for advancing agricultural practices, specifically for wheat, rice, and maize, has been segregated and enumerated in Table 2.1. As outlined in the same, 320 documents have been taken out specifically related to these crops from a total of 1938 for the decade 2015-2024. In coherence with the presented statistics, the highest number of publications has been accounted for wheat, i.e., 70 in the soil content sensing category, whereas Maize has the least publications, i.e., 4 in the disease detection category.

Table 2.1: Number of filtered publications

Agricultural practices category	Filtered Documents			
	Wheat	Rice	Maize	Total
Disease Detection	6	5	4	15
Irrigation scheduling	27	26	27	80
Nutrient Deficiency	16	12	17	45
Soil Content Sensing	70	60	50	180

Further, the increase in publications year over year in each area of Disease detection, Irrigation scheduling, Nutrient deficiency detection, and Soil content sensing has been noticed. The actual growth of disease detection has been observed from 2021 to 2023, as presented in Figure 2.4. Wheat is leading with a 40% share of publications in 2023. Wheat's prominence in 2023 publications over rice and maize [70] can be linked to the urgent need to tackle its climate sensitivity, its vital role in global food security [71], [72], and advancements in technology that have enhanced the feasibility and impact of wheat research. The publications for maize also show a noticeable increase from 2022 to 2023, indicating a rising research interest in disease detection for this crop. Also, the growth of water requirements by the fields is observed in Figure 2.5. It reveals that maize received the highest focus in 2021. Publications for rice and wheat on this topic display varying rates of increase over the period from 2015 to 2023, highlighting fluctuating but consistent interest in efficient water management across different crops. In Nutrient deficiency, Maize shows a maximum number of publications in 2021 (Figure 2.6). In addition, there has been a rise in the publications related to rice from 2019 to 2021. However, there are fluctuations in the number of publications related to

wheat. In Soil content sensing, publications on wheat fluctuate from 2015 to 2021, but a sudden rise has been observed in 2022 and 2023. Similarly, rice publications also fluctuated from 2015 to 2019 but rose from 2020 onwards. For Maize, publications fluctuated for the entire period as depicted in Figure 2.7.

2.4.2 Share of Artificial Intelligence in Agricultural Practices

The percentage share of research related to AI usage in agricultural practices during the period of 2015-2024 has been outlined in Figures 2.8 to 2.11. In coherence with the presented data, the research on disease detection in wheat dominated the total research publications by 40%. Moreover, significant work has been reported on rice and maize, with a substantial share of 33% and 27% in total publications, respectively [73]. Furthermore, it has been noted that the research on wheat, rice, and maize captures an equal share in irrigation scheduling. In addition to this, the greatest amount of research has been done again in the field of wheat nutrient requirements (i.e., 37% of the publications), followed by maize and rice with 32% and 31%, respectively. Furthermore, research publications on maize carry the maximum share, i.e., 39% of the publications in the study of soil content sensing, along with wheat and rice capturing 36% and 25% of the total publication share, respectively. Maize, known as the "queen of cereals" for its high genetic yield potential and adaptability to various climatic conditions, is also experiencing a transformation with the rise of AI technologies. Across various agricultural domains, except for soil content sensing, wheat sees the highest application of AI. As the third most harvested and consumed grain globally, wheat faces substantial losses due to diseases [74], [75]. To address these challenges, over 40 research centres worldwide [76], [77] including those in the United States, Argentina, Turkey, China, Germany, India, and Australia, are dedicated to advancing research on perennial grain crops. Moreover, wheat's nutrient richness [78] aligns seamlessly with the Sustainable Development Goals aimed at eradicating malnutrition.

Innovations like cost-effective IoT devices and UAVs [32], [79] are now complemented by advanced soil content sensing technologies. These tools gather detailed data on soil health, nutrients, and moisture, which is then analysed with machine learning algorithms to optimize planting strategies and improve yield outcomes. As a cornerstone crop for human nutrition, animal feed, and ethanol production [80]

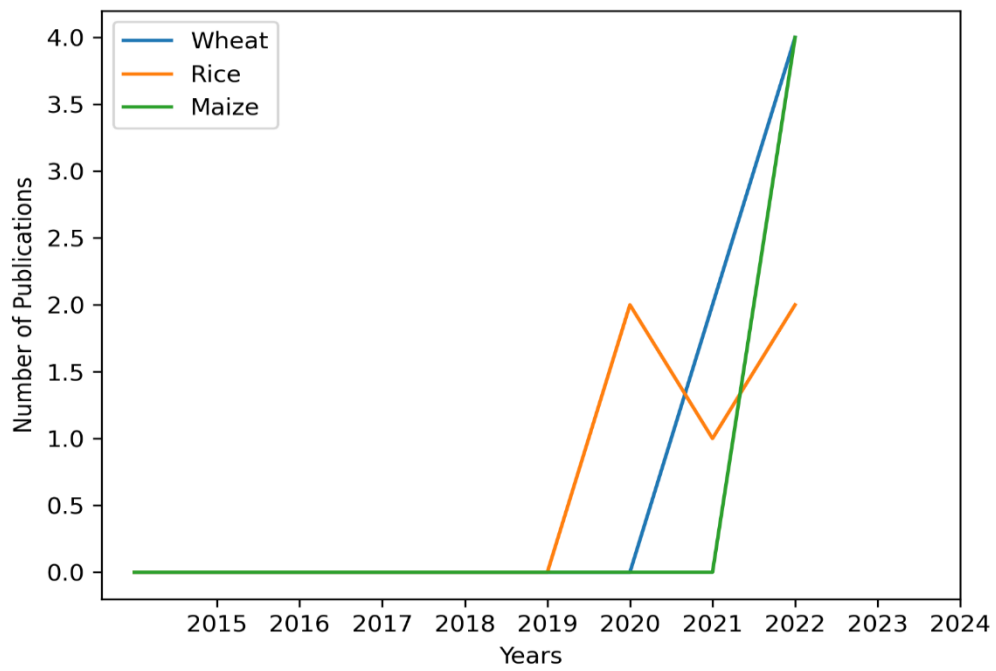


Figure 2.4: Year-wise publications concerned with Disease Detection

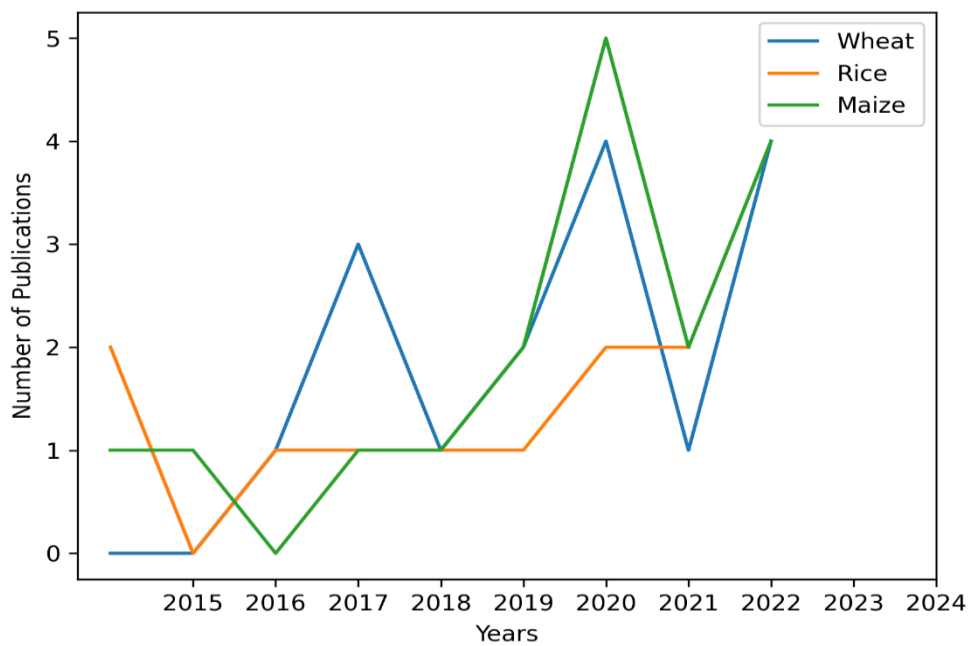


Figure 2.5: Year-wise publications concerned with Irrigation scheduling

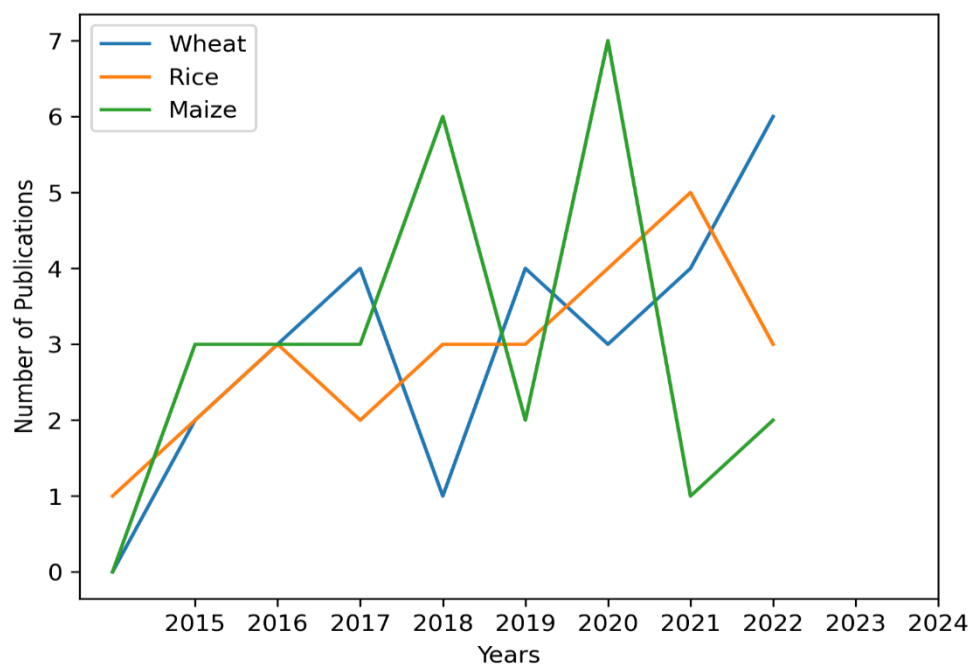


Figure 2.6: Year-wise publications concerned with Nutrient deficiency detection

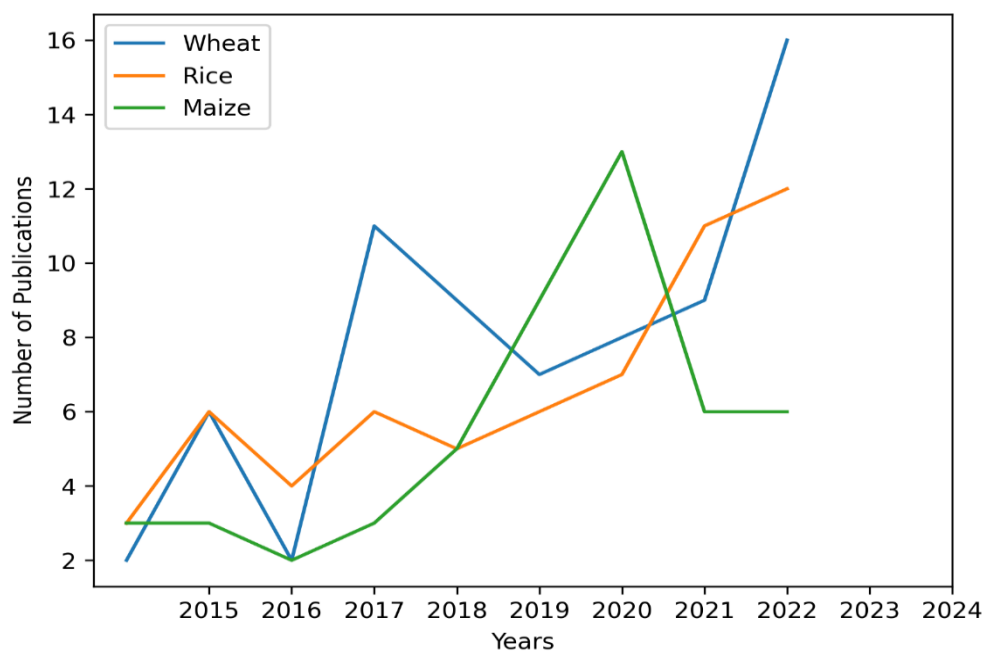


Figure 2.7: Year-wise publications concerned with Soil content sensing w.r.t different crops

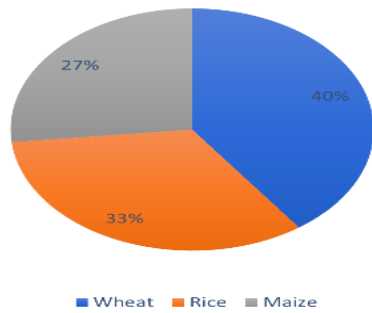


Figure 2.8: Share of AI-related publications in Disease Detection

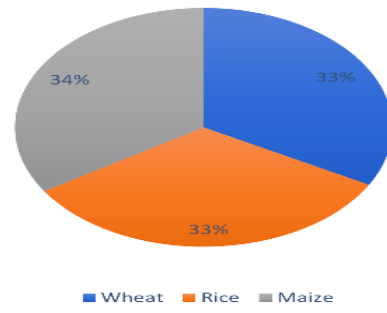


Figure 2.9: Share of AI-related publications in Irrigation Scheduling

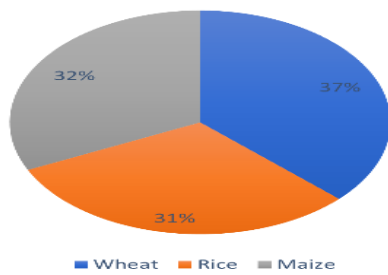


Figure 2.10: Share of AI-related publications in Nutrient Deficiency Detection

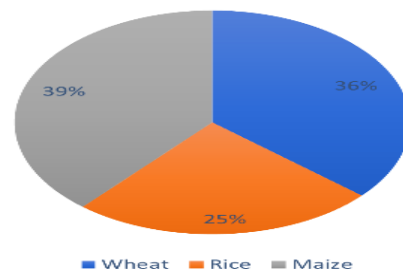


Figure 2.11: Share of AI-related publications in Soil Content Sensing

cultivation is poised to benefit significantly from AI-driven insights, ensuring sustainable and efficient farming practices.

2.4.3 Geographical distribution

Top productive countries

A total of 115 nations have made significant research contributions in agriculture from 2015 to 2024, as displayed in Figure 2.12, the global distribution of research papers. With 1938 research documents, India leads the field with 874 documents. Next in line are China with 635 contributions, the USA with 457, Australia with 283, and Pakistan with 198 research materials. To add, less than 1% of the contributing countries have published research in this area. Apart from this, the top 10 most productive nations in

the field of agriculture have been enumerated in Table 2.2. It has been inferred that in

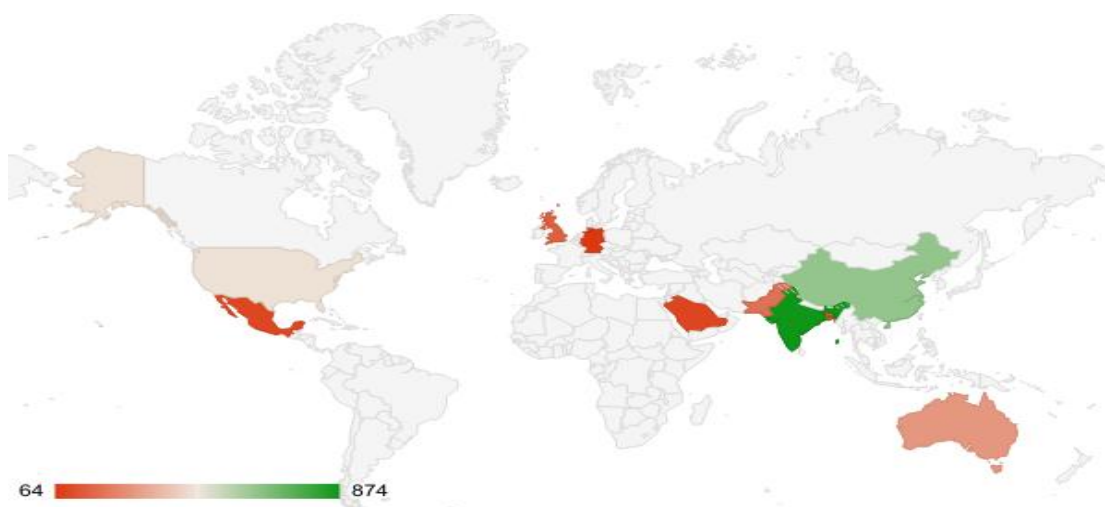


Figure 2.12: Research activities worldwide from 2015 to 2024

Table 2.2: Top Ten Productive Countries

Country	Documents	Citations	Total Link strength
China	635	24200	1080
India	874	17953	871
United States	457	24219	820
Australia	283	9834	672
Pakistan	198	6209	529
United Kingdom	155	8801	436
Bangladesh	116	2686	288
Saudi Arabia	94	1419	273
Mexico	97	4840	270
Germany	64	1956	244

all categories, most of the documents have been provided by India, China, and the USA. This can be attributed to the fact that India and China, predominantly agrarian economies, are making substantial investments driven by research and development. Improving rural infrastructure through subsidies and adopting increasingly liberalized agricultural policies [81] are also goals of these countries. In contrast, the USA has a strong, industrialized agricultural sector that relies heavily on technology, innovation, and extensive research efforts.

Countries collaboration

Collaboration among nations is essential to address global food demand, persistent malnutrition, and agricultural challenges. Joint efforts can focus on developing high-yield, climate-resilient crop varieties capable of withstanding erratic weather, pests, and diseases. Promoting diversified [82] farming systems, such as intercropping, can enhance sustainable food production, stabilize harvests, and reduce reliance on harmful agrochemicals. Shared resources and research can improve irrigation, optimize water use, and support breeding efforts for crops like rice to adapt to evolving diseases and environmental stresses. Such global cooperation ensures more robust and sustainable agricultural systems for the future.

Further, the network of cooperation between several nations can be perceived from Figure 2.13. The criteria to demonstrate the interconnection among nations have been framed as a minimum of 5 documents required for the selection of 59 nations out of 115 in total. Further, based on links and total link strength, it can be concluded that China has made the top notch with 56 links with a total link strength of 1080, with India coming at second position with 56 links and a total link strength of 871. Also, the USA and China have maximum collaboration with a link strength of 210. Other countries compared to these nations are Australia (green node), Pakistan (green node), and the United Kingdom (red node), which have a maximum number of publications and have conducted a sizable amount of cooperative research records.

Co-authorship data, while useful for analysing collaboration, has limitations. It assumes active collaboration, though some authors may have minimal involvement, and norms

for co-authorship vary across disciplines, potentially overrepresenting collaborations in Science, Technology, Engineering, and Mathematics (STEM) fields. Additionally, it emphasizes quantity over the quality of partnerships. Database biases further limit the accuracy, as regional journals, non-English publications, and smaller outlets are often underrepresented, marginalizing contributions from developing countries and less-resourced areas.

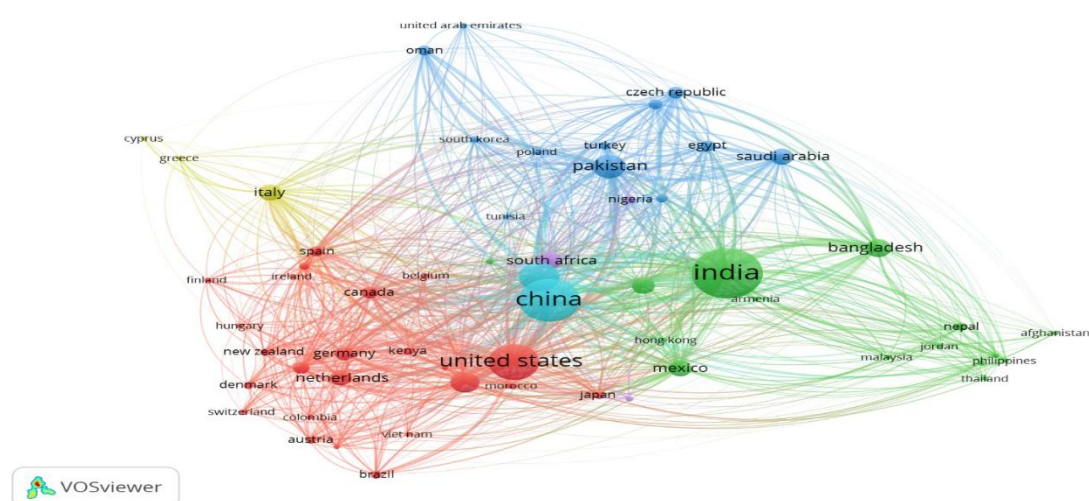


Figure 2.13: Countries' collaboration network based on citations concerned with the presented study

Source: Scopus; data retrieved on 28th November 2023

2.4.4 Citation analysis

In a scientometric study, citation analysis of journals is necessary to identify the most prominent journals within the given subject. The top-cited journals for each agricultural activity are shown in Table 2.3 along with their total citations (c), number of publications (p), total share of publications (p%), impact factor (IF), and citations per publication (cp), considering the aforementioned information. According to the analysis, the Journal of Nanoparticle Research has been concluded as the most influential journal in the soil category, with 441 citations, followed by International Soil and Water Conservation Research in the soil category, with 436 citations. With an

impact factor of 9.473, *Environmental Science: Nano* is a prominent, high-impact journal specializing in nanoscale materials and their interactions with the environment. Its scope covers both the positive applications and potential risks of engineered, natural, and incidental nanomaterials in air, water, soil, and other environmentally significant systems. Further, *Science of the Total Environment* is a high-impact international journal with an impact factor of 10.3, focusing on interdisciplinary research. Journal, focusing on soil management and conservation, has an impact factor of 4.5 and is particularly relevant for studies on nutrient deficiency and soil health.

Table 2.3: Influential Journals in the field of carried research

	Source titles	C	No. of Publications(p)	%p	IF	cp
Disease Detection	Microbiological Research	110	1	2.7	6.1	110
	Applied Microbiology and Biotechnology	91	1	2.7	3.9	91
	ACS Sustainable Chemistry and Engineering	114	3	8.3	7.1	15.33
	Environmental Science: Nano	244	1	2.7	9.473	244
	Journal of Nanoparticle Research	441	1	2.7	2.1	441
Irrigation Scheduling	Agricultural Water Management	122	18	11.467	5.9	42.5
	ACS Sustainable Chemistry and Engineering	114	1	0.6343	9.1	114
	Science of the Total Environment	176	10	6.367	10.3	32.3

	Ecotoxicology and Environmental Safety	127	1	0.633	7.4	127
	Environmental Science and Pollution Research	128	6	3.826	5.9	49.5
Nutrient deficiency	Science of the Total Environment	160	5	4.54	10.3	53
	Archives of Agronomy and Soil Science	156	3	2.72	2.3	56
	Soil and Tillage Research	113	5	4.54	7.07	61.8
	Journal of the Science of Food and Agriculture	197	1	0.9	3.64	197
	Environmental Research Letters	153	1	0.9	5.8	153
Soil content sensing	International Soil and Water Conservation Research	436	6	2.89	3.770	121.33
	Soil and Tillage Research	185	52	25.12	7.07	37.78
	Archives of Agronomy and Soil Science	156	12	5.79	2.242	31.08
	Journal of Soils and Sediments	125	1	0.48	2.8	125

Most Cited articles

The most highly quoted articles in each agricultural practice driven by AI have been identified and listed in Table 2.4, in addition to the name of the journal, the publishing

year, and the citations. It has been found that the most cited paper across all categories is Bhatt R's Sustainability Issues on rice-wheat cropping system in the International Soil and Water Conservation Research journal in the category of soil nutrient deficiency detection. This publication was published in 2016 and has received 206 citations. During analyses, it was found that the publications related to soil nutrient deficiency detection have the most citations. However, as indicated in the table, the low citation counts for recent research papers on disease detection can be attributed to a factor [83] AI applications in agriculture are still in their infancy, and advanced methods such as deep learning and federated learning in disease detection require time for validation and practical field implementation. Additionally, these approaches are relatively new in the academic domain. Citations typically take time to grow as researchers need to read, interpret, and incorporate recent findings into their work.

Table 2.4: Most cited articles related to the undertaken study.

	Sub- category	Title	Journal Name	Year	Citation
Disease detection	Wheat	Early Recognition of Wheat Powdery Mildew Disease Based on Mask RCNN	2022 International Conference on Data Analytics for Business and Industry, ICDABI 2022	2022	3
	Rice	Rice Diseases Multi- Classification: An Image Resizing Deep Learning Approach	2021 International Conference on Decision Aid Sciences and Application, DASA 2021	2021	6

	Maize	Revolutionizing Maize Disease Management with Federated Learning CNNs: A Decentralized and Privacy-Sensitive Approach	2023 4th International Conference for Emerging Technology, INCET 2023	2023	5
Irrigation scheduling	Wheat	Improving/maintaining water-use efficiency and yield of wheat by deficit irrigation: A global meta-analysis	Agricultural Water Management	2020	77
	Rice	Effect of water management and silicon on germination, growth, phosphorus, and arsenic uptake in rice	Ecotoxicology and Environmental Safety	2017	127
	Maize	Maize plant nitrogen uptake dynamics at limited irrigation water and nitrogen	Environmental Science and Pollution Research	2017	128
Nutrient deficiency	Wheat	Effects of manganese nanoparticle exposure on nutrient acquisition in wheat (<i>Triticum aestivum</i> L.)	Agronomy	2018	82
	Rice	Effect of nutrient management on soil	Environmental Monitoring	2018	22

		organic carbon sequestration, fertility, and productivity under rice-wheat cropping system in semi-reclaimed sodic soils of North India	and Assessment		
	Maize	Conservation agriculture and precision nutrient management practices in maize-wheat system: Effects on crop and water productivity and economic profitability	Field Crops Research	2018	48
Soil content sensing	Wheat	Sustainability issues on rice–wheat cropping system	International Soil and Water Conservation Research	2016	206
	Rice	Soil physical properties, yield trends, and economics after five years of conservation agriculture-based rice-maize system in north-western India.	Soil and Tillage Research	2016	118

Maize	Long-term effect of conservation agriculture in maize rotations on total organic carbon, physical and biological properties of a sandy loam soil in north-western Indo-Gangetic Plains	Soil and Tillage Research	2016	141
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Citation distribution

Citations are an authentic representation, demonstrating the significance of research articles published. An examination of the distribution of citations in publications has been presented in Table 2.5 for agricultural practices from the standpoint of AI. In the disease category of the same statistics, 70% of publications have 1-4 citations in the wheat category, and 30-40% of publications have not been cited by other than rice. Also, there is no document that has received over 11 citations in disease detection.

For irrigation scheduling, it has been implied from the statistics that 14-22% of publications are in each division of scale, with more than 100 citations in the case of wheat. Whereas rice and maize account for 4% and 7% of publications cited above 100. Also, nearly 20% publications lie in the 1-4 and 5-10 citation scale in each category of rice and maize.

Most research documents on nutrient deficiency in reference to wheat have received 10-20% citations in each division of scale, except 1-4 and above 100. Publication in each crop of Nutrient deficiency, that is, wheat, rice, and maize, does not exceed the scale of 100 citations. In addition, 15-30% of publications have been cited in each slab of scale, except for 1-4 and above 100 in rice crop. Likewise, in Maize, 15-25% of publications are cited in each division of scale except above 50.

The citation structure of publications in soil content sensing indicates that documents with above 100 citations for wheat have been 3.22%, while 12% of publications have been determined in rice, in addition to 11.11% of publications for the maize crop. Further, nearly 30% of publications lie in the 21-50 citation scale in the case of wheat and rice. It is also observed that many publications in the maize subcategory have been classified on a 5-10 scale.

Table 2.5: Citation distribution of publications in each considered category

		0	1-4	5-10	11-20	21-50	51-100	>100
Disease Detection	Wheat	30	70	0	0	0	0	0
	Rice	6.25	18.75	75	0	0	0	0
	Maize	37.5	62.5	0	0	0	0	0
Irrigation scheduling	Wheat	22.2	14.81	14.81	14.81	18.5	18.5	0
	Rice	4	20	20	16	24	12	4
	Maize	7.4	18.51	18.51	14.81	22.2	11.1	7.4
Nutrient deficiency	Wheat	12.5	31.25	12.5	12.5	18.75	12.5	0
	Rice	18.18	45.45	18.18	18.18	27.27	18.18	0
	Maize	23.52	17.64	17.64	17.64	23.52	0	0
Soil content sensing	Wheat	12.9	19.3	12.9	12.9	32.25	6.4	3.22
	Rice	8	16	8	16	32	8	12
	Maize	16.67	11.11	22.22	16.67	16.67	5.55	11.11

2.4.5 Co-occurrence analysis of keywords

Co-occurrence analysis of keywords helps identify the main topics of research in disease detection, nutrient deficiency of crops, soil content sensing, and irrigation

disease control, physiology, microbiology, soil pollution, biochar); Cluster 3(Agriculture, nitrogen, fertilizer application, China, greenhouse gases, water quality, manure, nitrous oxide); Cluster 4(Urea) and Cluster 5(Microbial activity). While the clusters highlight key research areas, gaps remain in integrating emerging technologies like precision agriculture and AI, addressing social and policy aspects such as farmer welfare, and exploring specific climate resilience topics like biodiversity and extreme weather adaptation. Additionally, there is limited focus on intersectional research linking sustainability, economics, and technology adoption. In the subsequent data analysis, various key elements of agriculture have been listed in Table 2.6, including the average publication year (m), total link strength (TLS_k), links between keywords (L_k), and frequency of recurrence (F_k).

Table 2.6: Important areas of research

Keywords in disease detection	F_k	L_k	TKS_k	m	Keywords in Irrigation Scheduling	F_k	L_k	TLS_k	m
Disease Detection					Irrigation Scheduling				
Convolutional neural networks	26	15	163	2022	Agriculture	48	18	182	2017
Learning systems	15	15	115	2023	Crop yield	35	18	172	2018
Agriculture	22	15	107	2022	Maize	29	17	143	2017
Disease detection	16	15	100	2022	China	34	18	138	2017
Federated Learning	11	14	90	2023	Zea mays	25	17	137	2017

Leaf disease	12	15	89	2023	Wheat	28	18	136	2018
Crops	16	15	87	2022	Water use efficiency	29	18	135	2017
Diseases	11	15	79	2023	Crops	32	18	131	2018
Diagnosis	10	14	70	2023	Crop production	23	18	122	2018
Disease control	14	15	70	2022	Rice	25	18	119	2017
Deep learning	14	15	68	2022	India	24	18	117	2017
Disease classification	10	15	66	2023	Triticum aestivum	20	17	110	2017
Food Supply	10	15	57	2021	Water	23	18	108	2017
Plant disease	10	12	26	2021	Water conservation	20	18	106	2017
Nutrient Deficiency					Soil Content Sensing				
Nutrients	37	23	200	2019	Organic carbon	114	19	667	2019
Agriculture	30	22	185	2019	Carbon	66	19	421	2020
Fertilizers	22	23	143	2019	Nitrogen	70	19	404	2020
Nonhuman	14	23	116	2021	India	77	19	372	2019
Nitrogen	15	23	112	2020	Wheat	73	19	361	2019

Phosphorous	15	22	100	2020	Crops	65	19	356	2019
Nutrient availability	14	22	84	2019	Fertilizers	60	19	351	2020
Wheat	12	23	81	2020	Soil Quality	74	19	344	2019
Carbon	10	22	79	2020	Soil Conservation	60	19	325	2019
Nutrient Management	13	23	79	2020	Carbon sequestration	66	19	322	2019
Fertilizer application	12	23	72	2020	Crop production	62	19	299	2020
Crop yield	13	23	68	2021	Conservation agriculture	78	19	202	2020
Nutrient uptake	10	18	42	2020	Article	84	19	483	2020
Nutrient use efficiency	10	17	24	2020	Soil organic matter	65	19	361	2019
Crops	16	21	67	2020	Soils	153	19	752	2020
Maize	11	21	66	2020	Agriculture	195	19	901	2020

2.4.6 Author Analysis

The authors' analysis has been performed in this section utilizing a 3-field plot for every category of agricultural practices. A three-field plot, developed using the R-based biblioshiny application, integrates a web interface for comprehensive analysis of science mapping data. This study utilizes the tool to visualize relationships among institutions, authors, and countries [84].

A Sankey diagram visually represents flows between data points, with path widths indicating quantities, aiding in path analytics, and simplifying complex data understanding. Along with this, the magnitude of the rectangular box indicates the quantity of documents in a specific area. The boxes' large size suggests that the entity is dominant. To add, Sankey diagrams connect these 3 domains, i.e., Author-Affiliation-Country. Sankey diagrams are used to depict details regarding relationships. Furthermore, interesting facts from the plots have been deduced as follows:

1. Figure 2.15 represents a 3-field plot of published work based on disease detection. The top 20 productive authors have been selected based on their maximum publications. Kukreja from India has the highest number of publications and a strong relationship with Chitkara University, followed by White from the USA, who has a strong relationship with Connecticut Agricultural Experiment Station.
2. Another 3-field plot of nutrient deficiency-related articles has been displayed in Figure 2.16. Out of 20 influential writers, (i) Kumar from India dominates with the maximum publications linked to ICAR institutes, (ii) Patra Ak also has a significant number of publications.
3. Apart from this, the 3-field plot of irrigation scheduling-related publications has been presented in Figure 2.17. In this, out of the top 20 authors, Jal ML from India dominates with the maximum documents strongly linked to the ICAR, the Indian Council of Agricultural Research.
4. Lastly, the 3-field plot of soil content sensing-associated publications has been displayed in Figure 2.18. Herein, out of the top 20 significant authors, Lal r from

India has the maximum publications strongly linked to ICAR Indian Agricultural Research Institute.

The three-field plot is a valuable tool for visualizing relationships among authors, institutions, and countries, but it is not free from biases. Institutional policies and disparities in research funding can distort the representation, with well-funded institutions or regions dominating the visualization due to greater access to resources and networks. This often overshadows contributions from underfunded or less visible entities, creating a skewed perception of global research dynamics.

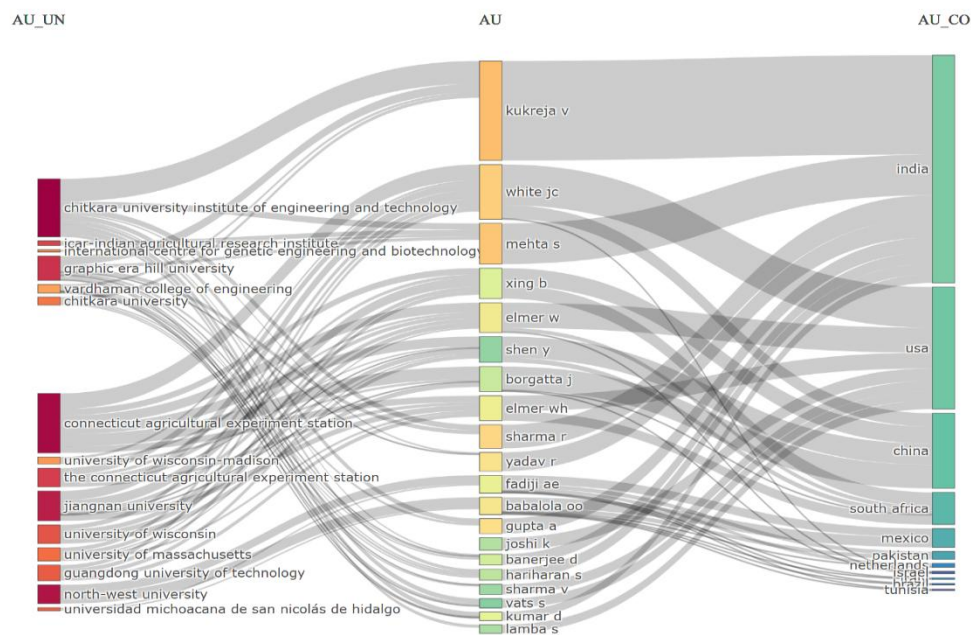


Figure 2.15: Three-field plot for disease detection based on the number of publications

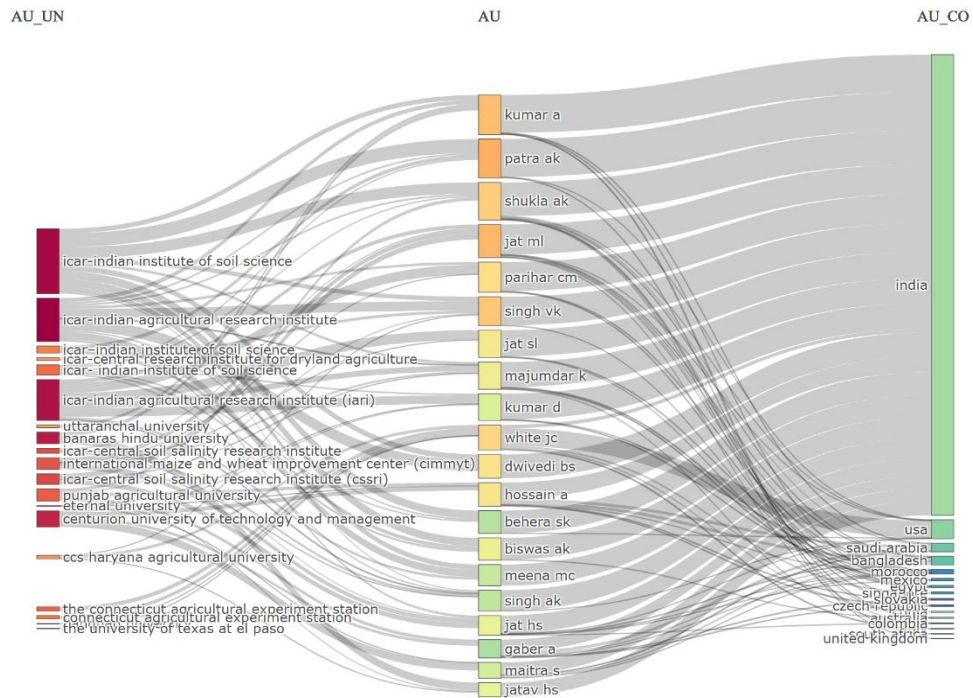


Figure 2.16: Three-field plot for nutrient deficiency based on the number of publications

Regional differences in publication practices further exacerbate these biases, as research from countries with limited access to high-impact journals or non-English publications may be underrepresented. Additionally, the metrics chosen—whether total publications, citations, or other indicators—strongly influence the interpretation. Metrics focusing on quantity may prioritize volume over impact, while citation-based metrics may disproportionately highlight established researchers or institutions.

To mitigate these biases, normalization techniques could be applied to balance disparities, and a combination of metrics might provide a more comprehensive view. Transparent justification of metric selection would further enhance the fairness and credibility of the analysis, enabling a more balanced understanding of global research contributions.

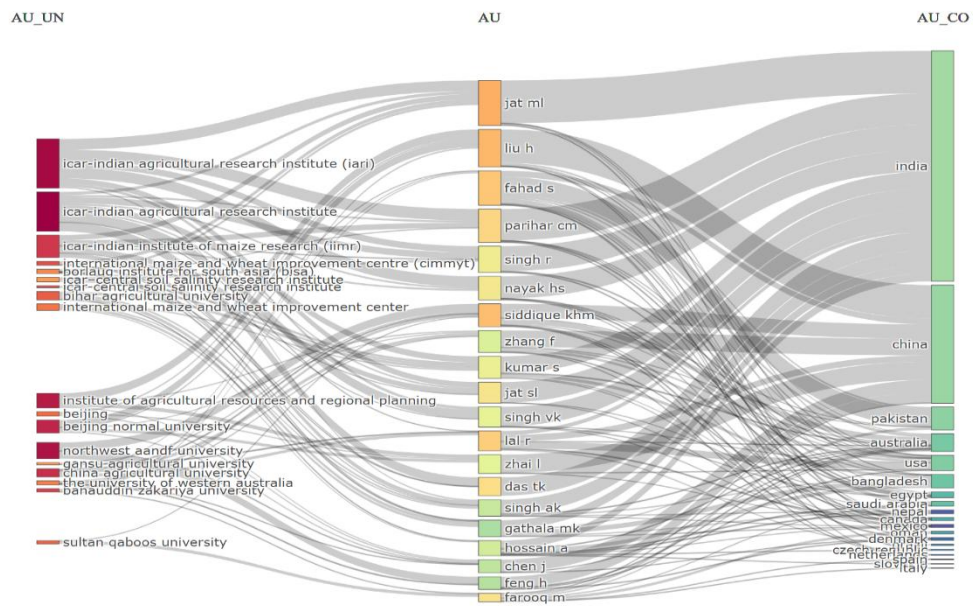


Figure 2.17: Three-field plot for irrigation scheduling based on the number of publications

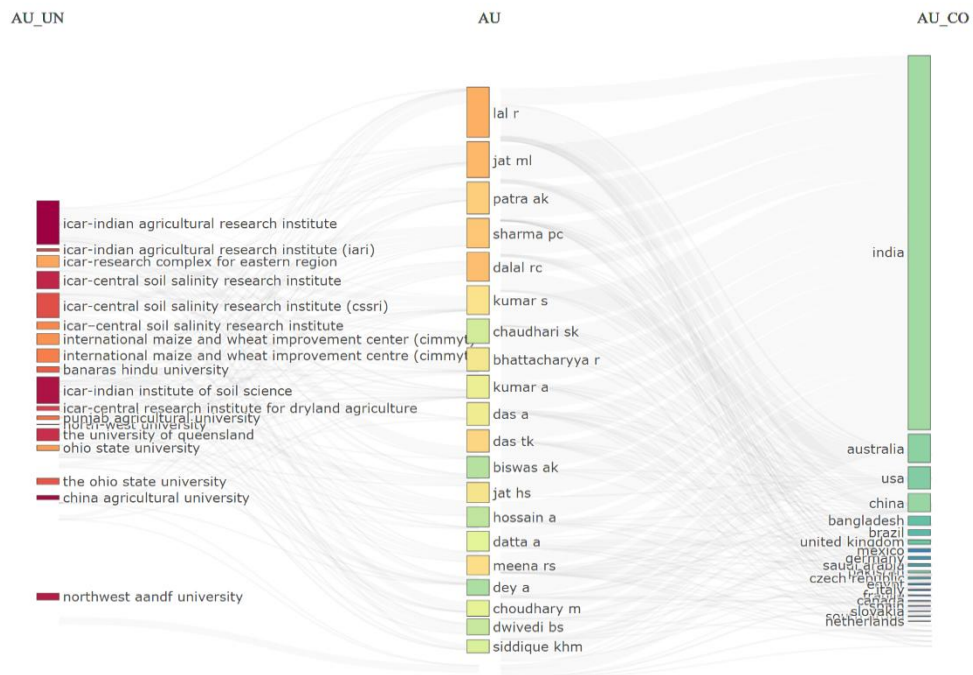


Figure 2.18: Three-field plot for soil content scheduling based on the number of publications

2.4.7 Institutional Analysis

The tremendously diversified citation network amongst institutions has been indicated by the high density of linkages as presented in Figure 2.19. The network illustrates strong research partnerships between institutions, with central nodes like ICAR (Indian Council of Agricultural Research) driving knowledge dissemination. Frequent collaborations enhance visibility and reputation, while dense clusters foster efficient information sharing within groups. Interconnected clusters enable cross-disciplinary exchange, promoting holistic agricultural research. It can be identified from the same that Stockbridge School of Agriculture (Blue cluster), Indian Council of Agricultural Research (Red Cluster), Academy of Biology and Biotechnology (Yellow Cluster), College of Resources and Environmental Sciences (Green cluster), The UWA Institute of Agriculture (Orange cluster), University of Naples feredico ii (Violet cluster) and Institute of Agricultural sciences (Brown Cluster) have received maximum citations by their respective clusters. Stockbridge [85] offers AS, BS, MS, and PhD programs with experiential learning, internships, and access to top researchers, making UMass a leader in agricultural sciences. Research spans diverse areas, including sustainability, agroecology, climate change, plant sciences, and regenerative agriculture, while students gain practical skills by managing the UMass Student Farm. ICAR is India's apex body for coordinating agricultural research [86] and education, with 113 institutes and 74 universities, making it one of the largest systems globally. It has driven the Green Revolution and boosted food production significantly, ensuring food security and advancing agricultural education while excelling in innovative research recognized worldwide. The Academy of Biology and Biotechnology likely emphasize biotechnological advancements in agriculture, such as genetic modification and molecular breeding. Its work aims to enhance crop yields and pest resistance, focusing on innovative, technology-driven solutions. The College of Resources & Environmental Sciences (CRES), China [87], [88] advances research in soil, water, agro-meteorology, and ecological sciences, hosting key national and international programs. With notable faculty, field stations, and high-impact publications, it fosters innovation in sustainable resource and environmental management. The research themes at UWA, Australia [89], address sustainable agriculture and food systems through innovative solutions. Key areas include optimizing crop and livestock systems,

efficient water use, functional food development, agricultural engineering, and enhancing agribusiness ecosystems to meet global food security and environmental challenges. The Agriculture Department of the University of Naples Federico II, Italy, contributes to advancing sustainable agriculture through innovative research in crop science, soil management, and food systems, addressing global agricultural challenges [90].

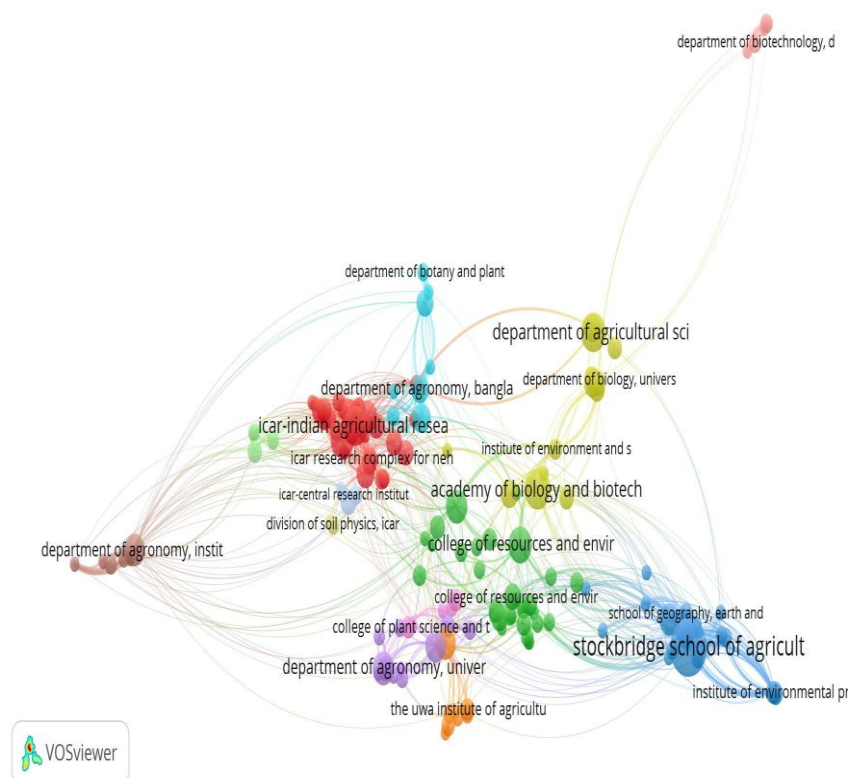


Figure 2.19: Coupling network among institutions

2.4.8 Coupling Analysis among Journals

As illustrated in Figure 2.20, the bibliographic coupling network between journals shows several clusters. These include the primary organizations in each of the network's clusters: Environmental Science and Pollution Research (Red Cluster), Agronomy (Green Cluster), Science of Total Environment (Blue Cluster), and Soil and Tillage Research (Yellow Cluster).

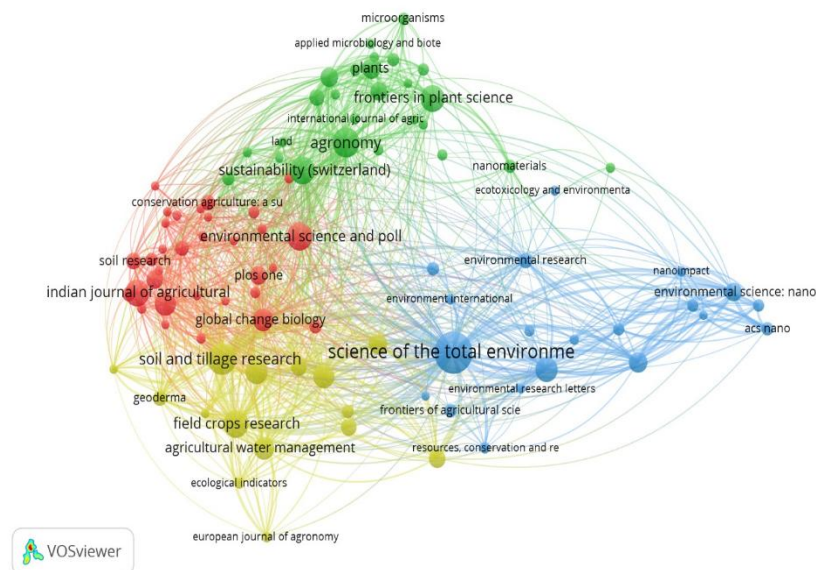


Figure 2.20: Coupling network among journal

Further, the journals in the respective clusters, which have been mentioned significantly for citations, are "Science of the Total Environment", "Soil and Tillage Research", "Agronomy", and "Field Crops Research". It's vital to note that the journals that are not part of any cluster indicate that, despite being important publications, they have no references in common with any other journal in the network. For instance, the Journal of Basic Microbiology focuses on primary research with microorganisms and innovative imaging techniques.

Sustainable practices, internet connectivity, and technological innovation are critical to agriculture's future. In this direction, journals can usher the agricultural industry to use innovations like AI, robotics, and biotechnology [91], [92] to boost productivity and efficiency to feed the world's expanding population [93]. Prioritizing climate resilience, ethical behaviour, and environmental sustainability all at the same time is also essential [94], [95].

2.5 Literature Review

The investigation into automating agricultural practices has become increasingly relevant considering current developments in the machine learning sector. Therefore, this section further reviews research on automated disease detection, nutritional

deficiency, irrigation scheduling, and soil content impact as shown in Figure 2.21 in various crops using statistical approaches and machine learning. To get an overview of agricultural practices, this part (i) classifies the many strategies currently in use and (ii) examines the main ideas and standardized procedures found in the current literature. In view of the aforementioned, a structure with four characteristic branches—Disease detection, Nutrition deficiency, Irrigation scheduling, and soil content sensing has been created. This has been followed by an extensive and methodical analysis of current techniques. In addition, a comprehensive survey that highlights the salient characteristics and constraints of the contemporary state-of-the-art has been provided.

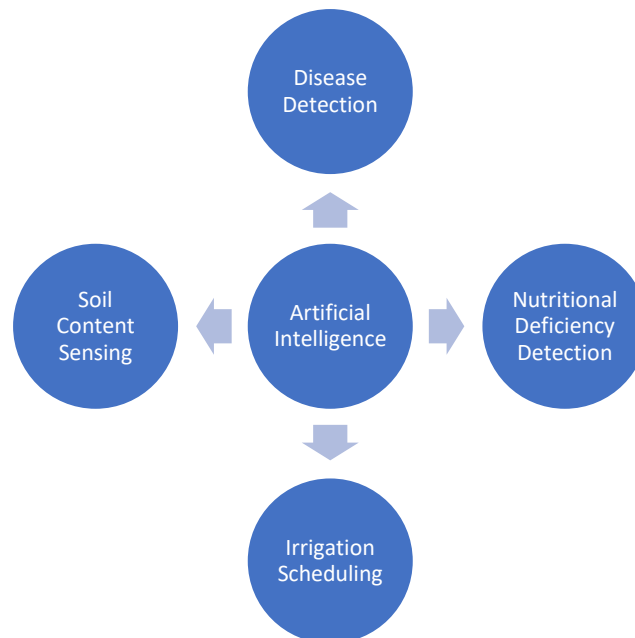


Figure 2.21: Distinct AI-dependent agriculture domains

2.5.1 Disease Detection

Diseases are one of the major factors that lead to huge food loss across the world. The early detection of diseases can play an important role in preventing damage to the crops. Recently, artificial intelligence has been doing a great job in agriculture for disease detection.

Lakshay in 2021 used machine learning algorithms [47] to categorize wheat diseases. The large wheat disease classification dataset (LWDCD2020) has been used to classify the following diseases: wheat loose smut, tan spot, powdery mildew, leaf rust, fusarium

head blight, crown & root rot, black chaff, karnal bunt, and wheat streak mosaic. CNN, the core neural network, has been efficiently trained to accept images and label them with disease classes. CNN outperformed pre-trained networks VGG-16 and Resnet, accuracy is improved significantly.

In 2022, Ananda [17] emphasizes the recognition and categorization of illnesses in various plants, particularly tomatoes and grapes. Utilizing pre-trained CNN-based VGG16 models, the performance has been enhanced. The VGG16 model has been trained and tested after the augmentation of data and the preprocessing done on the dataset. With the proposed research work, the accuracy for tomatoes increased by 95.71% and for grapes by 98.40%. Further, Table 2.7 enumerates the various models used in research along with the datasets on which algorithms have been trained. Parameters on which multiple studies have been evaluated have also been mentioned, in addition to key findings.

Amandeep, in 2023, framed an automated system [43] for rice to detect the disease of leaf blast. The colour-slicing method is used to extract the desired image of leaves from the background. Gray Level Co-occurrence Matrix is further utilized to deduce features, contrast, correlation, energy, and homogeneity to determine the texture of leaves. A variety of machine learning classifiers, including random forest, KNN, decision tree, XGBoost, AdaBoost, and a histogram-based gradient boosting technique, use the retrieved features as input. After analysing various performance metrics, the author concluded that the random forest classifier method gives a maximum accuracy of 99.10%, sensitivity of 99.05%, and specificity of 99.05%.

In 2023, Vitor [28] conducted research to identify tomato bacterial spot disease, which negatively impacts tomato output on a huge scale. Firstly, a novel data reduction process was created to produce the reduced datasets. Twelve crucial wavelengths were found from the hyperspectral camera's first 300 scans. These wavelengths have the largest weighted spectral components and are therefore most important for correctly identifying plants damaged by TBS. Two normalisation techniques have been employed to preprocess the data: one is a standardisation approach, and the other is unit vectorisation as part of a dynamic range expansion process. Reduced datasets and time-limited stages of disease development were used as input variables in the models. Five

optimized machine learning algorithms (MLAs) were used to detect TBS early in transplant houses. These algorithms included Support vector machines (SVM), ensemble boosting trees (EBT), weighted K-nearest neighbors (WeKNN), partial least squares discriminant analysis (PLSDA), and linear discriminant analysis (LDA). After cross-validation, the PLSDA that was trained using the dataset that had been pre-processed using the standardization method produced the most optimal mean accuracy. On early TBS detection, the PLSDA technique had the maximum F1 score, which is 90% overall.

Table 2.7: Disease detection publications

Reference Study	Model Used	Dataset	Parameters	Key- Points
Goyal et al. [47] (2021)	CNN	LWDCD 2020 Dataset	Accuracy 97.88%, Precision, recall, and f-score 0.98	10 types of wheat diseases have been identified, and accuracy is improved with moderate usage of resources
Paymode et al. [17](2022)	Visual Graphics Geometry16	Plantvillage dataset	Accuracy 98.04% for grapes and 95.71% for tomatoes	A pre-trained model improves accuracy for the given dataset
Singh et al. [43] (2023)	Color slicing + GLCM to extract texture features. Various classifiers- random forest, kNN, decision tree, XGBoost, AdaBoost, and Histogram-based gradient boosting algorithm- were used to classify	Not available	Accuracy 99.10%, sensitivity 99.05%, specificity 99.05%. F1score 98.69%, False discovery rate 1.28%	Random Forest achieves High Accuracy.

Gontijo et al. [28] (2023)	LDA, PLSDA, Weighted K-Nearest Analysis, SVM, EBT	Not Available	PLSDA F1-score 90%	A new approach for data reduction has been proposed to accurately diagnose asymptomatic TBS.
Ibrahim et al. [96] (2025)	ResNet50	NPDD	Accuracy 99.8 %	High Computational cost

Ibrahim et al. (2025) employed the transfer-learning ResNet50 architecture [96] to categorize eleven classes of pepper, potato, and tomato crops, including 3 healthy and 8 diseased classes. In total, 25940 images from the New Plant Diseases Dataset (NPDD) have been used to train, validate, and test the model with 70%, 20%, and 10%, respectively, over 30 epochs. The study further integrates AI with a Raspberry Pi-controlled pivot to provide real-time diagnosis of diseased leaves. It employs SIM800 GSM/GPRS to alert farmers about classified disease classes. Moreover, it automates the spraying of fertilizers to cure diseased plants. The proposed method achieved a test accuracy of 99.8%, 100% precision, 99.92% recall, and an F1-score of 99.91 %. Nevertheless, a mobile application, PLANTUM, assists farmers in automating treatment with irrigation infrastructure.

Remarkably advanced algorithms have been designed to detect diseases of the crops at the earliest stages for crops such as wheat, rice, tomatoes, and grapes. Following this, there is a large scope to explore image-based techniques along with the quantification of severity in other crops. Therefore, a comprehensive framework that can also recommend the correct fungicide based on the extent of disease in the banana crop has been designed in Chapter 3.

2.5.2 Nutritional Deficiency

Nutrient imbalances frequently cause problems for crop production. The leaves of plants frequently exhibit symptoms of malnutrition. Consequently, nutrient shortages can be identified by looking at the color and form of leaves. Agriculture is increasingly

using computer vision-based autonomous picture processing to diagnose nutrient deficiencies. Table 2.8 depicts the major datasets of images used in the research.

The literature research reveals that several machine learning algorithms have been trained in several studies to identify nutritional deficits in a variety of flora. If the detection of the loss minerals concentration can be executed early enough, production can be raised. For optimum growth, crops require 16 key nutrients, namely macronutrients and micronutrients, in a regulated ratio. In general, macronutrients are necessary for the growth of plant cells and tissues and are concentrated more than micronutrients. N, P, K, Ca, S, and Mg are macronutrients, whereas Fe, Zn, Cu, and Mn are micronutrients.

To identify nutrient deficiencies in rice, Talukar et al. [31] in 2023, developed a highly accurate DECNN model. Pre-trained models, including DenseNet121, DenseNet169, DenseNet201, modified InceptionV3, and modified InceptionResNetV2, have been used in several tests with an appropriate number of pooling layers, dropout layers, and dense layers added on an upgraded dataset from Kaggle with 1156 images, of which 333, 383, and 440 images, 333 and 383 are damaged by Phosphorus, Potassium, and Nitrogen deficiency, respectively. Test accuracy has significantly improved on an individual basis. The maximum testing accuracy is achieved by Modified DenseNet169, which incorporates the suggested layer, augmentation, and transfer learning methods. Ultimately, 98.33% accuracy was attained by the combination of improved DenseNet169, DenseNet201, and InceptionV3 models, where their respective weights are as follows: $W_k = [0.4, 0.1, 0.2]$, $K=1, 2, 3$.

In 2023, Rahadiyan et al. [29] combined three types of features: color, texture, and shape to determine nutrient deficiency in chilli plants. Hu moments and centroid distance are used to represent forms, texture features are determined by LBP and GLCM, and color values by HSV and RGB. The same multi-layer perceptron architecture is utilized for training as well as testing each feature and its combinations. The optimal performance is reached on RGB images, with GLCM implemented, Hu moments further capture features, and Centroid Distance has been considered. Furthermore, the MLP architecture employed in this work is contrasted with earlier research using CNN, SVM, Random Forest, and Naïve Bayes. Results obtained by

CNN are the finest with 97.76% accuracy, with SVM and MLP following it. Despite CNN's higher accuracy, MLP achieves a high rate of success in the case of diagnosing plant health issues in a basic agricultural setting.

This review has also found that many datasets have been created for researchers and students who can design better machine learning models and train them with the generated dataset to achieve high accuracy, like banana [30]. Images of banana leaves from several categories, including Robusta, Rasthali, Musa acuminata (Dwarf Cavendish), Poovan, Monthan, and Elakkibale, make up the produced dataset. Eight classes of nutrients are represented by deficiencies in the images: sulphur, calcium, iron, potassium, manganese, magnesium, and zinc.

Another dataset, which can catalyze research about the properties of coffee leaves, is also available [77]. The CATIMOR coffee, CATURRA coffee, and BORBON coffee variety datasets from cultivation in Peru are presented in this article. Agronomists used a physical structure to identify the leaves with nutritional deficits, created a controlled atmosphere, and took digital camera pictures. The collection includes 1006 leaf photos categorized by nutritional inadequacies (nitrogen, sulfur, iron, and more). This dataset, named Coleaf, includes photos to train and validate algorithms to identify and categorize nutritional deficits of coffee plant leaves.

Table 2.8: Nutritional deficiency dataset sources

Reference Study	Dataset
Talukar et al. [31]	Kaggle
Rahadiyan [29]	Not available
Sunitha et al. [30]	Mendeley Data
Tuesta-Monteza et al. [77]	Mendeley Data

Existing studies have considered the categorisation of nutrient deficiencies of crops from visual symptoms of discoloration and chlorosis. However, other factors, such as soil parameters, have been completely neglected. Therefore, a framework has been presented in Chapter 4 that suggests the correct fertilizer amount after thoroughly analysing images, in addition to consideration of soil factors to mitigate the nutrient shortage.

2.5.3 Irrigation Scheduling

Approximately two-thirds of freshwater worldwide is used for agricultural irrigation, straining water supplies due to population growth and extreme climate change. Therefore, it is imperative to optimize irrigation systems for increased application efficiency to conserve water.

In 2020, Yang et al. [48] introduced a DRL-based irrigation scheduling method for maximizing net return on irrigation application. With this method, the volume of irrigation for each zone is calculated at each time step while accounting for crop growth stage, soil moisture, evapotranspiration, and precipitation probability. It has much more state space and irrigation option capacity than the prior methods. DRL approximates the Q function by ANNs to process multi-dimensional sensor inputs as observations of the real world. Large volumes of sensor data can be handled with ANNs, which also makes the suggested irrigation strategy scalable. According to the outcomes of the simulation, this method can accurately represent complex irrigation scenarios and calculate the amount of water to apply, resulting in a higher net return. It was demonstrated to be able to overcome problems with inadequate data by integrating with the AquaCrop model, enabling the system to identify workable, profitable solutions while continuously learning throughout the production season. Tests with various crop kinds and weather scenarios revealed that, for the most part, the suggested strategy performed better than the other methods examined. All irrigation strategies will be put to the test in real-world field settings in subsequent research.

In 2021, Chen et al. [97] suggested the optimal model for irrigation based on short-duration information of weather forecasts. The method's applicability to Nanchang, China's paddy rice, is illustrated. Stations close to Nanchang provided the weather data during the rice season between 2012 and 2019. Local farmers' choice of either conventional or flooded irrigation efficacy in conserving water has been assessed. According to the findings, there was room for improvement and learning in the daily rainfall forecasting performance. After training, the Deep Q-Learning model's simulations show that, as opposed to traditional practices of irrigation, it took advantage of saving water from the needless water supply, saving 23 mm of irrigation water,

cutting down on outflow by 21 mm, and timing water supply, considering no appreciable loss in production. The Deep Q-Learning approach, which draws lessons from previous irrigation experiences, and the risks associated with inaccurate weather forecasting were avoided.

In 2021, Gu et al. [35] developed an NN model for scheduling irrigation based on soil moisture. Firstly, intraday soil moisture is predicted at various soil levels and used as input to the NN model, along with climate data. The Field irrigation dataset and Water Stress dataset (Simulations of Root Zone Water Quality Model) have been utilised to train and test the water-consuming and water-supplying sub-models. Using the NN, irrigation is started when the expected soil water content falls to a defined level. The amount of water was adjusted to refill the field's root zone soil water content. Testing an NN ensemble model improved scheduling performance with respect to water saving and yield maintenance. The NN ensemble-based irrigation scheduling approach beat the RZWQM2-WS method by 20 percent. The developed NN ensemble model and the irrigation scheduling technique can be a choice to calculate the moisture of the soil and to schedule water efficiently. This model has an R^2 near 1, and other parameters, NRMSE, NMAE, and NMBE values closer to zero.

In 2023, Devarajan et al. [33] described a DRL-based system. Q-Learning Ant colony optimization is used to unload tasks, for instance, identification of fire and pests, irrigation scheduling, crop development, soil, climate, and field monitoring. Depending on the delay, energy usage, and processing capacity, the Modified ACO-DQN model assigns the load to the edge, fog, or cloud network. Following the assignment being transferred to computers (edge, fog, or cloud), the second step involves the prediction and monitoring of various agricultural activities. Secondly, the RL-DQN model predicts and monitors agricultural task activities. Lastly, experimental results indicate a significant improvement in the performance evaluation parameters. Table 2.9 highlights all the major findings of the research papers on water requirements and their management.

Liu et al. (2025) proposed an intelligent IoT-based irrigation system [98] that employs fuzzy logic for irrigation decisions, a DNN for irrigation prediction, a wireless sensor network, and the open shortest path first (OSPF) routing algorithm to communicate

sensor nodes. A network of sensors collects real-time data, including temperature, humidity, soil moisture, rainfall, and light intensity. Further, decisions based on fuzzy computing for irrigation scheduling, while the DNN predicts the optimum irrigation method after analysing environmental and historical data. Furthermore, OSPF, along with fuzzy logic, identifies the best route between a pair of nodes based on energy, bandwidth, and distance. The proposed system displays superior performance in terms of active node count of 36, higher residual network energy of 35.12 J, longer network lifetime of 6124 rounds, lower delay of 11.52 s, and higher packet delivery ratio of 68.54%. Thus, the proposed system exhibits strong performance in terms of energy efficiency and water conservation in the real world.

Table 2.9: Irrigation scheduling publications

Reference Study	Model	Dataset	Parameters	Key Points
Yang et al. [48] (2020)	DRL	Weather data supplied by Aquacrop software	80%, 50%, and 30% Plant Available Water, Uniform irrigation in mm	Determines precise water application amount
Chen et al. [97] (2021)	Deep Reinforcement Learning based on Q-Learning	Data Sharing Service System of China Meteorological (http://data.cma.gov.cn), Weather China (http://www.weather.com.cn).	False Alarm rate from 0.14 to 0.49, Missing Alarm rate from 0.20 to 0.39, Threat Score between 0.38 and 0.70	Conserve irrigation water, Increases rainfall utilization

Gu et al. [35](2021)	NN	Filed irrigation dataset (http://ccc.atmos.colostate.edu/~coagmet/)	Determination coefficient (R^2) above 0.92, Normalized mean absolute error (NMAE), Normalized root mean square error (NRMSE), and Normalized mean bias error (NMBE) within 8%	Irrigation scheduling method in real-time
Devarajan et al. [33](2023)	Deep reinforce ment learning based on Q- learning	Not Available	Precision=98.5 %, Recall=99.1%, F-measure= 98.1%, Accuracy=98.5 %	Models apply to real-time
Liu et al. (2025) [98]	Fuzzy logic	Not available	Active node count=36, Network residual energy=35.12J	Not adaptable to a dynamic environment

The techniques developed to automate irrigation of the fields are based solely on data from weather stations. In this context, a framework is developed that integrates data from not only weather stations but also from soil sensors, as proposed in Chapter 5.

2.5.4 Soil Content Sensing

The various stages of growth of crop growth, since the onset of germination of the seed, involve all mineral elements in the soil to varying degrees. A detailed comparison of the results of various research methodologies to detect soil nutrient or moisture content has been illustrated in Table 2.10.

In 2018, Kouadio et al. [99] collected yield data of Robusta coffee for small-scale farms in one of Vietnam's provinces and examined algorithms- random forest (RF), multiple

linear regression (MLR), and extreme learning machine (ELM)- which inferred the intrinsic correlations among fertility parameters of soil. During the independent testing phase, the most accurate estimate of coffee yield was produced by an ELM model that was created using a combination of predictor variables. Normalized metrics demonstrated the high degree of accuracy that the ELM model could produce.

In 2023, Nti et al. [80] examined several tree-based learning models to predict yield and adaptability depending on variables including pH, temperature, humidity, and rainstorms. The dataset obtained via Kaggle includes macronutrient amounts, a range of soil pH, rainfall level, temperature, and humidity values. With this dataset, data-driven suggestions for improving the environment and nutrition, which amount to an increase in crop output, were developed. With an astounding 99.32% accuracy rate, models like XGBoost and LightGBM beat popular models like AdaBoost and RF. These results imply that crop management techniques might be much improved, and crop yields could be optimised by the suggested models.

In 2023, Liu et al. [50] proposed an optimum technique built upon the Gaussian over histogram for obtaining distinctive characteristics from soil pictures. An identity matrix with 32 distinctive parameters drawn from 8 colour spaces is created to infer the multidimensional information included in the soil pictures. Meanwhile, three variable analytical methods are used to identify a subset of ten parameters. Then, using 32 and 10 characteristic parameters, 4 frameworks for Soil Water Content are created, and their performance has been compared based on evaluation parameters.

In 2023, Chinilin et al. [100] demonstrated a three-dimensional modelling approach to predict the distribution of Soil Organic Carbon content both vertically and laterally in soil of Russia, as well as the region where a prediction model can be used without risk, using the Random Forest technique and spatial cross-validation. Further, topography and climatic parameters are integrated with data from remote sensing, such as profile depth and temperature seasonality, which allows for reliable results in estimating the spatial variation of SOC. This proposed framework has a limited number of soil profiles that it can use for SOC modelling.

In 2023, Dasgupta et al. [26] demonstrated a hybrid ensemble Machine Learning-based Digital Soil Mapping method to spatially evaluate and to map micronutrients, which are Zn, Cu, Fe, and Mn, more accurately than 14 base learners in India along the plains of the Ganga. The findings of this research paper can help researchers better understand the factors that influence the geographical variability of soil micronutrients, and further, this can be utilized as a regional-scale micronutrient base to analyse the potential for plant breeding and create an economical agribusiness.

Gunasekaran et al. (2025) AI-based smart system [101] to assess soil fertility and recommend crops. Kaggle dataset has been employed with 1,980 samples and 12 soil attributes. Boron, copper, electrical conductivity, iron, manganese, nitrogen, organic carbon, phosphorus, potassium, pH, sulphur, and zinc are captured by the microcontroller, ATmega32u4-based hardware. The dataset is pre-processed with min-max normalization and SMOTE to balance various classes. To identify the best prediction model for soil fertility, thirteen models have been trained. Random Forest outperforms other models with 92.42 % accuracy. Moreover, a hybrid model, MLP-LSTM, recommends the crop with 97 % accuracy through a mobile application. All the models have been trained with Stratified K-Fold Cross-Validation with K = 5. Training is performed five times, and performance parameters are averaged across 5 folds. The reliability of the system is confirmed since measured values lie closely to laboratory results.

Table 2.10: Publications concerned with soil content sensing

Reference Study	Model	Dataset	Parameters	Key Points
Kouadio et al. [99] (2018)	Extreme Learning Machine	Not Available	RMSE $\pm 13.6\%$, MAE $\pm 7.9\%$, Willmott's Index 0.9952, Nash-Sutcliffe efficiency coefficient, Legates	more trustworthy when forecasting coffee yield with several inputs.

			0.406, and McCabe's Index 0.431	
Nti et al. [80](2023)	Ensemble models of tree-based (e.g., XGBoost and LightGBM)	Kaggle	Accuracy 99.32%, Precision 99.34 %, Recall 99.39 %, F1-score 99.34 %	allocating resources more efficiently creating better irrigation schedules customizing agricultural operations
Liu [50] (2023)	Gaussian fitting Gray Histogram (To extract features) +ML Models (PL SR, RF, SVM, GPR)	Not Available	Coefficient of Determination $n \geq 0.95$, Root Mean square error $\leq 2.01\%$, <i>Ratio of Prediction to Deviation</i> ≥ 4.95 , Ratio of Performance to InterQuartile distance ≥ 6.37	Precise soil water content prediction Detailed insight into mapping soil moisture fields
Chinilin et al [100] (2023)	Random forest and spatial cross-validation technique	Not available	R^2 0.45, 1.41g/kg RMSE and Concordance correlation coefficient 0.63	Supports Soil Management Identify environmental drivers of SOC spatial variation
Dasgupta et al. [26] (2023)	ML algorithms+ Ensemble model	Not available	R^2 0.52 for Zn and 0.63 for Fe	Encourages nutrient-based subsidy Recommendations towards micronutrient-enriched food

Gunasekaran et al. [101](2025)	Random Forest for fertility assessment, MLP-LSTM for crop recommendation	Kaggle	Accuracy=92 % for Random Forest and Accuracy=97 % for MLP-LSTM	Validation with Lab values
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The literature reported turns out to be incompetent in terms of the incorporation of soil-related factors in agriculture. Therefore, soil variables are incorporated in the decision-making process in the frameworks designed in Chapters 4 and 5.

2.6 Conclusion

This paper highlights a scientometric analysis of research documents on agricultural practices driven by artificial intelligence from 2015 to 2024, using the Scopus database. This study examines the impact of artificial intelligence on agricultural practices, including year-by-year growth in publications, the most productive countries, distribution of citations, prestigious journals, authors, and institutions, most cited articles, and important study fields. This study's findings include the following:

- The study found that soil content sensing has received greater attention in the research between 2015 and 2024 than other agricultural practices due to increased monitoring of soil fertility properties. It supports researchers in conducting research on agricultural practices, including disease detection, nutrient deficiency, and irrigation scheduling.
- Although staple crops are still necessary for food security, their continued use in the fight against hunger, malnutrition, and food insecurity depends on sustainable methods. To ensure their resilience in a changing climate, future research should focus on finding crops that maximize the portfolio effect in a variety of soil and climate situations.
- Majorly, the increase in publications has been observed in each crop over time for irrigation scheduling. Conversely, the number of publications on disease detection began to increase in 2019 and then rose steadily in 2020 and 2021 for wheat and maize crops. Many fluctuations have also been observed in the pattern of research documents

related to nutrient deficiency and soil content sensing. Researchers can use these strategies to identify solutions to various barriers in the agricultural domain.

-India, China, and the USA are the most dominant countries in terms of AI use and research on agricultural practices from a geographical perspective. These nations' contributions match the geographic distribution of human needs to a great extent. But still, geography points to the necessity of international cooperation in research across the world. This is the ideal time for all countries in the world to concentrate on developing technologically based solutions for the control of agricultural dangers.

- In just 1938 papers, the studies have received 62721 citations overall. With 206 citations, the papers published in 2016 have received the most citations up to the time this document is being written. Remarkably, 63.67% of articles have fewer than 10 citations or none. This is a natural result of the literature's ongoing production. The number of citations for the high-calibre work is expected to rise over time.

- Apart from this, Environmental Research Letters, Science of the Total Environment, and International Journal of Environmental Research and Public Health are the top three journals for AI research on agricultural practices. When it comes to institutes, the Indian Agricultural Research Institute is ranked highest among them.

- Keyword examination has been done in this study to identify the main research areas. This analysis looks at AI for future research on precise agricultural activities. It also describes future research opportunities in this area.

- Co-authorship data with other markers, such as joint funding, projects, and conference appearances, to further hone understanding of international research collaboration. Coverage biases can be reduced by combining multiple bibliometric databases. To get a whole global picture, it is also critical to acknowledge regional and language differences while examining collaboration patterns

-The fundamentals of deep learning have been reviewed thoroughly, and an extensive overview of current research on the use of deep learning in farming for its various practices. Key research points, datasets with links, algorithms, and performance evaluation metrics have been meticulously identified. After this thorough investigation,

the current and next trends in artificial intelligence have brought attention to the new research issues in agriculture

- The future involves intelligent crop planning, smart farming practices, and a farm-to-fork approach for crops other than popular crops. AI will be used to optimize resource use, predict fertilizer requirements crop-wise, improve crop yields, and connect farmers to markets.

- Less popular crops, such as cash crops, can be explored for better production by decreasing consumption of resources in terms of pesticides, fertilizers, and water, and adopting technology to make more informed decisions at the correct time.

- Advanced algorithms can be designed for early detection of diseases, nutrient deficiency, and automate the utilization of water as per specific needs to avoid excess as well as shortage of water requirements for cash crops to maximize yield.

Consequently, encouraged by intrinsic drawbacks related to the existing literature in the current chapter, the contribution of this dissertation has been presented in the subsequent chapters.

Chapter 3

CNNx: Optimizing Smart CNN Models for Efficient Banana Disease Detection and Severity Estimation

Bananas are the most popular fruit consumed worldwide and are ranked the fourth most crucial crop for human consumption, following cereals—wheat, rice, and corn. According to the OECD–FAO Agricultural Outlook 2025–2034 [102] the banana market size is expected to increase to 166 million tonnes by 2034, having grown from 139 million tonnes during 2022–2024 at an average annual growth rate of 1.4%. The banana market’s expansion is driven by the increased awareness of health at the consumer level. Since bananas are a protein-rich source of dietary fiber, vitamins B6 and C, manganese, and potassium, they aid in proper metabolism, support nervous system functioning, and aid digestion. In addition to being consumed raw, they are also a component of various food products, including ice cream, breakfast cereals, and other desserts. Tropical fruits such as bananas are widely cultivated in many warmer climates worldwide. The market for bananas is dominated by the Asia-Pacific area, led by India [103], and has significant production levels.

Among the fruits consumed worldwide, bananas are susceptible to numerous leaf spot infections [45]. Plant diseases and pests are spreading, which is extremely concerning for the banana sector. Several fungal diseases affect banana plants, causing significant agricultural losses. Black Sigatoka (*Mycosphaerella fijiensis*) [42] appears as black streaks on leaves, causing large areas of leaf tissue to die. Panama disease, also known as Fusarium Wilt, causes yellowing, wilting of leaves, and plant death. Yellow Sigatoka (*Mycosphaerella musicola*) [40] causes yellow streaks on leaves that progress to brown or black streaks and leaf necrosis. Anthracnose (*Colletotrichum musae*) arises as black spots on fruits and leaves, often leading to fruit rot. Crown Rot is the rotting of the banana bunch’s crown, leading to premature fruit drop and spoilage. Cigar End Rot (*Verticillium theobromae* and *Trachysphaera fructigena*) arrives as dark, sunken lesions on the distal end of the fruit that resemble a burnt cigar. Moko Disease (*Ralstonia solanacearum*) leads to yellowing and wilting of leaves, vascular discolouration, and plant death. Botryodiplodia Rot (*Botryodiplodia theobromae*) varies from dark brown

to black lesions on the pseudostem and fruits, leading to rot. Cordana (*Cordana musae*) reduces photosynthesis and weakens the plant. Pestalotiopsis (*Pestalotiopsis* spp.) causes tiny yellow halos to encircle dark brown to black marks on leaves that can expand, merge, and lead to severe necrosis. These pathogens impact banana production, becoming a major threat to banana cultivation and food security.

Conventionally, farmers assess banana leaves with their naked eyes to identify the kind of infection and predict the quantity of fungicides to curb the illness. However, this is mostly error-prone, unable to prevent the spread of the disease, and ineffective chemical treatments. To tackle these issues, AI models along with IoT devices have been integrated to create smart agricultural systems that can monitor crops regularly and provide immediate feedback on plant health. Primarily, many artificial intelligence algorithms, such as SVM, KNN, random forest (RF), ensemble boosting tree [104], and Gaussian Naïve Bayesian [28], have been used for categorization and diagnosis of diseases. Numerous feature extraction methods, including methods based on color, entropy, shape, and texture, are also used to separate the affected area from the complete image [47]. The methodologies may also require calculated features using the Gray-level Co-occurrence Matrix, Local Binary Pattern [43] and Histograms.

Currently, the agriculturists have been leveraging several novel techniques [39] such as modified generative adversarial network (MGAN)–modified faster recurrent convolutional neural network (MFRCNN) [105] with fuzzy ensemble, the BAT Optimization Technique with the KNN algorithm, vision transformers, and BananaSqueezeNet to determine banana leaf diseases to alleviate the incurred banana yield losses. However, each of these strategies has certain disadvantages. For example, the integrated MGAN and MFRCNN with a fuzzy ensemble is highly complex, making it computationally expensive and requiring significant processing power and memory. In addition, GANs and other techniques are used to generate artificial pictures of diseased banana leaves to supplement existing datasets. Enhancing the model's capacity to identify a wider range of circumstances has been the main objective. Furthermore, KNN is not ideal for large datasets because it requires distance computation between the test point and all other points, leading to high memory usage and slow query times. In contrast, vision transformers require a large labelled dataset to get trained to extract global context [106] from an image rather than local features.

Additionally, SqueezeNet is well-known for its small model size, which may not capture all relevant features in the data, leading to reduced accuracy in identifying complex disease patterns. Therefore, ongoing efforts are aimed at escalating the precision, effectiveness, and usefulness of AI-based solutions in the agricultural sector, ultimately helping to develop enhanced, productive, and sustainable farming methods. Even Researchers are integrating various models, for instance, CNNs, RNNs, LSTMs, and optimization algorithms to create hybrid models that utilise the strengths of each technique. However, the ability of CNNs to automatically derive and learn meaningful patterns from raw images makes them ideal for tasks involving the identification of plant diseases [107]. They can process incoming photos directly and generate precise classification results without the need for manual feature engineering, thanks to their end-to-end learning capability. Because plant illnesses can arise in a variety of settings, including different lighting, backdrops, and stages of infection, CNNs can be trained on sizable, diverse datasets and still generalise well to new data. CNNs are a good option for creating a dependable and flexible detection framework because of their high accuracy, scalability, and resilience to real-world fluctuations.

The current research focuses just on disease classification, frequently ignoring class imbalances, which diminishes the efficacy of both deep learning and conventional machine learning models. Furthermore, there is a lack of research that integrates disease severity with practical management, restricting the usefulness of automated detection systems for farmers. These drawbacks emphasize the need for innovative and reliable methods that can categorize a variety of banana illnesses, deal with inconsistent data, and offer severity-informed recommendations for efficient disease control.

The current research suggests a novel integrated architecture for automated banana foliar disease diagnosis and management to overcome these constraints. Although color-based lesion analysis, CNNs, and hybrid resampling techniques have all been used separately in earlier research, this study is the first to integrate these approaches into a single pipeline that addresses class imbalance [56], permits precise multi-disease classification and measures lesion severity. Additionally, the framework improves the applicability of automated detection systems by connecting severity estimation to practical fungicide recommendations and offering farmers helpful advice. Further, the main contributions of this research have been enumerated as follows:

- (a) Banana, a commercially significant cash crop that has received limited attention in prior disease detection studies, has been selected for early-stage disease identification.
- (b) To improve classification performance and address data imbalance, a hybrid resampling approach, SMOTE-ENN (Synthetic Minority Over-sampling Technique–Edited Nearest Neighbors), has been employed.
- (c) Enhanced Convolutional Neural Network architectures are proposed for the accurate detection and classification of banana plant diseases through systematic experimentation with dense layers, dropout regularisation, and fine-tuning of key hyperparameters.
- (d) Identifying the severity of the diseases and recommending fungicides based on severity grade.

The proposed work is presented as follows: the major contributions and current developments in the field are reviewed in Section 3.2. The suggested framework is delineated in Section 3.3, and the overall framework is explained and interpreted in Section 3.4. Section 3.5 illustrates the detailed implications of the experiments, while Section 3.6 wraps up the study by providing the significant outcomes of the results.

3.1 Literature Survey

3.1.1 Work related to Disease Classification

A reduction in the shelf life of harvested fruits is the main adverse impact of Banana Leaf Spot Diseases on export production. Banana leaves are susceptible to three common diseases: Cordana, Sigatoka, and Pestalotiopsis. To automatically identify these diseases at an earlier stage, significant research has been reported. The research focuses on AI-based algorithms that employ both machine learning (ML) and deep learning (DL) methodologies. These methods can accurately identify the sick lesions. In this context, the data set on banana leaf spot diseases (BananaLSD) from different parts of Bangladesh has been collected, and various models have been proposed to recognize and categorize diseases efficiently.

Among the reviewed works [56] represents a machine learning-based approach, where the authors proposed a technique for Banana Leaf Feature Extraction and Optimization. This method first extracts distinct features for each disease and then adjusts them to achieve high precision. An innovative hybrid method known as BAT+KNN has been

formulated by combining the BAT Optimization Technique and the K-Nearest Neighbors (KNN) algorithm with 95% accuracy. Driven by the echolocation behavior of bats, the BAT algorithm is used for refining the feature selection process and upgrading the overall classification accuracy. In addition to this, KNN classifies data points based on their similarity to neighboring points.

In contrast, most of the contemporary research is centered on deep learning-based approaches for disease classification and severity detection. For example, the study in [54] presented a method to train transfer learning networks based on CNN to analyze and identify diseases affecting banana leaves. The validation accuracy of the approach was 96.24%. Similarly, the method presented in [55] that a neural network with 8 convolutional layers, average pooling layers, dense layers, and an output layer. This deep architecture allows the capture of intricate patterns and details necessary for accurate disease prediction. The same dataset was used to assess the proposed model, and multiple deep learning models were also tested on it. A Tesla V100 GPU server running Python has been used for implementation, with a batch size of 64 over 30 training epochs. Compared to existing deep learning models, the experimental results show that the 8C-DCNN Neural Network acquired an accuracy of 98.75%, a precision of 96.42%, a recall of 98.75%, and an F1-score of 97.57%.

Research work reported in [57] demonstrates how banana leaf diseases can be classified visually using deep learning and Bayesian optimization, with no human assistance. A lightweight CNN model, 'BananaSqueezeNet', tailored for fast and efficient processing with fewer computational resources. The model achieved an accuracy of 96.25%, a precision of 96.53%, a recall of 96.25%, a specificity of 98.75%, an F1-score of 96.17%, and an MCC of 95.13%, performing remarkably well for the BananaLSD dataset classification.

Another work considered a dataset of 1288 images with three kinds of leaves: healthy, xanthomonas-affected, and Sigatoka-affected. The research work in [24] proposed an approach that combines the fuzzy rank ensemble with a Modified Generative Adversarial Network (GAN) and a Modified Faster Region-based CNN(MFRCNN) for classifying banana leaf diseases. The autoencoder has been integrated into the basic GAN design and is utilized for data augmentation. After this, MFRCNN extracts feature from high-resolution networks. The GAN and Faster RCNN ensemble models'

performance parameters - 98% accuracy, 97% precision, 96% F1-score, 98% specificity, and 98% sensitivity have been attained.

Recent investigations also highlight that Vision transformers have been employed for disease classification. The research in [108] utilized a dataset of 408 field photos that has been enhanced to 2856 samples for seven banana leaf diseases. Images are then divided into fixed-size patches, transformed into token embeddings, and then fed into a transformer encoder with self-attention layers of the Vision Transformer (ViT) model. This enables ViT to classify images and capture intricate spatial relationships. The ViT demonstrated effective classification after being trained for 100 epochs with a maximum accuracy of 96.88%.

Further, transformer models ViT-b16 and ViT-l16 were proposed for banana leaf disease classification. It has been predicted that ViT-b16 [109] outperformed the EfficientNet-B3, MobileNet-V2, GCN, and ResNet baselines with a maximum accuracy of 96.88% on the dataset, split into 70% training, 15% validation, and 15% testing. Both ViT-b16 and ViT-l16 rely on multi-head self-attention and deep transformer encoder layers, which demand powerful hardware and longer training times. The study also emphasizes the computational burden of transformer-based models, even though these results demonstrate their strong generalization capability. Nevertheless, the author also points out that ViT adds significant model complexity and needs large datasets and processing power for reliable training. Although the method exhibits improved accuracy, its complexity prevents widespread use in agricultural settings with limited resources.

Additionally, researchers have used advanced deep learning architectures [110] for banana leaf diseases, Cordana, and Black Sigatoka. Through data augmentation, a dataset of 900 field photos, 300 for each of the three classes, has been increased to 9000 images for training and assessment. Images are split in an 80:20 ratio for testing and validation, respectively. Three pre-trained convolutional architectures, VGG19, ResNet50, and EfficientNetB0, are utilized for classification. EfficientNetB0 has performed best among these since it strikes a better-balanced mix between accuracy and computational efficiency, which is important because deeper architectures like ResNet50 and VGG19 have high training requirements. The reported classification accuracies 88.33% for EfficientNetB0, 88.90% for ResNet50, and 87.22% for VGG19. EfficientNetB0's performance is marginally improved to 87.83% with augmentation.

On the contrary, these models demand high computational networks, which makes it difficult to implement in agricultural environments with limited resources, emphasizing the need for accurate yet portable models designed for field use.

After an extensive literature review, it has been inferred that both machine learning techniques and deep learning algorithms have been extensively utilized to determine banana diseases. Moreover, Vision Transformers are also being experimented with in agricultural fields, although their computational requirements limit their usage. The technology in these fields allows farmers to gain a more profound understanding and make more educated decisions. Also, this helps them to make well-informed decisions and respond quickly to changing conditions. Consequently, the present literature has been compiled in Table 3.1. A key limitation observed in earlier deep models is their computational complexity, which presents a challenge for the implementation of lightweight yet accurate models on mobile or edge devices for real-world applications.

Table 3.1: Analysis of Banana diseases

Author & Year	Diseases	Techniques	Performance Matrix	Key points
Triandasu [56] et al. (2024)	Cordana, Pestalotiopsis, Sigatoka	Feature Extraction by BL-FEOT Method Classification by BAT-KNN Hybrid Algorithm	Accuracy-95% Precision-94% Recall-94.5% F1 Score-94.8%	Higher Complexity
Altabaji [54] et al. (2023)	Cordana, Pestalotiopsis, Sigatoka	CNN	Validation Accuracy-96.24%	The model functions poorly on unknown data, but excels with training data
M.S. Devi [55] et al. (2022)	Cordana, Pestalotiopsis, Sigatoka	CNN	Accuracy-98.75%	Higher Complexity

			Recall-98.75% Precision-96.42% F1 Score-97.57%	
Bhuiyan [57]et al. (2023)	Cordana, Pestalotiopsis, Sigatoka	Bananasqueeze Net- a lightweight CNN	Accuracy-96.25% Precision-96.53% Recall-96.25% Specificity-98.75% F1 Score-96.17% MCC-95.13%	The model can be easily deployed on Mobiles.
Raja [24]et al. (2023)	Xanthomonas, Sigatoka	MGAN + MFRCNN with Fuzzy	Accuracy-98% Precision-97% F1 Score-96% Specificity-98% Sensitivity-98%	Higher Complexity
Saini [108](2024)	Black Sigatoka, Bract Mosaic Virus, Insect Pest Disease, Moko Disease, Panama Disease, and Yellow Sigatoka.	Vision Transformer	Accuracy-96.88%	Complexity and a large dataset
Tiwari [109](2024)	Healthy Leaf, Black Sigatoka, Bract Mosaic Virus Disease, Insect Pest Diseases, Panama Disease, Moko Disease, and Yellow Sigatoka	ViT-b16 and ViT-l16	Validation Accuracy for ViT-b16 - 96.88%	Require a large dataset and High Complexity
Jiménez [110] et al. (2025)	Cordana and Black Sigatoka	EfficientNetB0, ResNet50, and VGG19	Accuracies of 88.33%, 88.90%, and 87.22%, respectively.	Less Accuracy and more

				computation s required
Proposed Work	Cordana, Pestalotiopsis, Sigatoka	CNN	Accuracy- 96.86%Precision -Recall Specificity- F1Score	Lesser complexity, Severity Estimation

3.1.2 Work related to Severity Estimation in Plant Disease

Although disease classification offers category information, it is insufficient on its own to promote sustainable farming methods. As part of precision farming practices, it is essential to estimate the severity level of the damage. It may lead to effective chemical application, which minimizes the overuse of fungicides and reduces the financial burden on farmers. This subsection, with an emphasis on recent developments and a list of grey areas, has been discussed subsequently.

A study proposed a severity scale created by the plant pathologist at ICAR (Indian Institute of Maize Research, 2015) and Hooda et al. (2018) on maize leaf diseases [111] to overcome the shortcomings of disease classification. To determine the severity of Turcicum Leaf Blight (TLB) and rust, a manual visual assessment method using a standardized 1-to-9 rating scale has been conducted. The proportion of infected leaf area to total leaf area is used to award ratings. An image with less than 10% of the area infected shows the least amount of infection. It might result in the least amount of crop loss. When more than 80% of a territory is infected with a single disease, the severity is at its highest. By applying a preset formula to transform visual scores into percentage severity, this scale made it possible to quantify the impact of the condition. According to their data, rust had a higher severity (82.13%) than TLB (57.48%), highlighting the significance of estimating severity for better disease management. Despite its effectiveness, the method's reliance on manual observation and expert input limits its scalability for extensive field applications.

Another research also proposed a visual evaluation of the severity of plant diseases based on Standard area diagrams (SADs) [112] to increase accuracy and decrease human error. Best practices like rater training, the use of instructional aids, and appropriate scale selection are emphasized by the technique. To assess accuracy, bias, and reliability (both within and between raters), statistical techniques like Lin's

concordance correlation coefficient are employed. The fundamental idea provided is to use different kinds of scales —nominal, ordinal (qualitative and quantitative), and ratio (%-based) to estimate the percentage of impacted plant area based on visual clues.

By determining the ratio of affected area to the total leaf area, the technique divides plant disease severity into four categories: normal, mild, moderate, and severe. The framework consists of preprocessing images, segmenting them using a multi-gradient method, and extracting features using a Kohonen-based neural network and a pre-trained deep learning model [113]. Based on predetermined percentage criteria, severity levels are assigned using these features. Notwithstanding its effectiveness, the method has drawbacks, including labelling errors, a lack of real-world annotated datasets, and trouble managing several or overlapping infections in a single image.

Although estimating the severity of plant diseases has drawn great interest, the methods in use are mainly dispersed and have limited efficacy. The predetermined rating scales or manual visual scoring are labor-intensive, subjective, and inappropriate for widespread use. Although segmentation and deep learning allow for automation in certain image-based techniques, these approaches frequently contain labelling mistakes, a dearth of real-world annotated datasets, and poor generalization to difficult field settings are the main challenges. Furthermore, there is currently no severity evaluation estimation in the field of banana leaf spot diseases. These limitations serve as an impetus for a framework that emphasizes the necessity for a reliable and automated method to precisely determine the severity.

3.2 Proposed Framework for Smart Banana Disease Detection

This section presents a modular framework for smart disease monitoring in banana farming, as shown in Figure 3.1, that integrates real-time data collection, edge computing, deep learning, cloud storage, and mobile-based decision assistance [114], [115], [116] to support precision agriculture. From gathering environmental and visual data at the field level to providing farmers and regulators with actionable insights, the system makes sure that information flows smoothly across all levels, facilitating prompt and well-informed responses. The Intelligent Layer is a crucial part of this structure, where AI approaches help deep learning models classify and assess the severity of diseases, enhancing timely interventions and optimized resources. Firstly, the data

acquisition layer acquires raw data from banana farms, and the Edge layer further carries out initial preprocessing before passing it to intelligent systems for classification.

3.2.1 Data Acquisition Layer

This sub-layer is the backbone of the disease detection pipeline by directly collecting environmental and visual data from banana crop fields. Using Internet of Agricultural Things (IoAT) sensors placed strategically around the field, environmental data is gathered. The dynamic parameters, including temperature, humidity, and soil moisture, are continuously monitored by the sensors. However, leaf visual data is simultaneously recorded utilizing a range of imaging sources. Images are captured by satellite-based remote sensing systems, drones with high-resolution image sensors, mobile devices driven by farmers or field technicians, and cameras mounted in the field.

3.2.2 Edge Layer in Smart Banana Farming

The management of local processing and transmission of field data falls under the purview of this component. A router-based communication infrastructure has been established to connect field sensors, imaging units, and local processing systems by interfacing a variety of devices, including access points, antennas, and IoT gateways. The collected data is sent to edge devices, like workstations or local servers. The preliminary preprocessing, including noise reduction, resizing, and data normalization, is performed to enhance picture quality at the edge layer. The system's overall efficiency and responsiveness are increased by carrying out these actions at the edge, which also conserves network capacity and lowers transmission latency, in addition to minimizing data volume.

3.2.3 Intelligent Layer

The intelligent layer leverages cutting-edge artificial intelligence approaches for precise disease diagnosis and interpretability, which serves as the main analytical component of the proposed framework. To identify diseases like Cordana, Pestalotiopsis, and Sigatoka, machine learning and deep learning methods are used at this layer. These algorithms have been trained on substantial datasets of annotated photos of banana leaves. They classify photos accurately into healthy or diseased categories after extracting pertinent features from the input images. The layer also

determines the severity of infection in leaves. The severity measures prioritize the treatment choices by offering more detailed insights into the course of the disease.

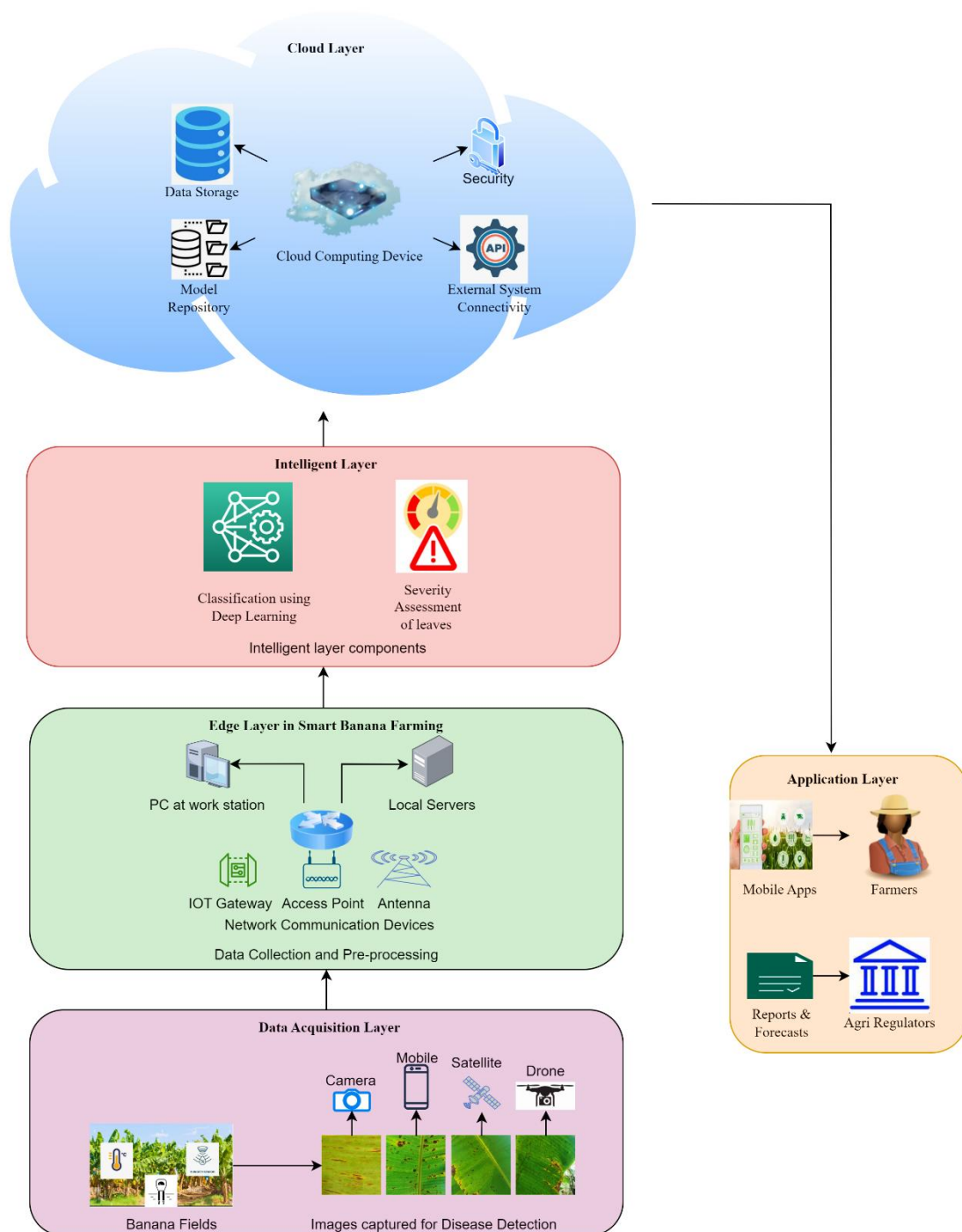


Figure 3.1: Proposed framework for smart banana disease detection

3.2.4 Cloud Layer

The cloud layer is the main center for handling data and models in the proposed framework because of its scalable processing power, generous storage, and strong interoperability. By hosting a model repository, it guarantees version control, facilitates recurring retraining, and permits smooth deployment across numerous edge or field devices. Furthermore, to facilitate long-term monitoring, ongoing model improvement, and thorough historical analysis, all field data, including high-resolution photos, sensor readings, and AI-generated inference results, are safely stored in the cloud. This layer applies robust security features like role-based access control, user authentication, and end-to-end encryption to safeguard sensitive data. Additionally, it facilitates external interfaces via APIs, making it possible to link platforms such as expert advising services, governmental agriculture portals, and weather forecasting systems. This degree of connectivity guarantees the framework's scalability, adaptability, and interoperability within larger agricultural ecosystems while improving its usefulness.

3.2.5 Application Layer

Farmers, agricultural specialists, and policy regulators mostly communicate with each other through the application layer. Mobile applications offer farmers visual feedback from AI-based analysis, real-time illness alarms, and practical suggestions for disease prevention and control. In the field, this enables them to act promptly and intelligently. The system creates interactive dashboards and thorough reports for agricultural experts and regulatory bodies at the same time. At the local and policy levels, these technologies enable data-driven decision-making by making it easier to track disease outbreaks, evaluate severity patterns, and develop region-specific intervention strategies.

3.3 Proposed Methodology

This section presents a proposed solution that includes feature extraction, preprocessing, data collection, and the suggested methodology. Classifying infections and determining their extent are the two main objectives achieved. Color thresholding is used to determine the degree of plant damage, and a Convolutional Neural Network

(CNN) is utilized for categorization. Figure 3.2 shows the specifics of the classification process, which is primarily covered in the following subsections:

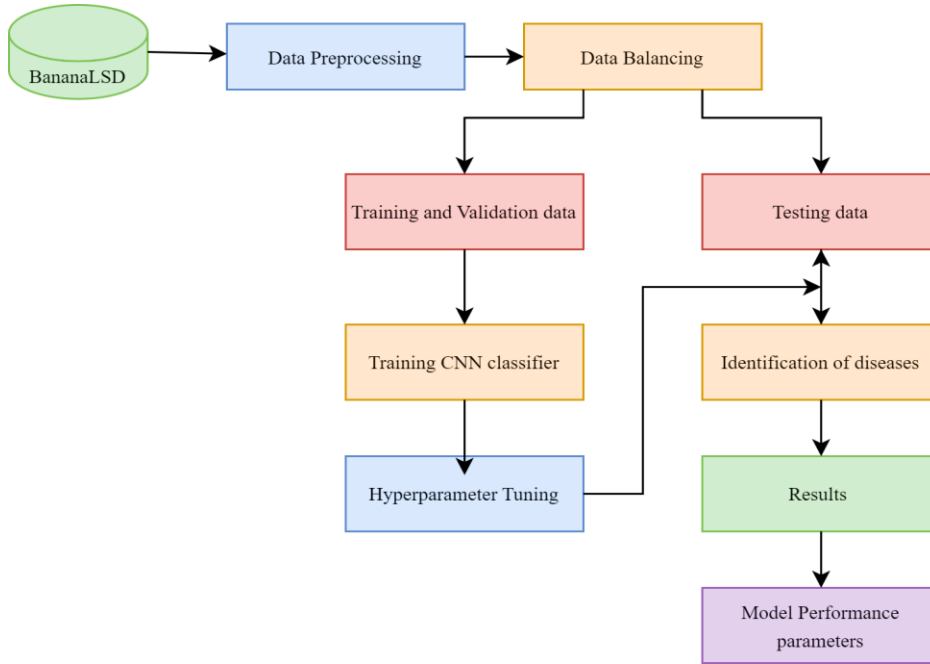


Figure 3.2: Stages of identification of diseases in the banana crop

3.3.1 Dataset

Images from three different classes of diseases are included in a dataset known as BananaLSD [45], which is available in the Mendeley database. The BananaLSD dataset comprises over 2500 photos of banana leaves taken in June 2021 from the Bangabandhu Sheikh Mujibur Rahman Agricultural University banana farm and adjacent local fields in Gazipur, Bangladesh (latitude: 24.036016, longitude: 90.401085). The dataset includes 937 images, which are bifurcated as follows: 129 pictures of healthy leaf samples, 162 of Cordana-affected leaves, 173 images of leaves suffering from Pestalotiopsis, and 473 images of Sigatoka-diseased leaves. To ensure variety, photos were taken in natural light with three smartphones' high-resolution rear cameras under various lighting circumstances, backgrounds, and angles. All photos (JPEG) were

scaled to 224×224 pixels to train the model. The dataset's photos have been separated for the frameworks' 80% training, 10% validation, and 10 % testing. Healthy and diseased images belonging to Cordana, Pestalotiopsis, and Sigatoka of this dataset can be observed in Figure 3.3.



Figure 3.3: A Pictorial view of leaf images of the BananaLSD dataset.

Table 3.2: Number of images after the data balancing technique

Disease	Number of raw images	Number of images after SMOTE-ENN
Cordana	162	447
Healthy	129	468
Pestalotiopsis	173	386
Sigatoka	282	473

3.3.2 Pre-processing of the images

Firstly, the training data has been divided by 255 to scale the pixel values of the image to the interval between 0 and 1. This provides consistent data to the model, accelerates convergence, and reduces the framework's sensitivity to fluctuations in the input data. This augments the reliability and efficacy of the models.

3.3.3 Data Balancing

A data balancing technique can enhance the performance of deep learning models by eliminating the models' bias toward majority classes. The dataset contains an unequal number of classes. Data resampling is performed by the Synthetic Minority Over-Sampling Technique (SMOTE) and the Edited Nearest Neighbors (ENN), also known as SMOTE-ENN [114], before training the CNN models. The SMOTE-ENN method applies over-sampling and then under-sampling to the data. Over-sampling adds

samples to the minority class, and under-sampling reduces the percentage of the high-number class to maintain the distribution of categories. The count of raw images and the count of images after SMOTE-ENN are listed in Table 3.2. It clearly demonstrates the balance achieved in the dataset to improve the classification accuracy of the models.

3.3.4 Classification

Convolutional neural networks are largely successful in computer vision tasks. Consequently, CNNs have been used to extract attributes from raw photos and perform categorization. Figure 3.4 delineates the CNN's fundamental design. Different levels with specific functions have been combined to achieve the final recognition. Features are calculated by a convolutional layer, which identifies and finds various attributes from the input image. The maximum pooling layer is further utilized to downsample the input representation, reduce dimensionality, and make the model more computationally efficient. The classifier then uses these extracted features to categorize the image. The classifier section consists of a flattened layer and fully connected layers, followed by an activation layer, often using the SoftMax function. The SoftMax layer produces output values that represent the probabilities of each category. The highest probability score of the class is chosen to determine the anticipated class. In the subsequent subsection, there is an explanation of each layer individually:

3.3.4.1 Convolution layer

Convolutional layers are employed to extract features from images. The convolution layers apply kernels with preset sizes to perform the convolution process. The expression below is used to calculate feature extraction at several layers in a CNN[117].

$$H_i = b_i + \sum_{j=1}^n X_j * K_{ij} \quad (3.1)$$

where H_i is the Filter response for the i-th channel

X_j : input channel index

K_{ij} : Sub-Kernel applied to the j-th input channel to produce the i-th feature map

In addition, the Rectified Linear Unit (ReLU) is employed to activate the output in the convolution layer, since it adds non-linearity to the image. The following equation provides it:

$$ReLU(P_i(u, v)) = \max(0, P_i(u, v)) \quad (3.2)$$

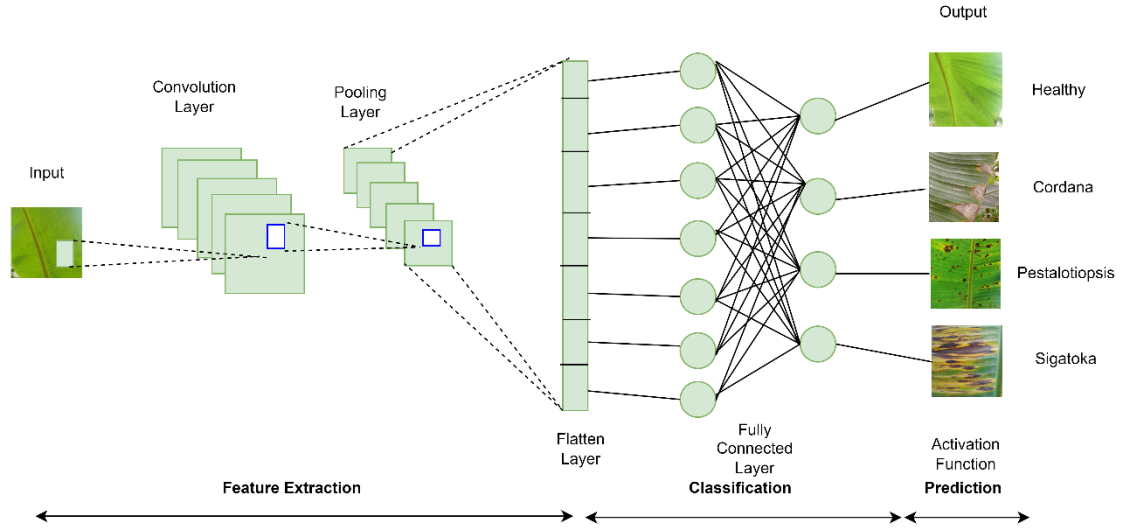


Figure 3.4: CNN architecture

3.3.4.2 Maximum Pooling Layer

The maximum pooling layer has been employed to minimize the dimensionality of the feature space and is represented as follows:

$$P_i(u, v) = \max_{m=0, \dots, f-1} [\max_k (K_{ij} * X_j)] \quad (3.3)$$

Where $P_i(u, v)$ is the value at position (u, v) in the output feature space for the i -th channel, and k refers to the channel index

3.3.4.3 Flatten Layer

Multidimensional data from the previous layers is converted to a 1-Dimensional array by the flatten layer to feed subsequent layers for classification.

3.3.4.4 Fully Connected Layer

Commonly termed as the dense layer, it accurately creates connections in a downward fashion to reach the final number of class levels, and is represented by the equation given below:

$$Z = WA + b \quad (3.4)$$

where Z is an M -dimensional vector representing the output of the dense layer

W indicates an $M \times N$ weight matrix of the fully connected layer; M refers to the number of input neurons, and N represents the number of output neurons of the dense layer

A is an input vector of N dimensions, which is the flattened version of the feature map after the ReLU activation

b is an M -dimensional bias vector.

3.3.4.5 SoftMax Activation Layer

To execute the classification task, all layers are combined using the SoftMax layer.

$$SoftMax(Z_m) = \frac{e^{Z_m}}{\sum_{m=1}^4 e^{Z_m}} \quad (3.5)$$

where m denotes the count of classes

3.3.5 Proposed Models

The symptoms of banana leaf illnesses can vary greatly, from tiny, localized spots to large, uneven lesions. It is challenging to design a rigid CNN model that can capture such a wide range of spatial patterns. To tackle this, modified versions of CNN models have been constructed using TensorFlow and Keras, a sequential model that combines multiple convolutional, max-pooling, flatten, dropout, and dense layers [107] for categorization. The CNN structure has been varied [118] to methodically investigate how changes in regularization, convolutional kernel size, and network depth impact the performance.

- (i) A shallow network, which is computationally efficient [119] but is limited in its ability to capture complex features.
- (ii) A deeper network [120], [121], which extracts richer representations but runs the risk of overfitting if improperly regularized by varying the number of convolutional layers.
- (iii) Disease symptoms appear at multi-scale levels; various kernel sizes (3×3 , 5×5 , and 11×11) have been used to assess multi-scale feature extraction [122], [123].
- (iv) Variations of dense layers evaluate how feature compression impacts classification accuracy.
- (v) Lastly, dropout rates investigate how regularization might help to reduce overfitting.

Further, it is necessary to ensure that the selected model is reliable and useful for field deployment. This study benchmarks these architectural changes to find out the best balance between accuracy, generalization, and computational feasibility. The following four different CNN models have been proposed in various settings to examine the wide range of results.

3.3.5.1 CNN1 Model

This structure employs a convolution block containing 32 filters consisting of a 3x3 kernel, activation, and L2 regularization. These are set to handle input images of shape (224, 224, 3). A maximum-pooling layer is used after this layer to reduce the spatial dimensions. This pattern of Convolution and maximum-pooling layers is repeated six times, each with the same configuration, to capture and reduce spatial features as illustrated in Figure 3.5. After the convolutional layers, a 0.25 rate drop of neurons has been implemented to avoid overfitting. Afterwards, the model is converted to a 1D array and attached to a 16-unit dense layer with ReLU activation. However, the class probabilities are provided by the last dense layer with four units, including SoftMax activation.

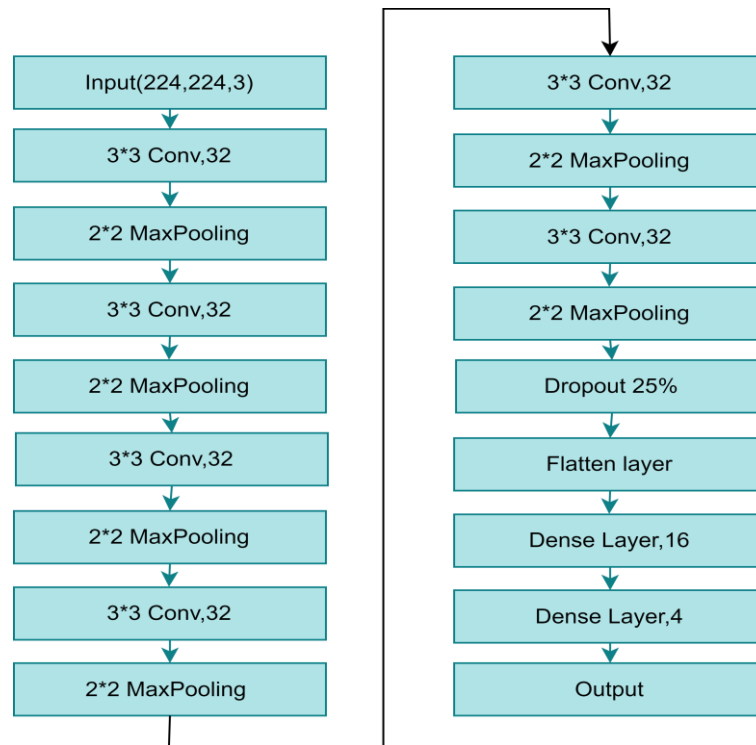


Figure 3.5: Proposed CNN1 Model

3.3.5.2 CNN2 Model

The model shown in Figure 3.6 starts with a convolution block featuring 32 filters, an 11x11 kernel size, ReLU activation function, and L2 regularization, designed to handle input images of shape (224, 224, 3). Afterwards, the max-pooling unit is utilized to reduce spatial dimensions. Similarly, the next convolution block with a 9x9 kernel is followed by a max-pooling layer. This pattern continues with Convolution layers having 7x7, 5x5, and 3x3 kernels, each succeeded by maximum-pooling layers. After the convolution and pooling blocks, the structure is flattened and connected to dense layers with 128 and 32 units, with a ReLU activation function at the end. Lastly, the output layer is a dense layer with 4 units and SoftMax activation. To enable the algorithm to learn both coarse- and fine-grained visual patterns, the proposed architecture progressively decreases kernel sizes in deeper layers and finds multi-scale spatial data.

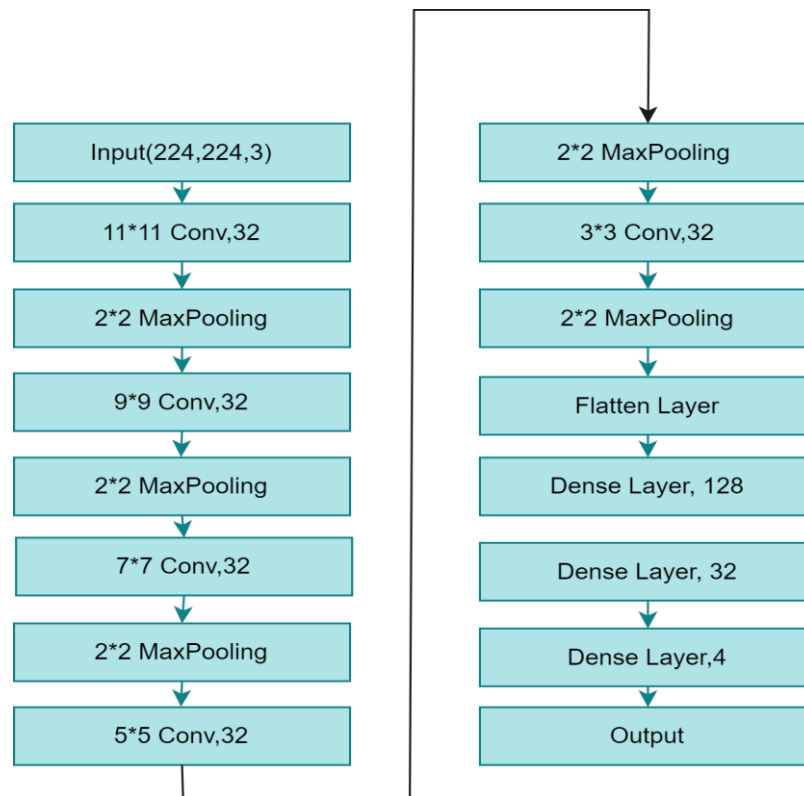


Figure 3.6: Proposed CNN2 Model

3.3.5.3 CNN3 Model

The CNN3 architecture incorporates multiple convolutional layers, max-pooling, and dense units for effective image categorization. The structure begins with two

convolution blocks featuring 32 filters, a 3x3 kernel size, ReLU activation, and L2 regularization, designed to handle input images of shape (224, 224, 3). The next convolution block also uses a 3x3 kernel, followed by max-pooling to reduce spatial dimensions. This pattern continues with two convolutional layers having 3x3 kernels, followed by maximum-pooling layers to progressively extract and down-sample features five times in total. After the convolution and pooling blocks, 25 percent of the neurons are dropped. The structure is then flattened and connected to dense layers with 64 and 16 units, employing the ReLU activation function. The final output layer is a dense layer with 4 units and SoftMax activation, which outputs the class probabilities. Figure 3.7 illustrates the layers of the architecture along with their relevant features.

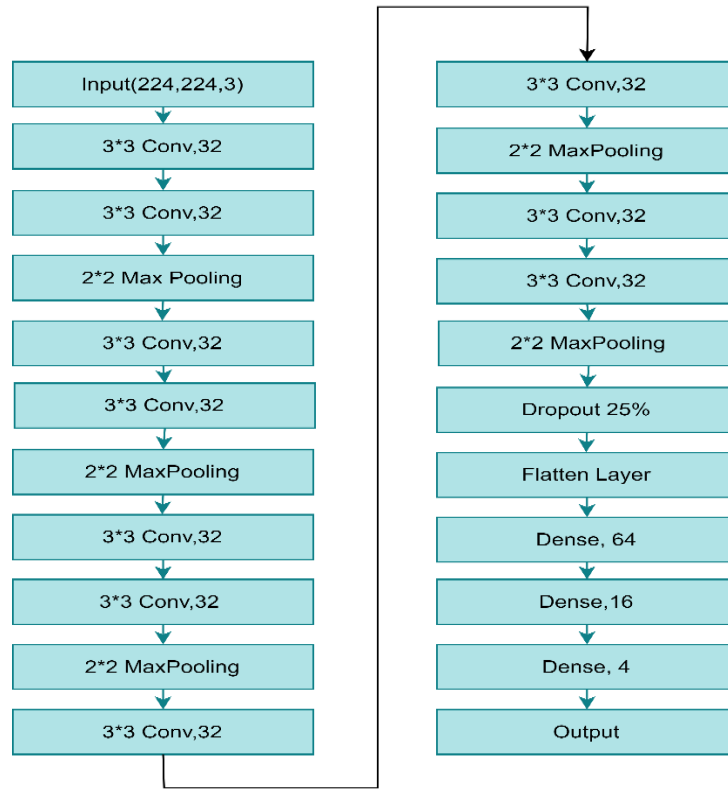


Figure 3.7: Proposed CNN3 Model

3.3.5.4 CNN4 Model

The CNN4 architecture comprises multiple convolutional layers with varying kernel sizes, interleaved with max-pooling layers. The structure starts with convolutional layers containing 32 filters, a 5x5 kernel size, ReLU activation, and L2 regularization, designed to process input images of shape (224, 224, 3). This is followed by another convolutional layer with a 3x3 kernel and then a maximum-pooling unit to decrease

spatial resolution. This pattern continues with additional convolution layers having 5x5 and 3x3 kernels, each pair succeeded by a Max-Pooling unit. This structure is repeated five times, as demonstrated in Figure 3.8. To avoid over-fitting, further neurons are dropped at a rate of 0.10 behind the consecutive convolution and pooling layers. To produce class probabilities, the structure is next flattened and connected to a fully connected level with 16 units. The final dense layer consists of 4 units to categorize different classes. With dropout regularization and repeated small kernels, CNN4 prioritises model robustness and simplicity.

Finally, the number of layers, kernel sizes, activation functions, regularization, and optimization parameters are the salient features that are summarized in Table 3.3 for all the proposed models.



Table 3.3: Parameter values of proposed CNN models

Model	CNN1	CNN2	CNN3	CNN4
Number of Convolutional Layers	6 with 32 filters each	5 with 32 filters each	10 with 32 filters each	10 with 32 filters each
Pooling Layers' Position	After each convolution-layer	After each convolution-layer	After every 2 convolution-layers	After every 2 convolution-layers
Dropout rate	0.25	None	0.25	0.1
Dense Layers	16 $\rightarrow$ 4	128 $\rightarrow$ 32 $\rightarrow$ 4	64 $\rightarrow$ 16 $\rightarrow$ 4	16 $\rightarrow$ 4
Kernel Sizes	3 $\times$ 3	11 $\times$ 11, 9 $\times$ 9, 7 $\times$ 7, 5 $\times$ 5, 3 $\times$ 3	3 $\times$ 3	Alternating 5 $\times$ 5 & 3 $\times$ 3
Activation Functions	ReLU after Convolution & Dense, SoftMax after Output layer	ReLU after Convolution & Dense, SoftMax after Output layer	ReLU after Convolution & Dense, SoftMax after Output layer	ReLU after Convolution & Dense, SoftMax after Output layer
Optimizer & Learning Rate (LR)	Adam, LR=0.0001	Adam, LR=0.0001	Adam, LR=0.0001	Adam, LR=0.0001
Loss Function	Categorical Cross-Entropy	Categorical Cross-Entropy	Categorical Cross-Entropy	Categorical Cross-Entropy

Furthermore, the complete disease identification algorithm is outlined in Algorithm 3.1. Step 1 illustrates image pre-processing using normalization and balancing by SMOTE-ENN. Step 2 designs the architecture of the deep learning algorithm by modifying different layers. Hyperparameters are also tuned to get maximum accuracy. Step 3 involves the training of the models until the last epoch is reached. Finally, step 4 executes the examination of the model to assess the accuracy and loss of the proposed models.

Algorithm 3.1 Deep learning algorithms for disease identification

Input: Raw Images from the Mendeley BananaLSD dataset, having 3 distinct types of Banana spot diseases and 1 type of healthy.

DS Labels = Cordana, Healthy, Pestalotiopsis, Sigatoka

Step 1: Data loading and preprocessing

- A. Load photos, resize to 224 by 224 pixels and perform normalization.

- B. Split data into training and testing subset.
- C. Apply SMOTE-ENN to handle class imbalance only to the training subset.

Step 2: Define Model

- A. Define the structure with convolutional levels, ReLU, max-pooling, flattening, dense layers, dropout, and SoftMax output.
- B. Tune the hyperparameters of deep learning to get maximum accuracy.

Step 3: Model Configuration and Optimization

- A. Feed the training dataset to the deep learning algorithm
- B. Compile the structure with categorical cross-entropy loss and optimizer as Adam.

Step 4: Calculation of performance metrics

For an epoch up to 200

- A. The model learns during training by updating the weights
- B. Record training and validation loss as well as accuracy

Testing

- A. Evaluation of trained model on the testing dataset
- B. Record testing accuracy, precision, recall, F1-score and ROC

3.4 Identification of diseases in plant images

A color thresholding method has been presented to detect and quantify the severity of banana leaf diseases. Figure 3.9 depicts the flowchart of the proposed technique after classification. Firstly, a color range in the HSV color space is used to segregate the green banana leaf from the backdrop using the color detection method [60]. Further, depending on the kind of illness, the input image is transformed to either the LAB or HSV color space after the leaf area has been determined. The various brown, gray, and yellow hues seen in Cordana and Pestalotiopsis lesions are adequately captured by the HSV color space under different lighting conditions [124]. Here, the hue component corresponds to the main chromatic, while the luminance and the color strength are represented by saturation and value. On the contrary, due to the capacity to discern

minute hue and luminance differences, the Lab color space is more suited for Sigatoka lesions, which exhibit faint yellow to brown streaks. Lab color space (CIELAB) separates: L: lightness, a: green–red, b: blue–yellow. The symptomatic (lesion) zones are extracted for each disease using a set of color thresholds. The typical color features of each disease are intended to be matched by these thresholds. Thresholds have been derived empirically by sampling representative lesion and healthy regions and observing their color distributions using OpenCV color space conversion functions. Morphological operations, such as opening or closing, are also employed to improve the lesion mask and remove noise after thresholding. The diseased pixels are divided by total leaf pixels to calculate the percentage of affected pixels as expressed in equation 3.6. The following is the general formula for determining severity:

$$\text{Severity Percentage}(S) = \frac{L_d}{L_d + L_h} \quad (3.6)$$

where L_d indicates the number of lesion pixels, and L_h indicates the number of green pixels.

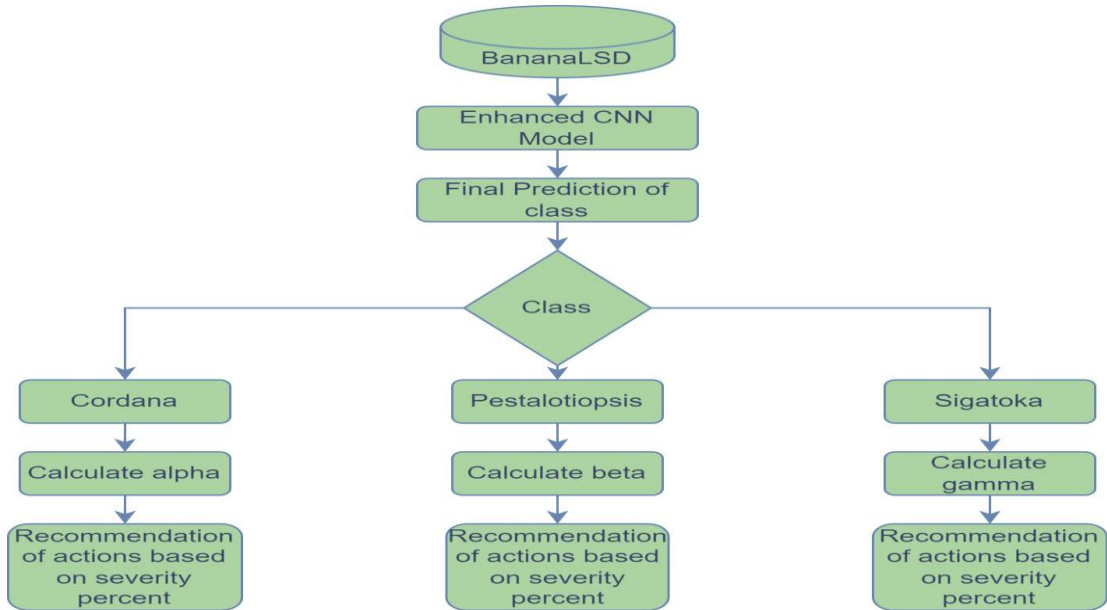


Figure 3.9: The flowchart of the severity estimation and fungicide recommendation

Severity calculations associated with each disease are expressed in equations (3.7) to (3.9). Cordana showcases characteristics such as yellow, light brown, and reddish-brown lesions. Its severity is computed using:

$$\alpha = \frac{Y_p + L_{bp} + R_{bp}}{Y_p + L_{bp} + R_{bp} + H_p} \quad (3.7)$$

where Y_p = count of yellow pixels, L_{bp} = count of light brown pixels, R_{bp} = count of reddish-brown pixels, and H_p = count of healthy green pixels.

Pestalotiopsis lesions are characterized by brown and reddish-brown. Its severity is calculated as:

$$\beta = \frac{B_p + R_{bp}}{B_p + R_{bp} + H_p} \quad (3.8)$$

Where B_p = count of brown pixels, R_{bp} = count of reddish-brown pixels, and H_p = count of healthy green pixels. Sigatoka typically appears as yellow, brown, and black streaks on the leaf. Its severity is given by:

$$\gamma = \frac{Y_p + B_p + K_p}{Y_p + B_p + K_p + H_p} \quad (3.9)$$

where Y_p = yellow pixels' count, B_p = brown pixels' count, K_p = black or dark lesion pixels' count, H_p = healthy green pixels' count.

Based on the percentage of infected leaf area, the disease severity in banana leaves has been evaluated and classified into four severity grades: Low (1–2%), Moderate (3–10%), High (>10–25%), and Very High/Epidemic (>25%). This grade was in accordance with the methodology proposed by [125], who emphasized the need for ordinal scores and disease indices for a consistent and quantitative assessment of disease in plant pathology. For the field actions, management advice has been linked to each severity level. In conjunction with better aeration and sanitation techniques, preventive and early curative sprays employing contact or systemic fungicides have been recommended for low and moderate severities. For efficient control, a rotation, or a mix of systemic and contact fungicides is advised for extreme severities. Aggressive and frequent combination sprays are recommended in epidemic conditions to diminish crop loss and preserve fruit output. Based on standard management guidelines from ICAR-NRCB, FAO, Ploetz (2015), CABI, and TNAU Expert System [126], [127], [128], [129] [130] the fungicides and treatment frequencies have been recommended.

Algorithm 3.2 Disease Severity Identification and Pesticide Recommendation

Input: RGB Images of banana leaves

Class Labels: Cordana, Healthy, Pestalotiopsis, Sigatoka

Step 1: Classification of Disease Type

- A. Resize and normalise the input image to 224x224 pixels
- B. Load the trained deep learning model
- C. Predict the disease class using the model

Step 2: Severity Detection Using Colour Thresholding

- A. Convert image to HSV or LAB colour space based on disease type
- B. Apply disease-specific colour thresholds to segment the lesion area
- C. Use morphological operations to clean the mask
- D. Generate a binary leaf mask to remove the background. Calculate the severity percentage
- E. If the predicted class is "Healthy", then Output: "No disease", Severity = 0%, Recommendation: "No action required". Otherwise, proceed to the severity percent and the recommendation of pesticides.

Step 3: Pesticide Recommendation

- A. If $0 < \text{Severity} \leq 3\%$, Recommendation: "Contact fungicides."
- B. Elseif $3\% < \text{Severity} \leq 10\%$, Recommendation: "Systemic fungicide"
- C. Elseif $10\% < \text{Severity} \leq 25\%$, Recommendation: "Fungicide combinations"
- D. Else: Recommendation: "Combination sprays."

Output: Detected Lesion Mask, Severity percentage, Pesticide recommendation

3.5 Results and Discussion

In this section, the proposed framework has been validated for disease detection and severity estimation through rigorous simulations. Initially, the system specifications have been defined. Furthermore, the performance evaluation of the proposed methods in the context of classification and treatment based on the severity of diseases has been presented. Subsequently, the proposed scheme has been compared with other schemes, namely EfficientNetB0, ResNet50, VGG16, and Vision Transformer.

Table 3.4: System Configuration

Component	Specification
Processor	13th Generation Intel(R) Core (TM) i7-13700HX, 2.10GHz
Operating System	Windows 11 (64-bit)
Device	HP Laptop

GPU	NVIDIA GeForce RTX 3050
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3.5.1 System Specifications

The immense simulations have been carried out on a 13th Generation Intel(R) Core (TM) i7-13700HX processor running at 2.10 GHz. The system is operated on a 64-bit version of Windows 11 on an HP device. It is also equipped with an NVIDIA GeForce RTX 3050 GPU Laptop with 6GB of memory, providing 12.9 GB of GPU memory. Table 3.4 enumerates the system configurations.

3.5.2 Result analysis of disease classification

The section presents the comparative evaluation of the sampling strategies and the proposed models after extensive training based on performance parameters and graphical evidence. Time and space complexity have also been computed to infer the computational costs of the models.

3.5.2.1 Training, Validation and Testing

The framework's variables, including batch size, learning rate, and number of epochs, as well as the optimizer and loss function, have been adjusted during training to obtain the best result. The models have been compiled using the Adam Optimizer, which employs categorical cross-entropy as the loss function, a learning rate of 0.0001, 200 epochs, and a batch size of 16, as enumerated in Table 3.5. An impartial assessment of the model has been conducted using the validation set to optimize hyperparameters. Finally, the test set has been utilized to give a last verification of the invisible data points in the real world after the model has been fully trained, confirming the model's correct operation.

Table 3.5: List of Hyperparameter values for Enhanced Models

Hyper-parameters	Value
Learning rate	0.0001
Number of Epochs	200
Batch Size	16
Optimizer	Adam
Loss Function	Categorical cross-

3.5.2.2 Performance Analysis

The success of this study in the classification has been evaluated using six criteria: accuracy, precision, sensitivity, specificity, F1 score and ROC. To ascertain whether the model can accurately detect every object, the framework's execution accuracy is evaluated. The parameters have been expressed as follows:

- (a) **Accuracy:** Concerning the framework, accuracy counts the percentage of instances that are properly predicted out of all predictions. It is a key performance indicator for classification tasks that demonstrates the model's ability to generalize to new data. Evaluates the proportion of all right predictions—both positive and negative—to all predictions made for overall accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3.10)$$

- (b) **Sensitivity (Recall):** It defines the reliability with which the model can calculate real positive predictions.

$$Sensitivity = \frac{TP}{TP+FN} * 100 \quad (3.11)$$

- (c) **Specificity:** It assesses the percentage of real negatives that are correctly detected.

$$Specificity = \frac{TN}{TN+FP} * 100 \quad (3.12)$$

- (d) **Precision:** It indicates the percentage of expected positive cases that turn out to be positive.

$$Precision = \frac{TP}{TP+FP} * 100 \quad (3.13)$$

- (e) **F1 Score:** It provides a harmonic mean of precision and sensitivity, offering an equilibrium between the two.

$$F1\ Score = \frac{2*Precision*Sensitivity}{Precision+Sensitivity} \quad (3.14)$$

Here, TP denotes True Positive for the banana crop model, which indicates the quantity or proportion of diseased banana cases that the model correctly forecasts. FP is an abbreviated term for False Positive, which is the proportion of healthy bananas that are mistakenly identified as sick. FN denotes False Negative, which is the amount or proportion of sick banana cases that are mistakenly reported as healthy. The number or percentage of healthy banana cases that the model correctly detects is represented by TN, which is True Negative.

(f) **Receiver Operating Characteristics (ROC):** The ROC curve indicates how effectively the classifier distinguishes between different classes by analysing the trade-off between the True Positive Rate and False Positive Rate. A higher Area Under the Curve (AUC) signifies better class discrimination capability.

3.5.2.3 Simulation Results

The simulation findings have been illustrated in Figures 3.10 to 3.13. Figure 3.10 depicts that the training accuracy starts around 0.3 and gradually increases for CNN1, plateauing around 0.9 towards the end of the epochs. The validation accuracy also shows similar behavior, as it initiates around 0.3 and then gradually increases to around 0.85, with some fluctuations, indicating potential over-fitting as the accuracy of validation constantly falls short of that of training. For CNN2, as shown in Figure 3.11, the training accuracy starts at 0.3 and reaches nearly 1.0 within the initial 50 epochs, remaining stable thereafter. Validation accuracy also starts around 0.3 and shows a rapid increase, reaching 0.95 within the first 50 epochs, but it exhibits more fluctuations compared to training accuracy, indicating overfitting. The third model, as shown in Figure 3.12, CNN3, performs similarly to CNN2 but with slightly more stable validation accuracy. Within the first 50 epochs, the training accuracy rapidly increases to approximately 0.9 from an initial value of around 0.3, remaining stable thereafter. Validation accuracy follows a similar trend, starting around 0.3 and rising swiftly to 0.9 within the first 50 epochs, with fewer fluctuations compared to CNN2. The CNN4, as shown in Figure 3.13, demonstrates steady improvement over time with significant variations in validation accuracy. Over 200 epochs, training accuracy steadily rises from 0.3 to 0.9. Considerable fluctuations are observed in validation accuracy, starting around 0.3 and eventually increasing to 0.85, with more variability compared to the training accuracy, indicating over-fitting.

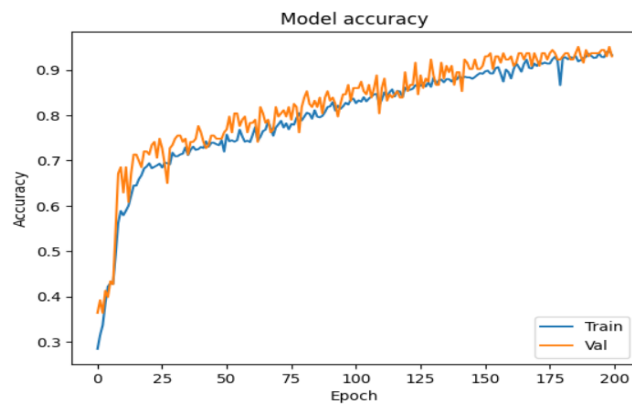


Figure 3.10: Accuracy vs Epoch for CNN1

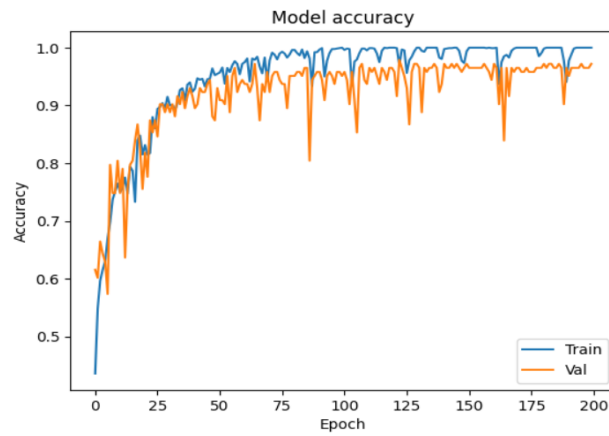


Figure 3.11: Accuracy vs Epoch for CNN2

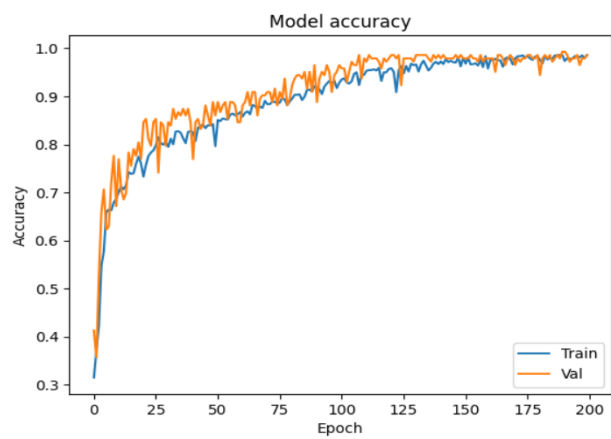


Figure 3.12: Accuracy vs Epoch for CNN3

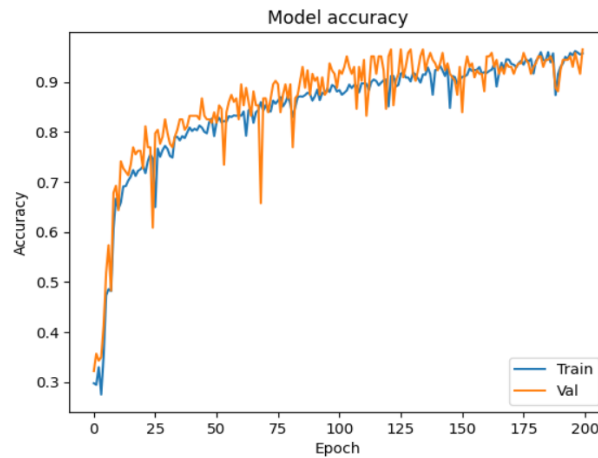


Figure 3.13: Accuracy vs Epoch for CNN4

Figures 3.14 to 3.17 illustrate the comparison between loss of validation (orange line) and training (blue line) for different CNN architectures. Graphs represent the loss behavior of four different CNN models, highlighting their effectiveness in learning and generalization over the epochs. The CNN1 graph shows a general downward trend in both losses, indicating an improvement in the model's long-term performance. The losses converge around a value of 0.4328. For CNN2, the training loss decreases smoothly, while the loss during validation shows more fluctuation but still follows a downward trend, converging around a value of 0.2121. For CNN3, similar to the previous plots, both losses decrease over time. The losses stabilize around a value of 0.3201. For CNN4, the losses decrease steadily and show less fluctuation compared to CNN2. The convergence occurs around a value of 0.3076.

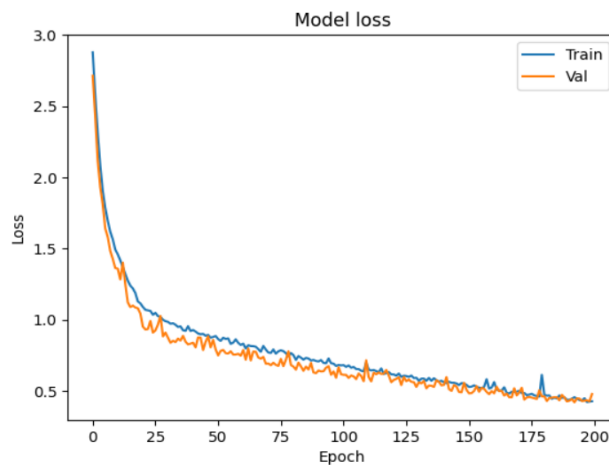


Figure 3.14: Loss vs Epoch for CNN1

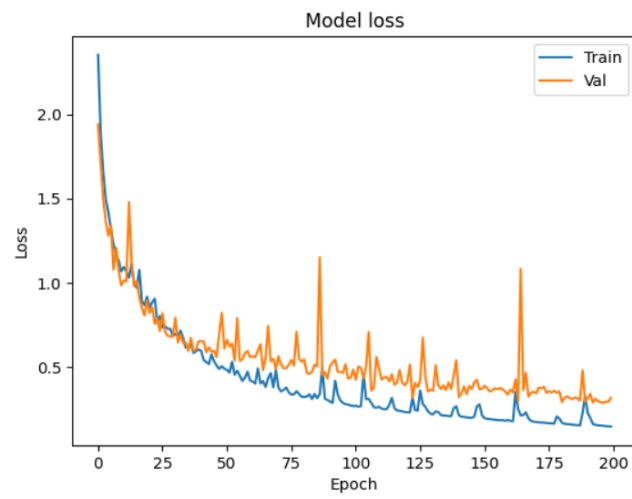


Figure 3.15: Loss vs Epoch for CNN2

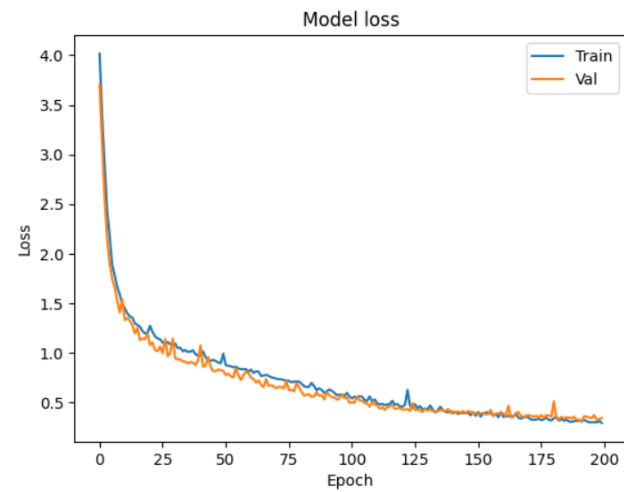


Figure 3.16: Loss vs Epoch for CNN3

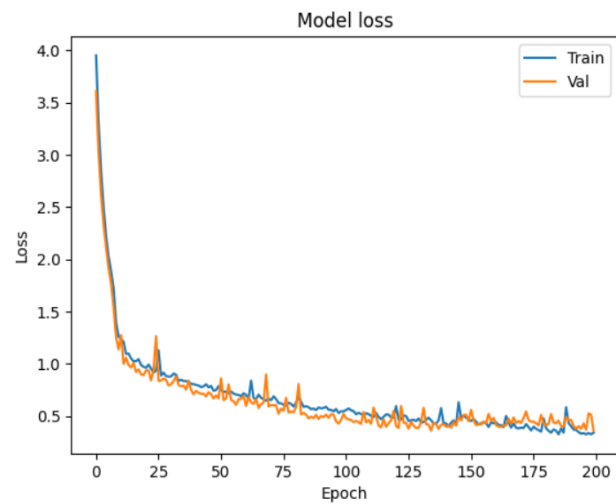


Figure 3.17: Loss vs Epoch for CNN4

In addition, each modified model has been assessed using a confusion matrix. The performance of the models has been summarized and visualized in the confusion matrix, which is demonstrated in Figures 3.18 to 3.21 for the four updated CNN models. Confusion matrices are useful for measuring the execution of machine learning and deep learning classification models. The confusion matrix row depicts the expected class, and the column indicates the instance's actual class. It is evident from the image of the confusion matrix that the number of test images is 159, including 47 for Cordana, 42 for healthy, 43 for Pestalotiopsis, and 27 for Sigatoka. In addition, CNN1 misclassifies Pestalotiopsis as the highest, while Cordana and Sigatoka are completely correctly classified. CNN2 misclassifies Pestalotiopsis and Sigatoka to some extent, but Cordana and healthy classifications are correct. CNN3 still has an error in the prediction of Cordana, healthy, and Pestalotiopsis, except for Sigatoka. CNN4 also demonstrates competitive classification performance across all classes, achieving 100% accuracy exclusively for the Sigatoka class. In general, CNN2 stands out the best amongst models.

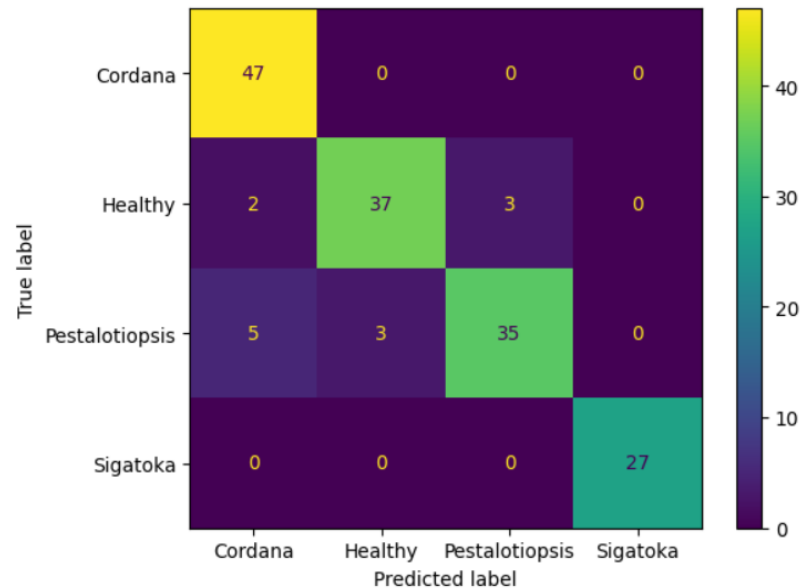


Figure 3.18: Confusion Matrix for CNN1

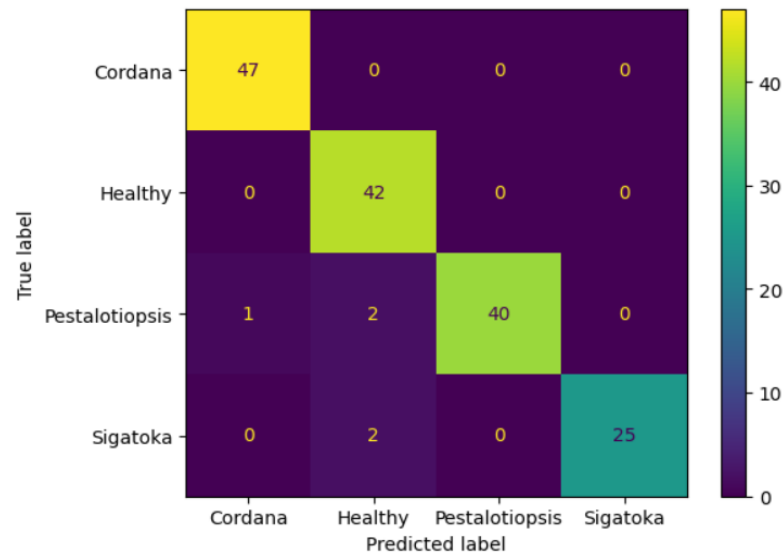


Figure 3.19: Confusion Matrix for CNN2

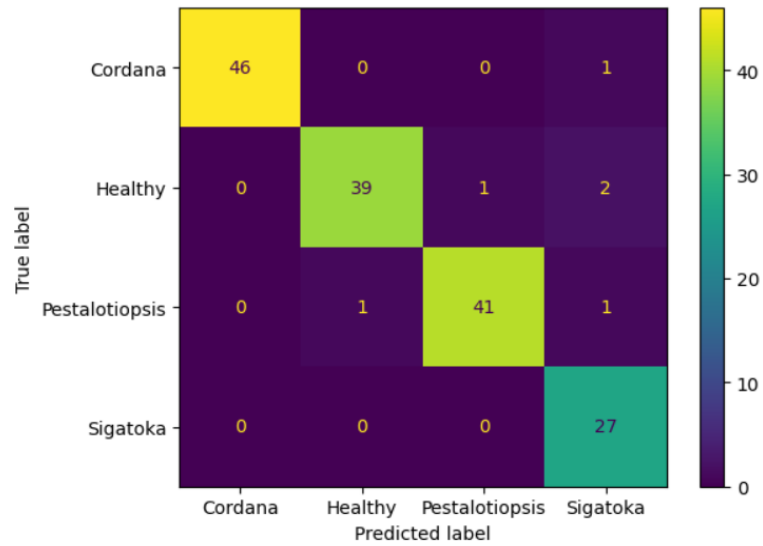


Figure 3.20: Confusion Matrix for CNN3

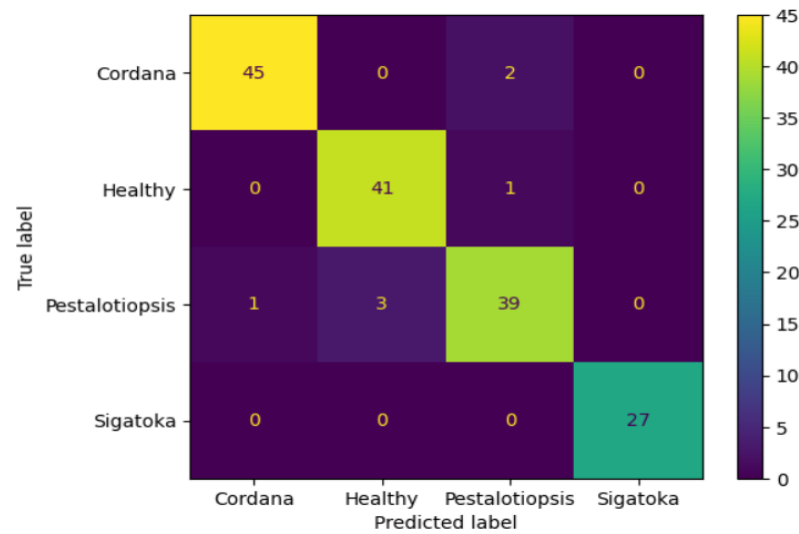


Figure 3.21: Confusion Matrix for CNN4

To facilitate analytical comparison, Figures 3.22 to 3.26 display the assessment parameters for each modified model in a bar visual graph. Moreover, Table 3.6 presents a comparison of all the models based on different parameters. The CNN2 model exhibited the highest accuracy (96.86%) in its positive predictions. It also achieved high specificity (98.92%), precision (97.31%), and the F1 score (96.74%), except for sensitivity (96.4%), which was slightly lower than the other models at 200 epochs. The CNN3 model achieved the highest sensitivity at 96.52%, but its accuracy is 96.23%, specificity 98.81%, precision 95.55%, and F1 score 95.91%. The CNN1 model has the

Table 3.6: Comparison of Accuracy, Sensitivity, Specificity, Precision, and F1 Score for proposed CNN architectures

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 Score (%)
CNN1	91.8	92.37	97.15	92.91	92.43
CNN2	96.86	96.4	98.92	97.31	96.74
CNN3	96.23	96.52	98.81	95.55	95.91
CNN4	95.6	96.02	98.49	95.97	95.97

lowest values for all parameters among all models. CNN4 ranked third in terms of all parameters except the F1 score, which is only slightly lower than that of CNN2. A detailed description is presented in Tables 3.7-3.10, where the performance matrix values are listed for individual classes.

Table 3.7: Performance parameters value for individual class in CNN1 Model

	Sensitivity(%)	Specificity(%)	Precision(%)	F1 Score(%)
Cordana	100	100	87.03	93.06
Healthy	88	95.79	92.5	90.193
Pestalotiopsis	81.3	93.38	92.10	86.36
Sigatoka	100	100	100	100

Table 3.8: Performance parameters value for individual class in CNN2 Model

	Sensitivity(%)	Specificity(%)	Precision(%)	F1 Score(%)
Cordana	100	100	97.91	98.94
Healthy	100	100	91.3	95.45
Pestalotiopsis	93.02	97.47	100	96.38
Sigatoka	92.59	98.5	100	96.15

Table 3.9: Performance parameters value for individual class in CNN3 Model

	Sensitivity(%)	Specificity(%)	Precision(%)	F1 Score(%)
Cordana	97.87	99.11	100	98.92
Healthy	92.85	97.47	97.5	95.11
Pestalotiopsis	95.34	98.29	97.61	96.46
Sigatoka	100	100	87.09	93.09

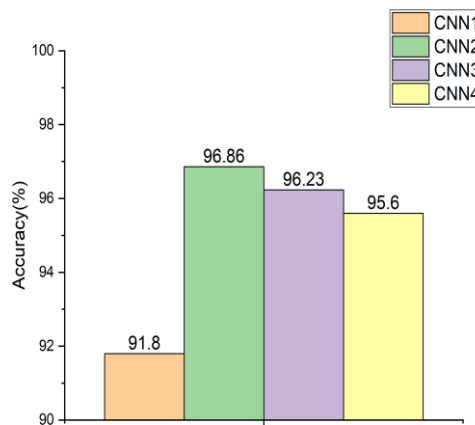


Figure 3.22: Accuracy

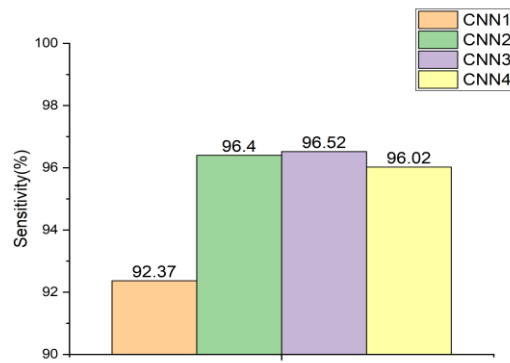


Figure 3.23: Sensitivity

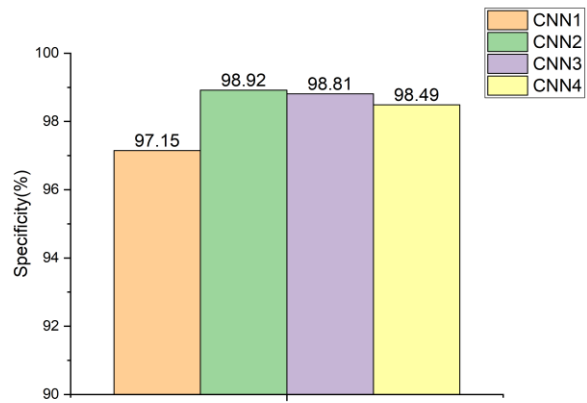


Figure 3.24: Specificity

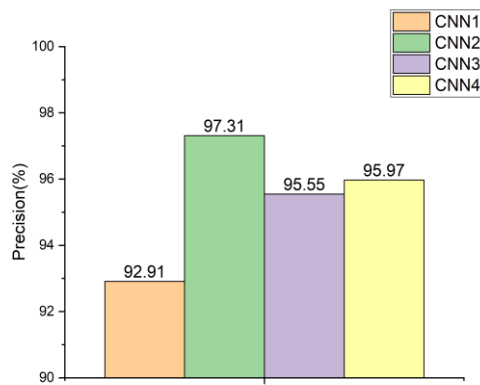


Figure 3.25: Precision

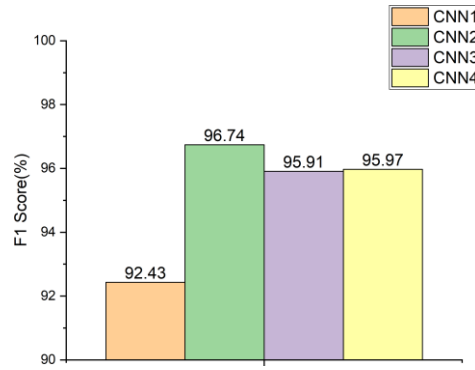


Figure 3.26: F1 Score

Table 3.10: Performance parameters value for individual class in CNN4 Model

	Sensitivity(%)	Specificity(%)	Precision(%)	F1 Score(%)
Cordana	95.74	98.23	97.82	96.76
Healthy	97.61	99.13	93.18	95.40
Pestalotiopsis	90.69	96.58	92.85	91.75
Sigatoka	100	100	100	100

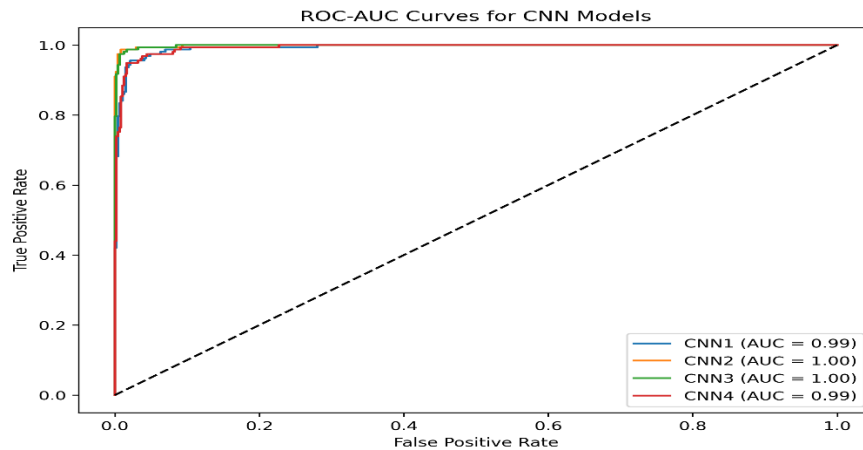


Figure 3.27: ROC curves of the CNN architectures

The ROC–AUC curves for each of the four CNN models (CNN1–CNN4) are shown in Figure 3.27. The curves' outstanding discriminative power is demonstrated by their AUC values, which range from 0.99 to 1.00. With a perfect AUC of 1.00, models CNN2 and CNN3 showed their capacity to differentiate between diseased and healthy classes across all thresholds. Additionally, CNN1 and CNN4 demonstrated strong performance, each with an AUC of 0.99. The significant generalization capacity of the

models is confirmed by the proximity of all curves to the upper-left corner, which indicates high true positive rates and low false positive rates. The ROC generally supports the suggested CNN architectures' stability and dependability for precise banana leaf disease classification–AUC analysis.

Table 3.11: Comparative evaluation of sampling strategies

Sampling Method	Accuracy (%)	Recall (%)	Specificity	Precision (%)	F1-Score (%)
No Sampling	85.11	81.38	94.53	83.06	81.85
SMOTE Only	92.11	93.34	97.4	92.68	92.39
ENN Only	91.58	92.51	97.22	91.61	91.76
SMOTE-ENN	96.86	96.4	98.92	97.31	96.74

To determine how various sampling techniques affect the performance of the model, we tested CNN2, the top-performing architecture, in four different scenarios: no sampling, SMOTE only, ENN alone, and the combination SMOTE-ENN. Table 3.11 illustrates the impact of class imbalance by showing that CNN2 without sampling performed the worst (Accuracy: 85.11%, Recall: 81.38%, F1-score: 81.85%). While ENN alone produced greater specificity (97.22%) and precision (91.61%), SMOTE significantly enhanced recall (93.34%) and F1-score (92.39%). The best results were obtained by the combined SMOTE-ENN technique, which had the highest F1-score (96.74%), Accuracy (96.86%), Recall (96.4%), and Precision (97.31%). These results show that the sampling approach has a significant impact on CNN2's improvements, with SMOTE-ENN offering the most stable and well-balanced performance.

3.5.2.4 Complexity

The main objective of this subsection is to examine the architecture's computational complexity. The time complexity [131] of a CNN is primarily determined by the computations in the convolution layers and fully connected layers. The max-pooling layer, which reduces the dimensions, has a negligible impact on time complexity and can be disregarded in the calculation. The equation for the number of operations involved in every convolution layer is given as follows, using Big O notation:

$$O(K.F^2.W^2.C) \quad (3.15)$$

Where K = Number of Filters, F=Filter's size, W=Dimensions of the output images, and C=Number of the Channels

Table 3.12: Execution time taken by CNN models

	Execution Time(microseconds)
CNN1	20.56
CNN2	175
CNN3	84.4
CNN4	110

Further, the time complexity for each fully connected layer is determined by the number of neurons in the previous layer and the current layer. The count of the operations can be computed by the following equation using Big O notation:

$$O(N, M) \quad (3.16)$$

Where N = the number of neurons in the earlier layer, M = the number of neurons in the present layer.

Finally, the total time complexity is the sum of the number of operations in both the convolutional layer and the fully connected layer. Furthermore, to calculate the execution time taken by different CNN models, the total number of operations involved in each model has been divided by the number of operations the processor can perform in one second. Table 3.12 illustrates the execution time taken by each model being executed on a 3050 NVIDIA GEFORCE RTX. It shows that CNN2 has taken the maximum execution time, while CNN1 has the minimum. Figure 3.28 displays the graphical view of the execution time taken by various CNN models.

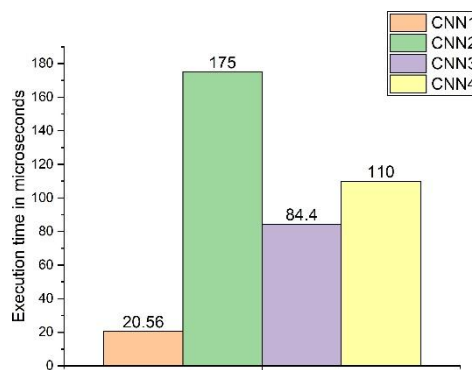


Figure 3.28: Execution time taken by CNN models

Table 3.13: Space complexity comparison of the enhanced models

Proposed Models	Trainable parameters	Number of parameterized layers
CNN1	47732	8
CNN2	220964	8
CNN3	103732	13
CNN4	151796	12

The number of trainable parameters and parameterized layers used to quantify the space complexity of the suggested CNN models is shown in Table 3.13. It comprises all of the memory required to store the input and model weights, as well as any extra memory needed for computation, including intermediate feature maps used for inference or training. CNN2 has the same number of layers as CNN1, but it has the most trainable parameters (220,964), making it the model with the highest space complexity. CNN1, on the other hand, has the fewest parameters—47,732—across eight layers. CNN3 and CNN4’s increased layer depth demonstrates that architectural optimization does not always imply that more layers are associated with higher parameter counts.

The suggested CNN2 model's classification accuracy (96.4%) is marginally lower than that of EfficientNetB0, ResNet50, VGG16, and Vision Transformer ViT-B/16 (all 100%), as shown in Table 3.14. Although it remains the best option for real-world applications, the computational cost and complexity of others are substantially higher. With just 220,964 parameters and a model size of 863.14 KB, it is incredibly lightweight and has a very low computational cost (2,100 MFLOPs). CNN2 is significantly more helpful for making practical decisions in illness management because it offers severity estimation, compared to other high-accuracy models. For real-time implementation in agricultural settings, CNN2 is the most effective and feasible model due to its combination of low latency, small memory footprint, and severity output.

Table 3.14: Comparison of the enhanced and existing models

Models	Parameters	Size	FLOPs	Test Accuracy	Severity Output
Efficient NetB0	4,135,975	15.78 MB	390,000	100 %	No

ResNet50	23,723,268	90.50 MB	3,870,000	100 %	No
VGG16	14,751,940	56.27 MB	15,500,000	100 %	No
Vision Transform er (ViT- B/16)	86,000,000	344 MB	5800,000, 000	100 %	No
Proposed CNN2 Model	220,964	863.14 KB	2100	96.4 %	Yes

3.5.2.5 Disease Severity Prediction after Classification

The results of the lesion detection and severity estimation process for three common banana leaf diseases—Cordana, Pestalotiopsis, and Sigatoka—have been presented in Figures 3.29, 3.30, and 3.31, respectively. Each figure illustrates the original input image, the detected lesion mask, and an overlay image indicating the diseased regions on the leaf surface.

Cordana disease lesions are effectively captured and segmented from the background using colour thresholding. However, the detected regions appear small in area and relatively distinct, as demonstrated in Figure 3.29. But the method yielded a low estimated severity of 1.45%.

Apparently, the Pestalotiopsis lesions in Figure 3.30 are more widespread and scattered across the leaf surface. The irregular and clustered nature of the lesions posed moderate challenges, but the method retains reasonable accuracy. Successful segmentation of multiple infected patches is indicated by the lesion mask, resulting in a severity estimation of 10.77%. Sigatoka disease presents a markedly more severe infection as shown in Figure 3.31. The lesions are elongated, streak-like, and cover a large portion of the leaf surface. The segmentation results in a densely populated lesion mask with a severity estimation of 28.31%. The results indicate robust lesion detection for large-scale infections despite some noise and over-segmentation in the mask.

Table 3.15 lists the recommended targeted fungicides and agronomic protocols for each disease based on severity levels [124], [128], [127], [128], [127] for 10 samples of Cordana, Pestalotiopsis, and Sigatoka. Firstly, the severity ranged from 1.45% to 18.25% for Cordana. Mild infections are treated with contact fungicides or cultural techniques at

10- to 14-day intervals. Moderate to severe cases require systemic or combination fungicides more frequently (every 5–10 days). While moderate instances (S4–S8) require systemic sprays such as Propiconazole or Azoxystrobin, low-severity samples (e.g., S3, S10) should be treated with Mancozeb or Chlorothalonil. At 5- to 7-day intervals, high-severity samples (S1, S2, S9) require treatment with either Difenoconazole + Mancozeb or Trifloxystrobin + Tebuconazole. Thereafter, Pestalotiopsis infection ranges from 1.7% to 29.3%. Contact fungicides are used to treat low-severity cases (such as S3, S7). Azoxystrobin + Difenoconazole or carbendazim + Mancozeb necessitate systemic and combination fungicides to treat moderate (S1, S5, S6, S8) and high/very high instances (S2, S4, S9, S10) cases. Notably, the greatest severity is displayed by Sigatoka (4.31%–82.64%). Every five days, vigorous post-rainfall combination sprays were needed for the majority of samples (S1–S4, S6–S8), which are classified as very high. Every five to seven days, samples with moderate to high severity (such as S9 and S10) receive systemic or combination treatment. Ultimately, this data-driven strategy reduces chemical overuse and improves precision in managing banana diseases by matching fungicide type and frequency with disease severity.

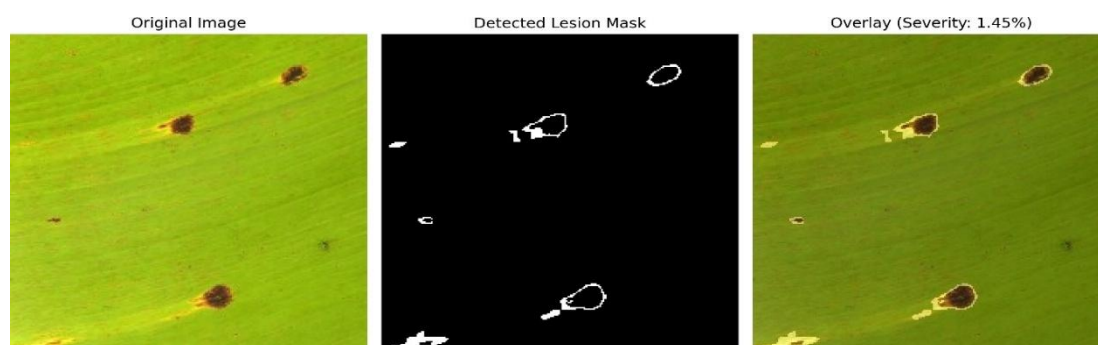


Figure 3.29: Lesion detection and severity estimation for Cordana disease. From left to right: original image, detected lesion mask, and overlay image showing affected areas.

Finally, it is inferred that the most severe of the detected leaf diseases is Sigatoka, which resulted in widespread leaf necrosis and possible yield loss. In contrast, Cordana and Pestalotiopsis leaf spots produce localized lesions with relatively little effect. These findings concur with past studies that Sigatoka is the most damaging banana foliar disease [132]. For HSV/LAB-based colour thresholding, which provides a quick and

easy method for quantification, it is used to quantify the severity of the lesions. This approach, however, occasionally overestimates or underestimates severity, especially in leaves with unequal or poor lesion distribution. Moreover, precise validation is limited by the laborious and difficult nature of manual annotation in the absence of trustworthy ground truth data.



Figure 3.30: Lesion detection and severity estimation for Pestalotiopsis disease. From left to right: original image, detected lesion mask, and overlay image showing affected areas.

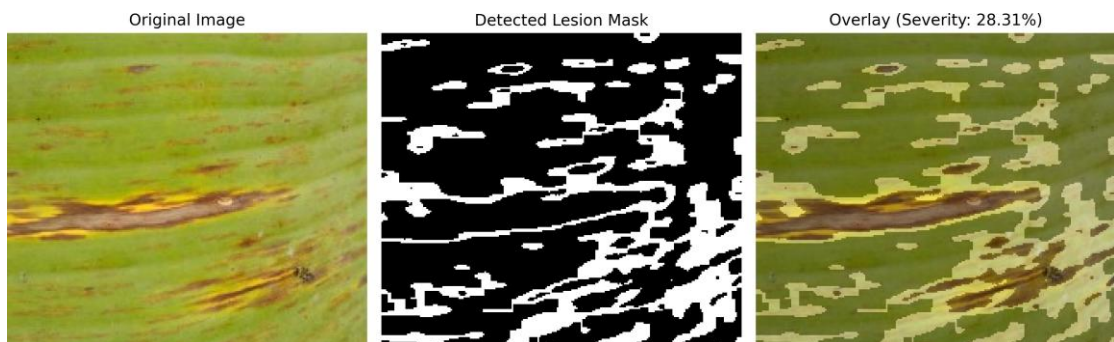


Figure 3.31: Lesion detection and severity estimation for Sigatoka disease. From left to right: original image, detected lesion mask, and overlay image showing affected areas.

3.6 Conclusion

A comprehensive approach is proposed for controlling banana leaf spot infections that merges improved Convolutional Neural Network (CNN) models with suggestions for treatment and disease severity assessment. Primarily, SMOTE-ENN is used to address imbalanced data and then gives the balanced data to the deep learning models. To find the most effective configuration, four different CNN architectures have been built by methodically modifying the convolutional, pooling, dense, and dropout layers. Metrics

accuracy, F1-score, sensitivity, specificity, and precision have been used to assess the model's performance. With the best classification accuracy of 96.86% in identifying infections linked to Cordana, Pestalotiopsis, and Sigatoka, CNN2 outperformed all other tested models.

By executing a thorough examination of time and space complexity, this study supports model optimization while highlighting computational efficiency beyond categorization. The suggested severity estimation module successfully fills the gap, in contrast to many previous methods that ignore lesion progression or rely on globally trained architectures that are unable to detect localized leaf disease patterns. The approach suggests tailored fungicide applications based on quantifiable severity levels, allowing for prompt intervention and reducing chemical overuse, thereby boosting economical and sustainable banana farming.

However, due to environmental unpredictability and its need for sizable annotated datasets, the current CNN-based approach may not be able to detect tiny or early-stage lesions. Transformer-based or lightweight self-supervised models should be investigated in future studies to improve generalization and lessen data dependency. Furthermore, the color-invariant characteristics, adaptive thresholding, or hybrid deep-learning segmentation techniques may enhance resilience to changes in illumination and the precise identification of dry or brown lesion areas. For future developments in automated disease monitoring and control in banana crops, the severity metrics developed in this work can be a useful reference point.

One of the aspects of plant health has been analysed in the current chapter; nutrients are also equally significant for crops' overall health management. In mitigating the shortage of nutrients, an integrated approach with the degree of intensity of the shortage becomes extremely significant. Therefore, a framework that incorporates efficient algorithms and the meticulous utilisation of fertilizers has been proposed in the subsequent chapter.

Table 3.15: Severity-Based Pesticide Recommendation for Banana Leaf Spot Diseases

Disease	Sample	Severity	Grade	Pesticides	Frequency
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Cordana	1	12.64	High	Fungicide Combinations: - Difenconazole+ Mancozeb - Trifloxystrobin+ Tebuconazole	Every 5-7 days
Cordana	2	18.25	High	Fungicide Combinations: - Difenconazole+ Mancozeb - Trifloxystrobin+ Tebuconazole	Every 5-7 days
Cordana	3	1.45	Low	Contact Fungicides: - Mancozeb (0.2%) - Chlorothalonil	Every 10-14 days
Cordana	4	5.89	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 7-10 days
Cordana	5	10.39	High	Fungicide combinations: - Difenconazole + Mancozeb - Trifloxystrobin + Tebuconazole	Every 5-7 days
Cordana	6	8.92	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 7-10 days
Cordana	7	5.24	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 7-10 days
Cordana	8	5.63	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 7-10 days
Cordana	9	16.9	High	Fungicide combinations: - Difenconazole + Mancozeb - Trifloxystrobin + Tebuconazole	Every 5-7 days
Cordana	10	2.28	Low	Contact Fungicides: - Mancozeb (0.2%) - Chlorothalonil	Every 10-14 days
Pestalotiopsis	1	4.14	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 7-10 days
Pestalotiopsis	2	21.31	High	Fungicide combinations: - Difenconazole + Mancozeb - Trifloxystrobin + Tebuconazole	Every 5-7 days
Pestalotiopsis	3	2.07	Low	Contact Fungicides: - Mancozeb (0.2%) - Chlorothalonil	Every 10-14 days
Pestalotiopsis	4	11.95	High	Fungicide combinations: - Difenconazole + Mancozeb - Trifloxystrobin + Tebuconazole	Every 5-7 days
Pestalotiopsis	5	10.77	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 7-10 days
Pestalotiopsis	6	5.34	Moderate	Systemic fungicides: - Propiconazole	Every 7-10 days

				- Tebuconazole - Azoxystrobin	
Pestalotiopsis	7	1.7	Low	Contact Fungicides: - Mancozeb (0.2%) - Chlorothalonil	Every 10–14 days
Pestalotiopsis	8	10.78	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 7–10 days
Pestalotiopsis	9	16.32	High	Fungicide combinations: - Difenoconazole + Mancozeb - Trifloxystrobin + Tebuconazole	Every 5–7 days
Pestalotiopsis	10	29.3	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	1	67.87	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	2	63.67	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	3	82.64	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	4	68.62	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	5	22.1	High	Fungicide combinations: - Difenoconazole + Mancozeb - Trifloxystrobin + Tebuconazole	Every 5–7 days
Sigatoka	6	28.31	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	7	55.45	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	8	35.43	Very High	Combination sprays: - Azoxystrobin+ Difenoconazole - Carbendazim + Mancozeb	Every 5 days and post-rainfall
Sigatoka	9	4.31	Moderate	Systemic fungicides: - Propiconazole - Tebuconazole - Azoxystrobin	Every 5–7 days
Sigatoka	10	12.2	High	Fungicide combinations: - Difenoconazole + Mancozeb - Trifloxystrobin + Tebuconazole	Every 5–7 days

Chapter 4

NutriSense-TL: An AI-Based Intelligent Framework for Banana Nutrient Deficiency Diagnosis and Severity Estimation

Bananas have been a staple meal for more than 400 million people in more than 135 countries and are one of the top five fruits consumed worldwide. The Food and Agriculture Organization, 2023, determines that the world produced about 126 million metric tons of bananas, with India leading the pack with 33.4 million metric tonnes [133], or more than 26% of the total. Despite its importance, banana growing is fraught with difficulties, including poor nutrient management, erratic growth, and inaccurate yield projections, which affect its quality and market value.

Conventional agronomic methods to control banana growth rely largely on farmer experience and recurring field evaluations. However, particularly in the presence of soil heterogeneity and fluctuating meteorological circumstances, such techniques frequently fail to accurately forecast fertilizer application during crucial growth phases such as fruit set and maturation. This discrepancy may impede crop growth and lower the overall yield quality.

However, precision farming and IoT-based monitoring systems can identify nutrient shortages early to avoid production losses. New directions in precision agriculture [134], [135] have been made possible by recent developments in AI, especially transfer learning (TL). TL greatly reduces the need for huge, labelled datasets in certain crops by allowing the application of pre-trained deep learning models to crop management practices. Moreover, by optimizing resource utilization based on precise requirements for nutrients, precision farming instruments can greatly increase sustainability. Therefore, to improve the intelligence and efficiency of farming processes, the proposed study focuses on combining AI and IoT technology for automated banana nutrient management.

Considering that essential minerals and nutrients are vital for plant growth and development, shaping their morphological and physiological characteristics [136]. Each nutrient plays a specific role in fundamental metabolic processes, directly

influencing plant health and productivity. Therefore, effective nutrient management is crucial to optimizing crop yield and ensuring sustainable agricultural practices that support both ecosystem balance and human well-being.

Building upon this requirement for accurate nutrient management, the current work highlights the significance of the micronutrients boron (B) and zinc (Zn) [137] and the macronutrient potassium (K) in sustainable banana cultivation. These nutrients are very important for fruit growth and marketability because fruit size is a key determinant of commercial value. A potassium deficit usually manifests as a slow darkening of the leaves, which can worsen to a deep brown discoloration in extreme situations. While boron deficit frequently affects new development, resulting in leaf curling and yellowing. Zinc deficiency, on the other hand, shows up in younger leaves as interveinal chlorosis and a reduction in leaf size. Crop production can be severely impacted by deficiencies in essential nutrients, underscoring the significance of early identification and focused treatment as a component of a sustainable farming approach.

Thus, it is crucial to maintain a balanced nutrient profile for bananas to guarantee both quality and profitability. This work goes beyond simple nutrient-deficiency classification by introducing a unified framework that also quantifies each deficiency's severity and integrates soil parameters to guide precise fertilizer recommendations. Thereby bridging the gap between research prototypes and practical field deployment. Thus, the study aims to solve the issues through four objectives:

1. To identify and categorize the nutrient deficits in banana leaves based on TL analysis for Potassium (K), Zinc (Zn), and Boron (B).
2. To determine the severity level of each deficiency using HSV color thresholding, intensity, and contour-based techniques.
3. To combine the Intermediate Severity Level with soil data (pH, organic carbon, and electrical conductivity) to increase the precision and detection of deficiencies.
4. To ascertain the necessary fertilizer dosage for deficits in K, Zn, and B while ensuring optimal input utilization and avoiding either excessive or insufficient application.

The suggested approach provides farmers with a dependable tool for accurate input management and fast nutrient diagnosis by combining deep-learning categorization, pixel-level severity quantification, and soil-based fertilizer recommendations into a

single pipeline. This enhances crop health, yield quality, and production sustainability while decreasing fertilizer overuse.

The methodology design, experimental analysis, and validation of the suggested NutriSense-TL system are thoroughly explained in the following sections. A thorough review of the literature on nutritional insufficiency detection and severity evaluation is discussed in Section 4.1. An elaborated framework highlighting the use of digital technologies in contemporary farming, data collection, edge, intelligent, and cloud layers, as well as fertilizer suggestions, is presented in Section 4.2. The proposed methodology, including the deep learning models, is detailed in Section 4.3. Section 4.4 highlights the results in terms of models' performance evaluation and severity estimation. Section 4.5 presents the detailed conclusion of the study.

4.1 Background

This section highlights the agricultural scene that has been changed dramatically due to recent advances in computer vision and machine learning, especially in the automated identification of nutritional deficits in crops. Because of its non-intrusive nature and potential for real-time application, image-based analysis employing colour and texture data has drawn immense attention among other approaches.

One prominent method reported in [138] combines color and texture features for nutrient deficiency classification. Using statistical measures, mean and standard deviation from multiple colour spaces (RGB, YCbCr, and CIELab), texture information is extracted using Dense SIFT. Further, classification was done on the feature set using a Random Forest algorithm with 705 leaf images. The model produced impressive results using the WEKA data mining platform, with 100% accuracy on the training set and 91.64% under 10-fold cross-validation. Furthermore, a web-based application has been created to make the model easily accessible through browsers and mobile devices for field applications.

In a subsequent investigation, the VGG16 convolutional neural network [139] was used to convert images into various color spaces (RGB, HSV, YCbCr, and CIELab) to explore the ideal color properties for leaf categorization. While all conversions produced encouraging results, histogram equalization in the YUV color space and subsequent conversion to RGB is particularly noteworthy, attaining 99.28% training

accuracy and 98.61% validation accuracy. The usefulness of this preprocessing method in enhancing model performance while reducing classification error has been corroborated by the classification report and confusion matrix.

Building on the foregoing research, a study used the ConvNeXtTiny model that has been pre-trained on ImageNet to identify eight nutrient deficits [140]. Foremost, data augmentation is used to overcome class imbalance, especially for underrepresented classes such as potassium insufficiency. Afterwards, the model was trained on the dataset using the Adam optimizer and categorical cross-entropy loss function. It obtained an overall accuracy of 87.89%. The potential of lightweight architectures for classification problems has been demonstrated in this work using cross-validation to maximize learning rate and regularization.

Further, relying on a single feature type is insufficient for accurate diagnosis, so the research emphasizes the importance of integrating multiple features. Six distinct plant health conditions have been classified using 5166 images. Color features (HSV and RGB), texture features (GLCM and LBP) [29] and shape features (Hu moments and centroid distance) have been extracted. These features and their combinations are evaluated using a consistent Multi-Layer Perceptron (MLP) architecture. Among the various combinations, the integration of RGB, GLCM, Hu moments, and centroid distance yields the highest performance. Furthermore, the study compares the performance of the MLP model against other established classifiers such as Support Vector Machine (SVM), Random Forest, Naive Bayes, and CNN. CNN achieves the highest accuracy at 97.76%, followed by SVM at 90.55%, and MLP at 89.70%. While MLP performs slightly lower than CNN, it still demonstrates effectiveness in plant condition identification.

The existing models [141] still face limitations that complicate accurate diagnosis. To address these shortcomings, an ensemble transfer learning approach has been designed for both nutrient shortage detection and yield-loss prediction. This approach is validated through two distinct trials: the first focuses on classifying images based on specific nutrient deficiencies, whereas the second estimates yield loss by assessing the severity of those deficiencies. The presented approach demonstrates high accuracy, achieving 99% for groundnut and 94% for rice in nutrient deficiency classification. In terms of yield prediction, the model estimates losses of 32.5% for rice and 28.34% for

groundnut, based on the severity of deficiency. The study employs two real-world crop datasets—4,399 leaf images from rice plants and 4,550 from groundnut—captured under natural conditions. The proposed ensemble transfer learning method outperforms traditional models and highlights its potential to address key issues of precision agriculture.

The researchers also introduced a Deep Ensemble Convolutional Neural Network (DECNN) model [31] aimed at the accurate determination of nutrient deficiencies in rice crops. They utilized and enhanced several pre-trained convolutional neural network architectures—namely InceptionV3, InceptionResNetV2, DenseNet121, DenseNet169, and DenseNet201—by incorporating additional layers such as dense, pooling, and dropout layers, alongside effective data augmentation techniques. These modifications led to significant improvements in evaluation metrics, including accuracy, precision, recall, and F1 score, when assessed on a publicly available Kaggle dataset. Among the revised models, DenseNet169 accomplished the highest individual test accuracy, increasing from 92% to 96.66%. Ultimately, the researchers developed an ensemble model combining the modified DenseNet169, DenseNet201, and InceptionV3 using a weighted averaging approach. This ensemble model achieved a superior testing accuracy of 98.33%, demonstrating the effectiveness of the DECNN framework for rice nutrient deficiency identification.

Another work utilizes image classification to identify vitamin deficits in banana leaves using an ensemble CNN (ECNN) model [59]. A publicly accessible banana leaf dataset was utilized to refine and evaluate six pre-trained deep learning models: VGG-19, InceptionResNetV2, InceptionV3, Xception, DenseNet169, and DenseNet201. The updated DenseNet169 was the most accurate of them all. Three ensemble models were also developed, and the best performance was obtained by InceptionV3+DenseNet169 (IncepV3Dense), which identified defects with a 93% F1 score and 98.62% accuracy. These findings demonstrate the dependency on deep learning models—in particular, CNNs—for the identification of dietary deficiencies as enumerated in Table 4.1. Even with the excellent accuracy, the models frequently need a lot of processing power, which makes it challenging to deploy them in real time on edge devices. Therefore, there is a need for models that are lighter and more efficient. In addition, hybrid systems that integrate CNNs and supervised learning have also been ensembled. However, the

efficacy of many current approaches in detecting holistic deficiencies is limited because they often only optimise a handful of characteristics.

Furthermore, assessing severity is also crucial because it can minimize monetary losses through fertilizer management and the preservation of robust crop growth. In this direction, a framework has been proposed [60] for the yield prediction based on the extent of nutrient deficiencies for groundnut and rice crops. The agricultural yield loss has been estimated, which calculates the proportion of crop yield loss depending on the degree of nutrient shortage. This is achieved by a color detection method using the HSV color space after the classification of N, P, and K classes using an ensemble model. The severity percentage is then calculated by the affected pixels in relation to the total number of pixels. Based on the relation between severity and yield, the percentage of crop yield loss for rice and groundnut crops is 32.5% and 28.34%, respectively.

Another study introduced two innovative systems—Image Analysis-based Severity Detection (IASD) [142] and a Severity Index Calculation Model (SICM) in addition to the YOLOv9 model to identify macronutrient and micronutrient deficiencies in coconut trees. These devices determine the degree of deficiencies and suggest appropriate fertilizers along with dosage. With 80% accuracy, 98.59% precision, and 80.37% recall, YOLOv9 outperformed the other four deep learning models tested on 5,720 photos. The automated system's dependability has been validated manually, facilitating effective administration of coconut plantations. Considering works outside the agricultural domain, such as in medical imaging, have also adopted feature-based severity estimation techniques. For instance, in the study [143], eczema severity has been classified as mild or severe using SVM after extracting 14 color and texture features from segmented regions. A severity index is then computed by combining area coverage, intensity of symptoms, and anatomical region. This structured approach inspires a potential model for nutrient deficiency severity estimation in crops, where lesion size (area score), visual intensity (color/texture), and location (leaf tip, edge, or center) could analogously contribute to an agricultural severity index.

Subsequently, there is a lack of integration between classification, nutrient deficiency severity assessment, and fertilizer recommendation systems that account for soil parameters. While crop yield models provide valuable insights, they often overlook direct quantification of deficiencies and corresponding corrective actions. Moreover,

current severity estimation approaches in agriculture either focus on yield loss prediction or developed for other crops (e.g., rice, groundnut, coconut). Rarely integrate soil parameters such as pH, organic carbon, and electrical conductivity. There is a lack of a structured system that combines the size, intensity of the color, and location of the injury into a severity index. The index together with site-specific soil data can be used to generate optimized fertilizer type and dosage recommendations for bananas. The drawbacks underlined in the present work have motivated the development of a smart framework leveraging the benefits of hybrid models that enhance feature learning, generalization, and stability of performance by combining the complementary strengths of various architectures.

Table 4.1: Inferences of various research papers related to Nutritional deficiency

Ref	Methodology	Crop Dataset	Integration Approach	Detected Deficiency	Results	Remarks
[138]	A leafcheckIT, a web and mobile app, uses Random Forest	Banana	No	N, P, and K	100% accuracy with training set validation and 91.64% with 10-fold validation.	-Macronutrient (N, P, and K) are considered -No real-world prediction
[139]	Histogram-equalized RGB, HSV, YCbCr, and CIELAB color space images as input to VGG16	Banana	No	N, P, and K	98.61% validation accuracy and 99.28% training accuracy	-A wide range of preprocessing operations -Macronutrient (N, P, and K) deficiency; -No real-world prediction
[140]	Deep convolutional neural network.	Banana	No	B, Ca, Fe, Mg, Mn, K and SA ⁺	F1 Score- 88%, 87.89% accuracy	Low accuracy
[31]	Pre-trained model and weighted ensemble model	Rice	Yes (ensemble)	N, P, and K	Accuracy with ensemble of 3 models- 98.33%	-Small dataset i.e.1156 images, Focused on N, P, and K, Neglected micronutrient.

						-Ensemble model complexity poses a challenge to the real world
[29]	Feature extraction- HSV and RGB for color, GLCM and LBP for texture, Hu moment and centroid distance for shape. Classifier-CNN, SVM and MLP	Chilli	No	Ca, Mg, S and MgS	Accuracy with CNN is 97.76%	Not explored advanced deep learning
[60]	An ensemble of shallow CNN and MobileNetV2	Rice and groundnut	Yes (Ensemble)	N, P, and K	99% accuracy for groundnut 94% accuracy for rice	Macro-nutrient (N, P, and K) - Computational cost of the ensemble is more
[59]	VGG-19, InceptionV3, InceptionResNetV2, Xception, DenseNet169, and DenseNet201	Banana	Yes	B, Fe, and Mn	98.62 % validation accuracy	-No real-world Prediction -High computational cost
Proposed work	DenseNet169+ MobileNetV2	Banana	Feature-level fusion	B, K, and Zn	95.10% validation accuracy	-Classification of macro and micro nutrients -Severity Estimation -Fertilizer prescription

4.2 NutriSenseTL: A Smart Framework

To address the challenge of accurately diagnosing nutrient deficiencies in banana crops and recommending appropriate fertilizers, a multi-layered intelligent framework has been proposed in this section, as shown in Figure 4.1. The proposed framework integrates image analysis, soil parameter evaluation, and automated actuation [143], [144], [145],[146] while incorporating technologies like drones, robots, and UAVs. Further, the synergetic integration of wireless connection and DL facilitates automated agricultural activities and real-time decision-making.

The proposed NutriSense-TL framework is designed to fulfil the following requirements:

1. The framework must incorporate deep transfer learning capabilities to utilise pre-trained knowledge for efficient feature extraction from agricultural imagery and sensor data.
2. The framework must rely on a data-driven methodology to predict nutrient deficiencies and fruit development stages with high accuracy, even in cases of limited labelled agricultural datasets.
3. The framework must support severity-level estimation of nutrient deficiencies to enable precise, timely, and targeted agronomic interventions.
4. The architecture must be capable of integrating multi-modal data sources—such as images and soil nutrient profiles for holistic analysis.
5. The framework should be lightweight and computationally efficient to facilitate real-time deployment on edge devices in field conditions.
6. The framework must be expandable and adaptable across varying banana cultivars, soil types, and regional agroclimatic zones to ensure generalizability.

The proposed framework consists of four core layers: Data Acquisition Layer, Edge Layer, Intelligent Layer, and Cloud Layer, elaborated in the upcoming subsections.

4.2.1 Data Acquisition Layer

The data acquisition layer forms the core of the system by collecting both image-based and soil-related information from the field. High-resolution images of banana leaves are captured using field-deployed cameras. These images serve as the primary input for visual symptom analysis, which is critical in detecting nutrient deficiencies such as potassium, boron, or zinc deficiencies. Alongside visual data, the layer records key soil physicochemical parameters, including soil pH (range: 6.5 to 8.5), which affects nutrient solubility and microbial activity; organic carbon content (target < 0.5%), indicative of soil fertility and humus level; and electrical conductivity (EC) (maximum up to 0.7 dS/m), used as a proxy for nutrient and salinity levels. Additionally, the layer integrates with an automatic robotic spray unit, which can execute targeted fertilizer application based on the system's recommendations.

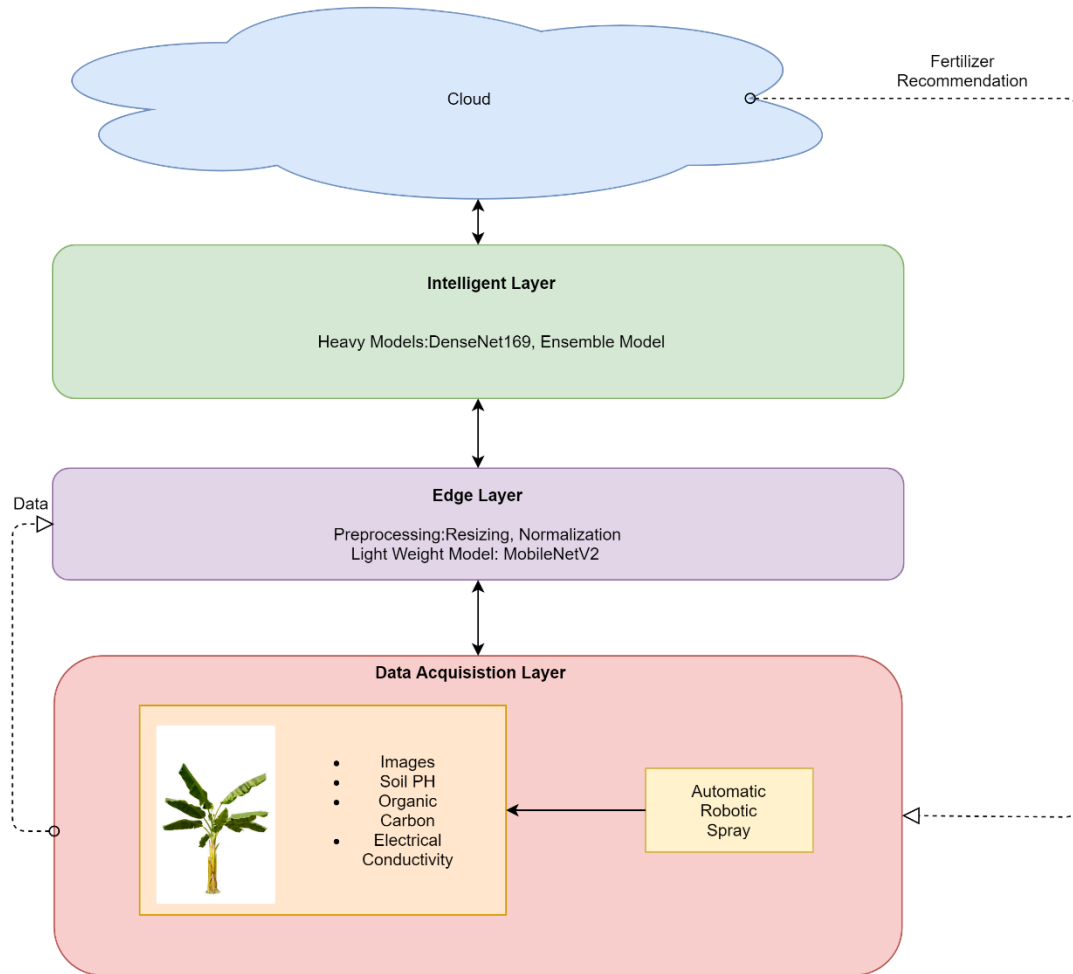


Figure 4.1: Conceptualized Framework for nutrient deficiency detection and precise fertilizer recommendation

4.2.2 Edge Layer

The layer enables real-time, local processing while reducing the dependency on continuous cloud connectivity. Image data is normalized and resized, with preprocessing steps such as background removal, color space transformation (e.g., HSV for color thresholding), and noise reduction. This layer further employs a lightweight deep learning model, MobileNetV2, which is modified for edge deployment. The model performs initial classification of banana leaf images into healthy or deficient categories. It allows for efficient decision-making in resource-constrained environments while maintaining acceptable classification performance.

4.2.3 Intelligent Layer

The intelligent layer operates more computationally intensive models for refined analysis. A heavyweight convolutional neural network, specifically DenseNet169, is

used for detailed classification of nutrient deficiency types and severity levels. DenseNet169's densely connected layers help in capturing complex patterns and gradients in the leaf symptoms, which are indicative of nutrient stress. To enhance model robustness and prediction accuracy, an ensemble model approach is also employed. The model combines multiple classifiers and integrates both image-based features and soil parameters (pH, organic carbon, EC). This hybrid approach ensures that fertilizer recommendations are not only based on visible symptoms but are contextualized with soil chemistry, resulting in personalized and site-specific nutrient management.

4.2.4 Cloud Layer and Fertilizer Recommendation

The cloud layer operates for long-term storage, model management, and recommendation services. It houses datasets, re-trains models periodically, and facilitates real-time communication between different system components. Upon final classification and analysis, the system generates fertilizer recommendations tailored to the detected nutrient deficiency, soil condition, and crop stage. A potassium deficiency in a field with low pH may prompt a split application of Muriate of Potash with a lime amendment. Similarly, low organic carbon may trigger a recommendation for farmyard manure (FYM) or vermicompost, combined with micronutrient foliar sprays. In contrast, high EC readings may limit certain fertilizer applications to avoid further salinization. The generated recommendations are sent to the robotic spray unit for execution, thereby creating a closed-loop feedback system that ensures precision nutrient management.

4.3 Methodology

This design consists of four main blocks: Dataset preparation, nutrient deficiency classification using hybrid models, severity estimation by incorporating soil parameters, and fertilizer recommendation. Initially, images of nutrient-deficient banana leaves were collected and pre-processed using resizing and normalization. This is followed by the concatenation of TL models, which are trained to categorize the deficiency classes. The intermediate severity value is computed based on intensity, affected area, and shape distortion. The severity value and soil inputs such as soil pH, electrical conductivity (EC), and organic carbon (OC) are used to classify the deficiency

into severity classes: mild, moderate, and severe based on the final severity index (FSI). Consequently, an appropriate fertilizer amount is applied. Thus, an automated framework to control nutrient deficiency has been designed to aid farmers.

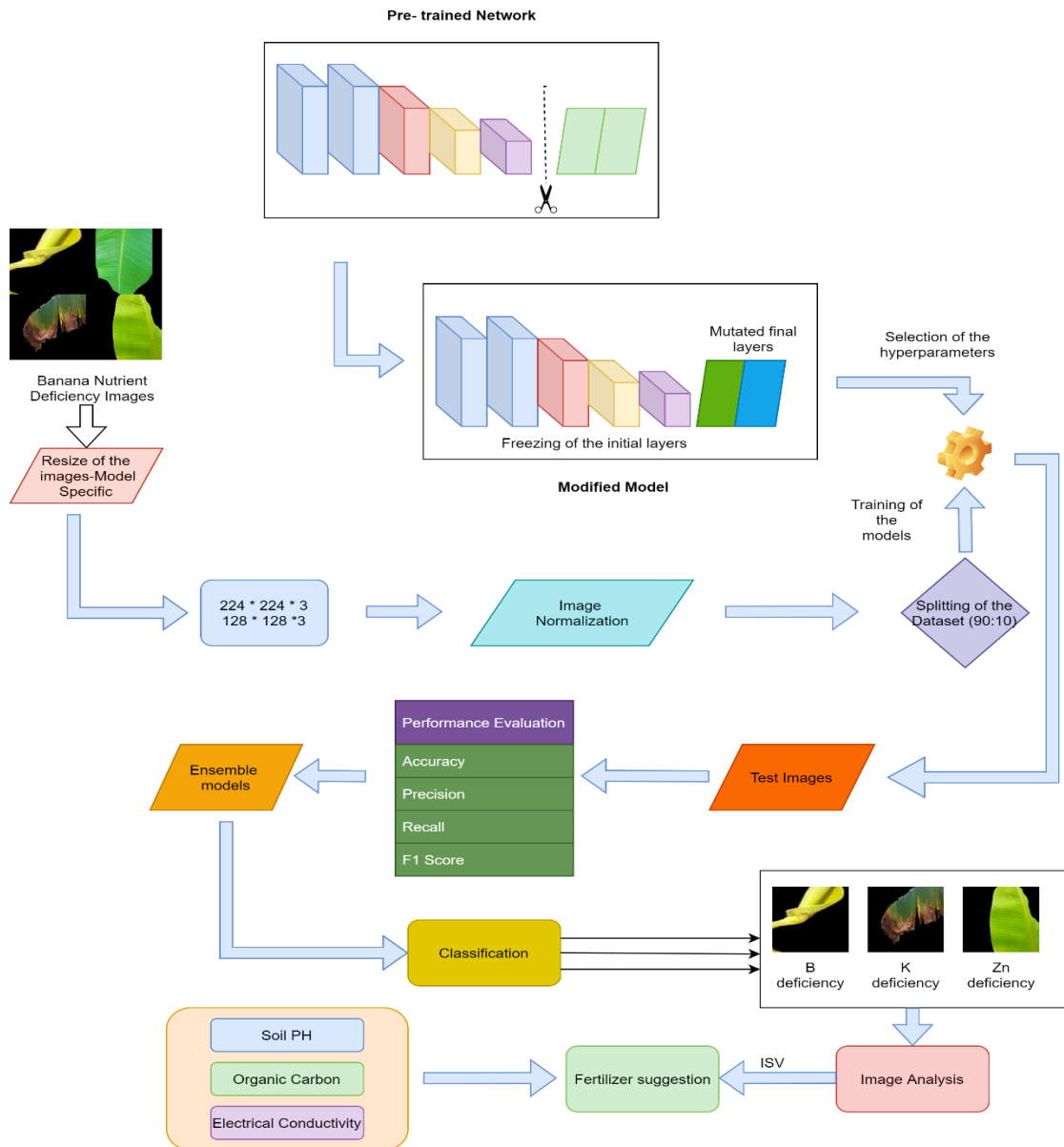


Figure 4.2: A visual representation of the progressive stages involved in conceptualising the proposed architecture

4.3.1 Description of Dataset

Firstly, the Mendeley dataset [30] “Images of Nutrient-Deficient Leaves of Banana Plants” has been used for this study. Banana leaf samples from a variety of cultivars in Karnataka, India, including *Musa acuminata*, Robusta, Rasthali, Poovan, Monthan, and Elakkibale, are shown in Figure 4.3. A total of 3,390 tagged images of banana leaves make up the dataset used in this study. Figure 4.4 illustrates the count of images in each category. It contains 840 pictures of potassium (K) insufficiency, 800 pictures of zinc (Zn) deficiency, 950 pictures of healthy banana leaves, and 800 pictures of boron (B) deficiency.



Figure 4.3: A pictorial view of leaf images comprising (a) Healthy, (b) Boron, (c) Potassium, (d) Zinc, Banana nutrient deficiency dataset

4.3.2 Image Preprocessing

Although the original dataset images are standardized to a size of 225×225 pixels, most modern convolutional neural network architectures—such as DenseNet169, MobileNetV2, and ResNet50 [148]—require an input dimension of $224 \times 224 \times 3$. Therefore, all images have been uniformly resized to $224 \times 224 \times 3$ to ensure full compatibility with the selected models and to maintain consistency across all experimental configurations. Following resizing, each image has been normalized by dividing its pixel intensity values by 255, thereby scaling the data to the range $[0, 1]$. This normalization step improves numerical stability during training, accelerates convergence, and ensures that all models operate on a standardized intensity scale.

The augmented dataset includes operations such as rotation, flipping, zooming, and contrast adjustments to achieve a balanced representation of all nutrient classes. Since these augmented images have been directly utilized, no additional augmentation is employed during the training phase. This decision maintains consistency with the

published dataset version and avoids artificially increasing the number of samples beyond what the dataset provides. A uniform black background and any unwanted noise or irrelevant artifacts have been manually removed from the dataset. The controlled and pre-processed nature of the dataset, therefore, eliminated the need for further denoising or background correction.

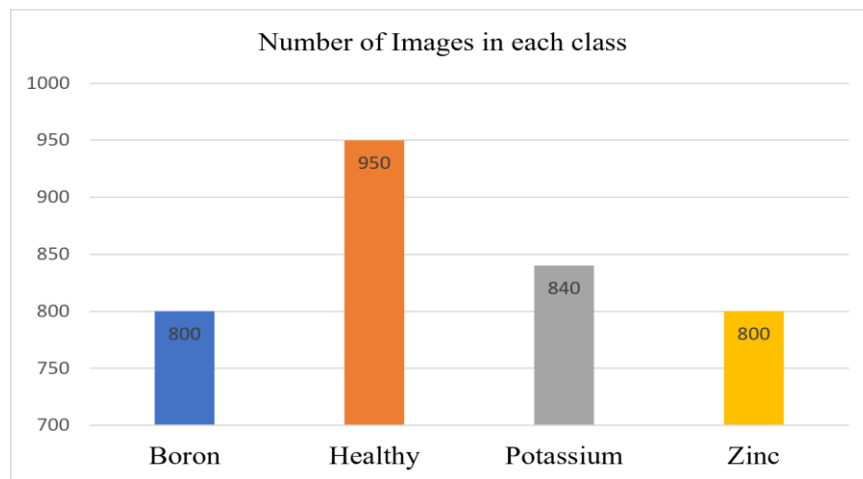


Figure 4.4: Number of images in each class

To enable multiclass classification using categorical cross-entropy loss, each image has been given one of four class labels: 0 to 3—Boron deficient, Healthy, Potassium Deficient, Zinc deficient. These labels are subsequently one-hot encoded. It is appropriate for use in a neural network’s output layer with SoftMax activation.

In addition, the dataset is separated into 81% training, 9% validation, and 10% testing using stratified sampling to ensure a balanced class distribution. 3,051 images have been used for training and validation, while 339 photographs have been retained for testing trained models’ adaptability to generalize to new data. Preprocessing steps have been further enumerated in Table 4.2, which details all the required operations for dataset preparation before training the models.

Table 4.2: Details of pre-processing and dataset preparation of the images

Operation	Measures	Description
Data	Loaded Mendeley	3,390 pre-processed images in 4 nutrient
Acquisition	Banana Leaf Dataset	classes (Boron, Potassium, Zinc,

Dataset Properties	Standardized black background, cropped leaf regions, augmented categories	Healthy) Dataset creators ensured clean, uniform images and balanced classes.
Resizing	Convert 225×225 to 224×224×3	Ensures compatibility with Transfer Learning Models
Normalization	Pixel value divided by 255	Pixel values normalized to [0, 1] improve convergence and stability.
Label Encoding	One-hot encoding	Converts 4 nutrient classes into a multi-class format for SoftMax classifiers.
Dataset Split	Stratified 81% training, 9 % validation, and 10% test	Maintains class balance and ensures fair evaluation.

4.3.3 Deep Learning-Based Classification

This section firstly presents an overview of different pre-trained models efficient for the classification of nutrient deficiency in the banana crop. Thereafter, efficient TL models are concatenated to design hybrid models.

Transfer learning is an efficient approach to machine learning that focuses on reusing previously acquired knowledge to address new but related problems more efficiently and effectively. Unlike traditional machine learning methods that learn solely from scratch, transfer learning exploits information from auxiliary domains to enhance performance in the target domain. Leveraging existing knowledge enables improved predictive modelling, especially when data patterns differ across domains.

Initially, several pretrained CNN architectures have been assessed for the categorization of nutrient deficiencies in banana leaves, including MobileNetV2 [149], EfficientNetB0 [150], VGG16, ResNet50 [151], DenseNet169 [152], [153], InceptionV3 [154], and Xception [155]. These TL models are modified by dense and dropout layers in addition to the number of neurons. The models are trained to 20 epochs and evaluated by performance metrics. DenseNet169 is the single model with the highest independent testing accuracy of 95.87%, followed by MobileNetV2 and ResNet50, both of which have competitive results. Nevertheless, poor generalization, overfitting, or bias toward spatial patterns are common problems with individual CNNs. As seen in Figure 4.5, the

framework progresses from standalone designs to hybrid feature-fusion models [156] to overcome these limitations and capture deeper, more varied feature representations.

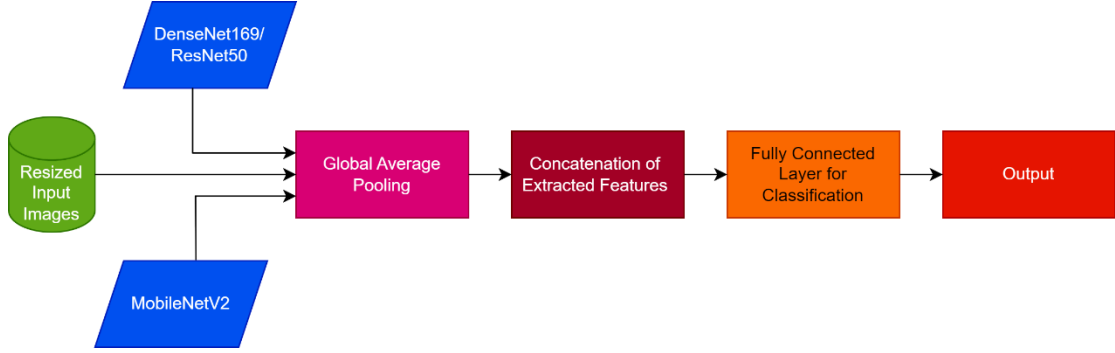


Figure 4.5: Architecture of Hybrid Model

Two hybrid configurations [60] have been proposed by combining the lightweight MobileNetV2 with two heavyweight backbones- DenseNet169 + MobileNetV2, and ResNet50 + MobileNetV2. Both hybrid models [157] have been trained with identical hyperparameters to ensure fairness in comparison. Complete layer-wise architectural specifications for the hybrids are provided in Table 4.3 and Table 4.4.

Table 4.3: Layer-wise description of the first proposed hybrid model

Layer (type)	Output Shape	Parameters
Input	(None, 224, 224, 3)	0
DenseNet169	(None, None, None, 1664)	1264288
MobileNetV2	(None, None, None, 1280)	2257984
GlobalAveragePooling2D	(None, 1664)	0
GlobalAveragePooling2D	(None, 1280)	0
Batch Normalization	(None, 1664)	6656
Batch Normalization	(None, 1280)	5120
Concatenate	(None, 2944)	0
Dense	(None, 64)	188480
Dense	(None, 64)	4160
Dropout	(None, 64)	0
Dense	(None, 4)	260
Total Parameters: 15105540; Trainable: 14907140; Non-Trainable: 198400		

The suggested hybrid model uses feature-level fusion via concatenation, compared to conventional ensemble techniques that rely on voting or probability averaging.

Table 4.4: Layer-wise description of the second proposed Hybrid Architecture

Layer (type)	Output Shape	Parameters
Input	(None, 224, 224, 3)	0
ResNet50	(None, 7, 7, 2048)	23587712
MobileNetV2	(None, 7, 7, 1280)	2257984
GlobalAveragePooling2D	(None, 2048)	0
GlobalAveragePooling2D	(None, 1280)	0
Batch Normalization	(None, 2048)	8192
Batch Normalization	(None, 1280)	5120
Concatenate	(None, 3328)	0
Dense	(None, 64)	213056
Dense	(None, 64)	4160
Dropout	(None, 64)	0
Dense	(None, 4)	260
Total Parameters: 26076484; Trainable: 25982596; Non-Trainable: 93888		

The early convolutional blocks of both backbones have been frozen during the epochs to overcome gradient imbalance, where the deeper network (DenseNet169/ResNet50) may dominate training. This technique keeps one network from being over-updated in comparison to the other. Even enables MobileNetV2 to make a significant contribution to the fused representation. Deep feature vectors are computed from the Global Average Pooling (GAP) layer. This guarantees that both lightweight and heavyweight networks produce fixed-length one-dimensional feature vectors while removing any dimensionality mismatch and enabling seamless concatenation without the need for additional projection or reshaping layers. Batch Normalization is applied to both feature vectors before fusion to stabilize the value ranges and to balance contributions during training by preserving uniform scaling across fused features. Before the final SoftMax layer performs four-class classification, the concatenated feature vector is run through two fully linked layers using ReLU activation and dropout regularization. This early fusion approach successfully combines complementary strengths: DenseNet169/ResNet50 store deeper morphological and structural patterns linked to dietary deficits, while MobileNetV2 captures lightweight texture-level inputs. The hybrid model creates a more dependable and broadly applicable classification

framework for the identification of nutrient deficiencies in banana leaves by integrating several learning perspectives and minimizing the drawbacks of individual models, as summed up in Algorithm 4.1.

Even though hybrid networks typically result in processing costs, the suggested model is nonetheless effective. Pretrained backbones, GAP layers, and a shallow classification head (two dense layers with dropout) are used to reduce the number of trainable parameters. A hybrid architecture that enhances resilience while preserving inference durations comparable to those of the heavyweight backbone alone combines computational efficiency from MobileNetV2 with robust semantic representations from DenseNet169 or ResNet50.

Algorithm 4.1 Hybrid Model for Multi-Class Nutrient Deficiency Classification

Input: RGB image dataset $D = \{(x_i, y_i),$

where $i = 1$ to N samples, $x_i \in \mathbb{R}^{224 \times 224 \times 3}$ and $y_i \in \{0,1,2,3\}$ class labels

Output: Trained hybrid model and classification performance metrics

Step 1: Data Loading and Pre-processing

1. Load class folders F_j with labels j , where $j \in \{0,1,2,3\}$
2. For each image $x \in F_j$
 - A. Resize x to 224×224 .
 - B. Normalize pixel values to $[0,1]$.
 - C. Append (x, j) to dataset D .
3. Split into training and testing sets.

Step 2: Hybrid Feature Extraction

1. Extract deep features from heavyweight model: $f_r \leftarrow \text{GAP}(\text{DenseNet169}(x))$ or $f_r \leftarrow \text{GAP}(\text{ResNet50}(x))$
2. Extract lightweight features $f_m \leftarrow \text{GAP}(\text{MobileNetV2}(x))$
3. Apply batch normalization:

$$\hat{f} \leftarrow \text{BatchNorm}(f_r), \hat{f}_m \leftarrow \text{BatchNorm}(f_m)$$
4. Fuse features $\leftarrow [\hat{f}, \hat{f}_m]$
5. Pass through a dense layer with dropout:

$$h = \text{ReLU}(W_1 f_{\text{fused}} + b1);$$

$h' = \text{Dropout}(h, p=0.3)$

Final prediction: $\hat{y} = \text{SoftMax}(W_2 h' + b_2)$

Step 3: Model Compilation and Training

Optimizer: Adam, learning rate $\eta = 1 \times 10^{-5}$,

Loss: categorical cross-entropy

Train for epochs 1 to 20 with batch size = 8

Record training in addition to validation loss and accuracy

Step 4: Evaluation and Prediction

Predict on test set: $\hat{Y}_{test} \leftarrow \text{argmax}(\text{model.predict}(X_{test}))$

Compute Accuracy, Precision, Recall, and F1 Score

4.3.4 Severity Estimation of Nutrient Deficiency

Following the classification of the leaf's nutrient deficiency, the methodology computes the severity level by integrating image-based analysis with relevant soil parameters.

4.3.4.1 Image-based Severity Estimation

Following the nutrient deficiency class predicted by the hybrid model, deficiency severity is calculated using the Intermediate Severity Value (ISV). The method changes the color space from the RGB color plane to the HSV plane [60]. Thereafter, the leaf area is segmented from the background. The image is represented in binary form with values of 0 or 1. The pixel value '0' represents black, whereas '1' indicates white, signifying the leaf area only. The leaf area matches the color criteria for green. To quantify the area of deficiency based on the number of white pixels in the deficiency mask, the upper and lower bounds for the color range in the deficiency mask have been fetched the color picker. Whereas the intensity mask is determined by the mean intensity of pixels in the leaf region. Both the affected area and mean intensity are used to calculate the ISV for K and Zn.

As mentioned earlier, potassium deficiency appears as brown or yellow discoloration along the leaf margins. Therefore, the approach required to effectively capture the characteristic signs of potassium deficiency, such as marginal yellowing, necrosis, and drying that begins in older leaves and progresses inward. In this direction, HSV color

space [124] thresholding is used to isolate these affected regions caused by nutrient deficiency. The leaf intensity is calculated using the mean intensity value V . Finally, the percentage of the leaf area exhibiting these symptoms is calculated. These two factors are summed to find the severity of the deficiency. Similarly, for zinc deficiency, characteristic interveinal yellowing is segmented using HSV color thresholds. The severity is estimated using the Intermediate Severity Value (ISV)—a weighted combination of affected area and normalized brightness from the HSV Value channel [142]. This approach quantifies zinc deficiency with a single score and displays the original image, mask, and segmented region for visual validation.

For potassium and zinc [158] the severity computation is based on both the spatial spread and the visual intensity of the affected regions. The affected area percentage is determined using the proportion of the number of non-zero pixels in the deficiency mask M_d to the total number of leaf pixels as follows:

$$\text{Area\%} = \frac{\text{CountNonZero}(M_d)}{\text{CountNonZero}(\text{LeafMask})} \cdot 100 \quad (4.1)$$

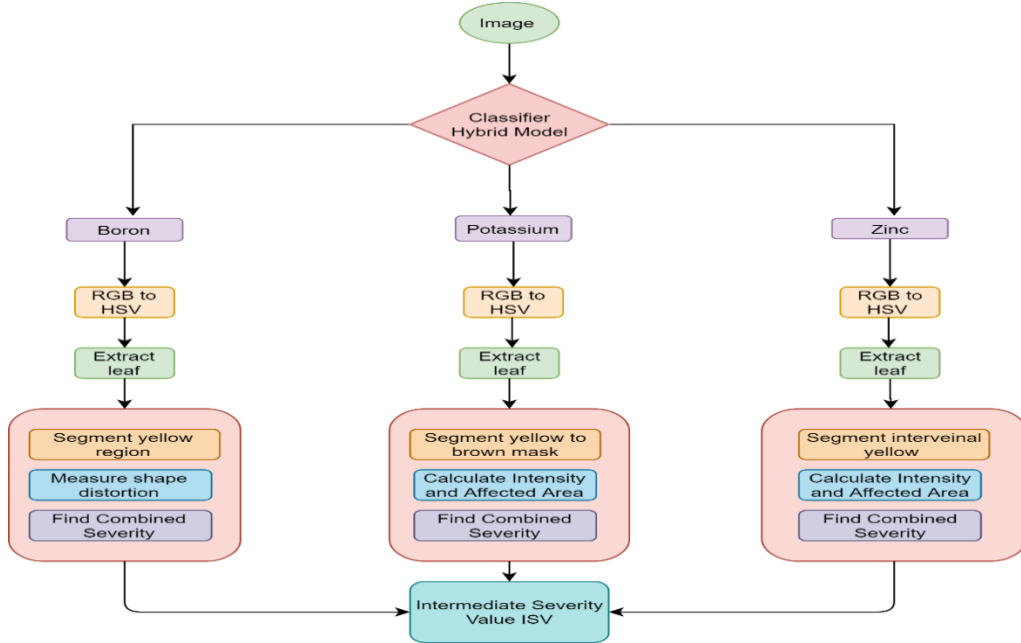


Figure 4.6: Image Severity Estimation

The normalized intensity of the deficiency region is calculated from the mean value of the V-channel of the HSV image. Let $V [M_d = 255]$ represent the V-values of pixels identified as deficient. The normalized intensity is given by:

$$\text{Intensity} = \frac{\text{mean}(V[Md=255])}{255} \quad (4.2)$$

The Intermediate Severity Value (ISV) has been computed by combining the two features using weighted contributions:

$$\text{Potassium/Zinc: } ISV = w_1 \cdot \text{Intensity} + w_2 \cdot \frac{\text{Area}\%}{100} \quad (4.3)$$

where w_1 and w_2 are the assigned weights for intensity and area, respectively, after experimenting for high accuracy.

For the severity of boron deficiency [159] in banana leaves, a different approach is adopted. This deficiency is characterized by traits like tip necrosis, brittle small leaves, and distorted growth. It is assessed by combining shape distortion analysis with yellowing features. The method uses HSV thresholding to segment yellow regions and convex hull analysis to measure leaf shape distortion. The grayscale image is enhanced using CLAHE, and the leaf area is segmented via thresholding. From the largest contour, the convexity defect (S_{shape}) and yellow region proportion (S_{color}) are extracted using formulas mentioned in Eq. 4.4 and 4.5.

To quantify boron deficiency based on both shape distortion and discoloration, two features are extracted from each segmented leaf. First, the leaf contour is used to compute the leaf area A_l and its convex hull area A_h . The shape deformation caused by boron deficiency is measured using the shape factor, defined as:

$$\text{Shape factor } S_{\text{shape}} = (A_h - A_l) / A_h \quad (4.4)$$

In addition, color-based symptoms have been captured by estimating the yellow area A_y through HSV thresholding. The corresponding yellow-area ratio is computed as:

$$\text{Yellow area ratio } S_{\text{color}} = A_y / A_l \quad (4.5)$$

Both features are combined to obtain the Intermediate Severity Value (ISV) for boron deficiency:

$$\text{Intermediate Severity Value (ISV)} = w_1 S_{\text{shape}} + w_2 S_{\text{color}} \quad (4.6)$$

where w_1 and w_2 represent the relative weights assigned to shape and color features, respectively. The complete description of the calculation of Intermediate Severity Estimations is described in Figure 4.6.

4.3.4.2 Role of Soil Parameters on Nutrient Deficiency Severity Estimation

Once the intermediate severity index is calculated, the ensuing objective is to consider other factors that affect the nutrients in plants. Since images have been taken from the Karnataka banana plantations [160], such as those in Hassan (Nittur, Tamlapura, Saligrama, Tarekere), Ramnagara (Garkalli), Shimoga (Bhadravathi), Davangere (Maganahalli, Channagiri), and Hosapete (Hosuru), show signs of nutrient deficiencies that are significantly impacted by regional soil conditions. Three important soil parameters—pH, organic carbon (OC), and electrical conductivity (EC)—have a direct correlation with the degree of zinc, boron, and potassium shortages seen in these areas.

4.3.4.3 Impact of Soil pH on Severity

Soil pH is a critical factor influencing the solubility and availability of essential nutrients to banana plants. When the soil becomes excessively alkaline ($\text{pH} > 7.5$), micronutrients such as zinc and boron convert into insoluble chemical forms that roots cannot readily absorb. As a result, zinc deficiency commonly leads to interveinal chlorosis in leaves, whereas boron deficiency causes leaf deformation, brittleness, and restricted new growth. In contrast, the optimal pH range for banana cultivation[160] lies between 6.5 and 7.2, where the majority of macro- and micronutrients remain bioavailable, supporting healthy root uptake and vigorous plant development. To quantify the contribution of soil parameters to deficiency severity, soil pH is normalized using min–max scaling given in Eq. 4.7:

$$\text{pH}_n = \frac{\text{pH} - 4.9}{9 - 4.9} \quad (4.7)$$

This normalized value allows integration with other soil indicators (organic carbon, EC) in the severity index model.

Algorithm 4.2 Severity Estimation for Nutrient-Deficient Banana Leaves (Boron, Potassium, and Zinc)

Input: Classified leaf images $\{I_i\}_{i=1}^N$ for classes: Boron, Potassium, Zinc.

Output: Severity metrics- Affected Area, Intensity, Intermediate Severity Value (ISV), and Severity Levels (Mild/Moderate/ Severe)

Step 1: Data Loading and Pre-processing

For each class folder $C_k \in \{\text{Boron, Potassium, Zinc}\}$:

- A. Read each image I and resize to 225×225 .
- B. Convert to HSV color space: $H, S, V \leftarrow \text{cv2.cvtColor}(I, \text{HSV})$.

Step 2: Class-specific Segmentation

Define HSV thresholds (L_k, U_k) for each deficiency type and generate a binary mask:

- A. Boron: $L_b = [5, 100, 20]$ to $U_b = [20, 255, 150]$
- B. Potassium: $L_p = [10, 100, 20]$ to $U_p = [30, 255, 200]$
- C. Zinc: $L_z = [22, 80, 120]$ to $U_z = [38, 255, 255]$

Step 3: Severity Metric Calculation

For Boron (shape and color based):

- A. Extract the leaf contour and compute leaf area and convex hull area.
- B. Determine the yellow-region area through color thresholding.
- C. Compute shape-based and color-based features.
- D. Calculate the Intermediate Severity Value (ISV) using a weighted feature combination.

For Potassium/Zinc (Area and Intensity Based):

Segment the leaf and generate the binary leaf mask.

- A. Detect affected regions to obtain the deficiency mask M_k .
- B. Compute the affected area percentage.
- C. Compute normalized intensity from the V-channel for affected pixels.
- D. Combine area and intensity features to obtain the Intermediate Severity Value (ISV).

Step 4: Integration of Soil Parameters (pH, OC, EC)

- A. Read soil parameters: pH, organic carbon (OC), and electrical conductivity (EC).
- B. Normalize pH to the range 6.5–8.5.
- C. Normalize organic carbon (OC) to the range 0.5–2.0.
- D. Normalize EC using its maximum allowable value (0.7).
- E. Use the normalized pH, OC, and EC values and combine them using predefined weights to obtain the Soil Influence Factor (SIF).
- F. Use the SIF in the computation of the final severity index.

- G. Fuse image and soil information to compute the Final Severity Index (FSI).
- H. Boron: FSI<0.1→Mild; 0.1-0.25→Moderate;>0.25→Severe
- I. Potassium: FSI<0.2 → Mild; 0.2-0.4→Moderate; >0.4 Severe
- J. Zinc: FSI<0.3 →Mild; 0.3-0.6→Moderate; >0.6 Severe

4.3.4.4 Impact of Organic Carbon on Severity

Organic carbon (OC) [160] is a key soil property that enhances nutrient retention, refines soil structure, and aids beneficial microbial activity. Low OC levels (typically < 0.5%) reduce the soil's ability to hold nutrients, which limits the accessibility of essential elements potassium and boron. This leads to increased severity symptoms in banana leaves. Conversely, soils with higher OC content (> 0.6%), such as those in regions like Shimoga, promote better nutrient cycling, root activity, and microbial interactions, which collectively improve the solubility and long-term availability of micronutrients boron and zinc. Organic matter also forms stable complexes with these nutrients, reducing their fixation and loss from the soil system. To incorporate OC into the severity estimation model, the measured OC values are normalized using a min–max transformation:

$$OC_n = \frac{OC-0}{2.1-0} \quad (4.8)$$

This converts OC into a unitless value between 0 and 1, where higher normalized values represent greater deviation from the ideal OC range for banana cultivation.

4.3.4.5 Impact of Electrical Conductivity

Electrical conductivity (EC) [160] is an effective indicator of soluble salt concentration in the soil and serves as a reliable measure of potential salt stress on plant roots. When EC values rise above 0.7 dS/m, as observed in some regions of Davangere and Hassan, the resulting high salt concentration competes with essential nutrients, particularly potassium, for root uptake. This competition from cations such as calcium, magnesium, and sodium reduces potassium absorption and leads to characteristic potassium deficiency symptoms, including marginal leaf burning, browning, and necrotic patches. In contrast, soils with low EC levels (< 0.5 dS/m) typically do not impose osmotic stress, allowing normal nutrient uptake. However, very low EC can also indicate low fertility or insufficient nutrient availability, which may indirectly affect plant vigor.

Therefore, maintaining EC within an optimal range is essential for balanced nutrient delivery, healthy root activity, and reduced severity of nutrient deficiency symptoms in banana cultivation.

To incorporate EC into the severity estimation model, soil EC values (*Wani et al.*, 2011) are normalized using a linear min–max transformation based on the acceptable EC range (0–0.7 dS/m):

$$EC_n = \frac{EC - 0.0}{2.5 - 0.0} \quad (4.9)$$

This converts EC into a unitless score between 0 and 1, where higher values indicate greater deviation from ideal soil salinity conditions.

Micronutrients like zinc and boron are less readily available in soils with high pH values (> 7.5), which are frequently found in sections of Hassan and Davangere (*Wani et al.*, 2011). This can lead to mild to severe symptoms of deficiencies. Like this, low levels of organic carbon (< 0.5%), especially in the drier areas of Ramnagara and Hosapete, result in a reduced ability to hold nutrients and biological activity, which exacerbates shortages in potassium and boron. Salinity stress is indicated by increased EC levels (> 0.7 dS/m) in some parts of Davangere and Hassan. This can hinder potassium uptake and exacerbate symptoms such as marginal leaf burning. Conversely, areas like Bhadravathi in Shimoga, which have a pH of 6.5–7.2, greater OC levels (> 0.6%), and low EC (< 0.5 dS/m), show less severe or moderate indications of nutritional deficiencies. The significance of incorporating site-specific soil data for precise nutrient deficiency diagnosis and efficient fertilizer management in banana agriculture is highlighted by the association found between soil fertility indicators and visible leaf symptoms.

To quantify the influence of soil conditions on nutrient deficiency, a Soil Influence Factor (SIF) has been introduced in the proposed study. The approach follows standard Soil Quality Index (SQI) methodologies, where normalized soil indicators are combined using weighted additive functions given by Eq. 4.10:

$$SIF = x pH_n + y OC_n + z EC_n \quad (4.10)$$

The weights x, y, and z reflect the relative contribution of pH, organic carbon, and electrical conductivity to nutrient uptake efficiency, consistent with agronomic literature on banana-growing soils. In this study, the Intermediate Severity Value (ISV)

is first computed from the leaf images to quantify the visual intensity of nutrient deficiency. After the severity is classified as mild, moderate, or severe, soil parameters—pH, organic carbon (OC), and electrical conductivity (EC)—are incorporated solely for determining the final fertilizer recommendation. The Complete methodology is described in detail in Algorithm 4.2, which captures symptoms like interveinal chlorosis, stunted growth, and narrow, undersized leaves.

4.4 Results and Discussions

Assessment of the structures is carried out using standard performance evaluation parameters, including accuracy, precision, recall, F1-score, and support, ensuring a comprehensive assessment of classification reliability. The modified models have been trained using the hyperparameters finalized after experimentation: learning rate = 0.00001, batch size = 8, epochs = 20, on a system equipped with an Intel i7 processor and 16 GB of RAM.

4.4.1 Comparative Analysis of Pre-trained CNNs

To establish a reliable baseline for hybrid model development, multiple pre-trained CNN architectures have been fine-tuned for nutrient-deficiency classification in banana leaves. Among all models, DenseNet169 has achieved the highest standalone accuracy 95.87%, demonstrating strong feature-reuse capability and deeper representational power compared to other networks, as depicted in Table 4.5. ResNet50 and InceptionV3 have also performed competitively, whereas lightweight CNNs such as MobileNetV2 and EfficientNetB0 have shown reduced accuracy due to limited depth and representational capacity.

Despite the strong performance of DenseNet169, single-model architectures exhibited limitations such as sensitivity to intra-class variations and reduced generalization to visually complex samples. To mitigate these issues, two hybrid architectures have been constructed by combining a lightweight feature extractor, MobileNetV2, with both heavyweight backbones, DenseNet169 and ResNet50. Both hybrids have been trained using identical hyperparameters to ensure fair comparison.

Among the two, the DenseNet169 + MobileNetV2 hybrid emerged as the optimal configuration, offering the best trade-off between validation accuracy, processing efficiency, and generalization. Notably, this architecture reduced overall parameter

count by nearly 45%, while maintaining competitive performance relative to heavy standalone models.

Table 4.5: Performance Parameters of various models

Models	Validation Accuracy	Validation Loss	Testing Accuracy	Precision	Recall	F1 Score
MobileNetV2	91.18	0.2552	91.15	91.15	91.15	91.15
EfficientNetB0	62.75	0.9841	69.91	69.91	69.91	69.91
VGG16	88.24	0.3672	91.74	91.74	91.74	91.74
ResNet50	91.83	0.3325	93.51	93.51	93.51	93.51
DenseNet169	94.12	0.2210	95.87	95.87	95.87	95.87
Inception	93.14	0.2659	92.92	92.92	92.92	92.92
Xception	71.90	0.7094	69.62	69.62	69.62	69.62
Hybrid (DenseNet169 +MobileNetV2)	95.10	0.1923	93.21	93.06	93.09	93.04
Hybrid (ResNet50 + MobileNetV2)	94.12	0.1704	91.74	91.69	91.63	91.63

4.4.2 Evaluation of Convergence Performance of Hybrid Models

After establishing the hybrid combinations, convergence behaviour has been examined from Figures 4.7 and 4.8 to assess training stability and optimization dynamics. The ResNet50 + MobileNetV2 hybrid demonstrated a smooth increase in training and validation accuracy, ultimately stabilizing around 94%. Loss curves declined gradually with minimal divergence, indicating controlled learning and low overfitting. In contrast, the DenseNet169 + MobileNetV2 hybrid exhibited superior convergence characteristics, with training and validation accuracies surpassing 95% and validation loss converging to 0.1923. The close alignment between training and validation trends demonstrates effective gradient flow and strong generalization. These observations show that hybridization effectively mitigates the weaknesses of individual CNNs by integrating complementary feature hierarchies. DenseNet169 contributes deep semantic features, while MobileNetV2 provides efficient low-level abstractions—resulting in smoother optimization, balanced gradients, and improved robustness.

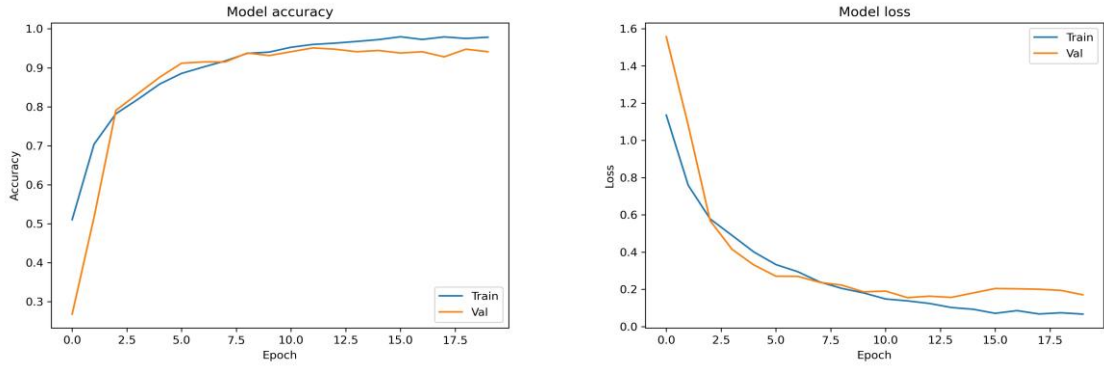


Figure 4.7: Graphical representation of (a) Accuracy vs Epoch (b) Loss vs Epoch for MobileNetV2 + ResNet50 Hybrid Model

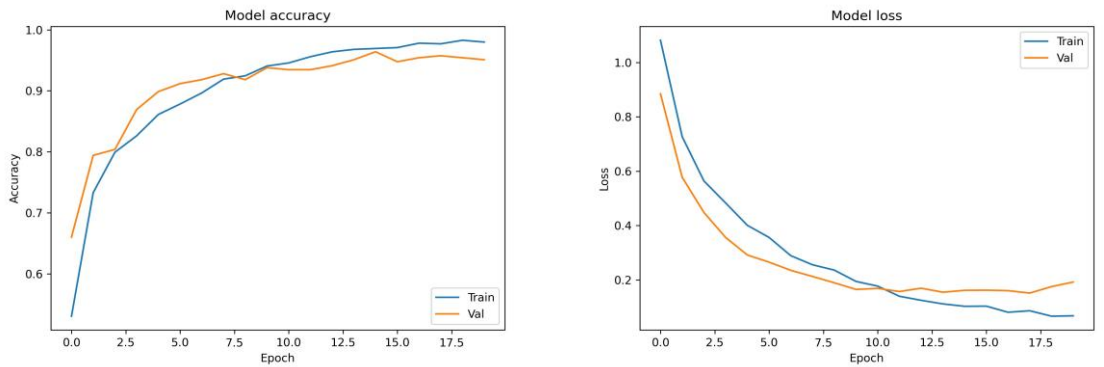


Figure 4.8: Graphical representation of (a) Accuracy vs Epoch (b) Loss vs Epoch for MobileNetV2 + DenseNet169 Hybrid Model

4.4.3 Comparative Performance Analysis for Each Model

A detailed class-wise evaluation depicted by Table 4.6 reveals distinct performance patterns across the four nutrient categories: Boron, Healthy, Potassium, and Zinc. Boron deficiency is comparatively easier to distinguish, and multiple models, including VGG16, ResNet50, Inception, and DenseNet169—achieve exceptionally high F1-scores. The DenseNet169 + MobileNetV2 hybrid also performs strongly in this category, demonstrating its ability to preserve high accuracy for classes with clear visual signatures.

The Healthy class shows greater performance variability. Some lightweight or shallow models misclassify mildly affected leaves as healthy due to subtle differences in texture or color. High-capacity models such as DenseNet169 and ResNet50 achieve the strongest performance, while the hybrid models also produce stable classifications, outperforming several individual architectures. This highlights the hybrid’s advantage in capturing fine-grained distinctions.

Table 4.6: Category-wise performance parameters for each model

Models	Metric															
	Boron				Healthy				Potassium				Zinc			
	P	R	F1	S	P	R	F1	S	P	R	F1	S	P	R	F1	S
MobileNetV2	96	92	94	79	97	89	93	102	89	94	91	79	83	90	86	79
EfficientNetB0	97	84	90	79	54	99	70	102	82	65	72	79	90	24	38	79
VGG16	91	100	95	79	94	90	92	102	96	91	94	79	86	86	86	79
ResNet50	93	97	95	79	93	95	94	102	95	95	95	79	93	86	89	79
DenseNet169	98	100	99	79	98	96	97	102	93	95	94	79	95	92	94	79
Inception	96	96	96	79	93	94	94	102	94	91	92	79	89	90	89	79
Xception	75	78	77	79	69	83	75	102	67	76	71	79	69	37	48	79
Hybrid (DenseNet169 + MobileNetV2)	95	97	96	90	98	93	96	91	90	95	93	79	90	87	88	79
Hybrid (ResNet50 + MobileNetV2)	91	96	93	90	93	91	92	91	91	94	93	79	91	86	88	79

Potassium deficiency is well-learned by most deep models, particularly ResNet50 and DenseNet169, both of which achieve high F1-scores. The DenseNet169 + MobileNetV2 hybrid maintains strong performance in this category, outperforming lighter models and showing improved robustness.

Zinc deficiency is challenging due to its subtle symptoms and visual overlap with other deficiencies. Standalone models show larger variance, with some architectures such as EfficientNetB0 and Xception performing substantially worse. Hybrid models provide more stable outcomes, benefiting from the combined representational power of the fused backbones. The DenseNet169 + MobileNetV2 hybrid achieves strong F1-scores in this class, confirming its improved feature capture capability for challenging categorization.

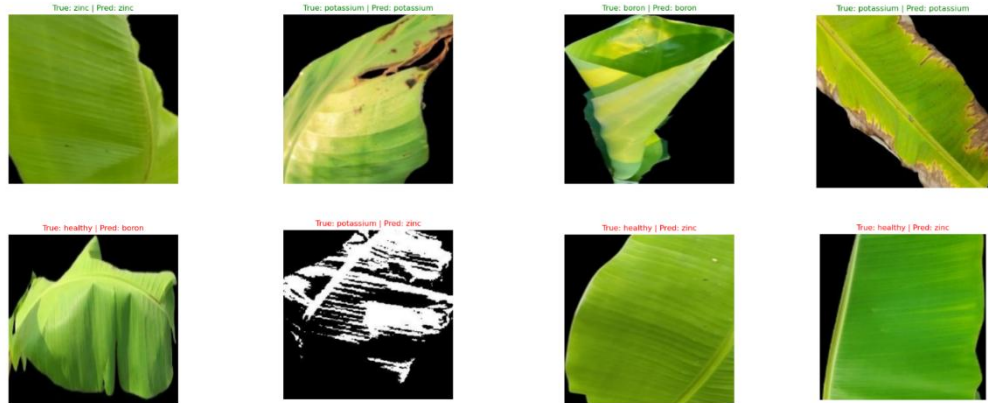


Figure 4.9: Misclassified and Classified images

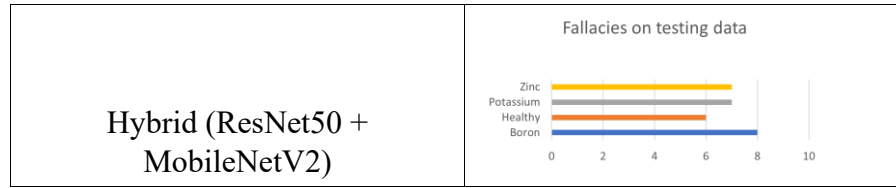
The class-wise error analysis presented in Table 4.7 provides additional insight into the reliability of each model across the four nutrient-deficiency categories—Boron, Healthy, Potassium, and Zinc. Lightweight models such as MobileNetV2 and EfficientNetB0 exhibit a higher number of misclassifications, particularly for the zinc and potassium classes, where visual symptoms are subtle and often overlap with other categories. EfficientNetB0 records the largest number of errors, consistent with its lower overall performance metrics. Intermediate models such as InceptionV3 and VGG16 demonstrate moderate fallacies but still struggle in distinguishing visually similar symptoms, especially in zinc-deficient leaves. In contrast, deeper architectures like ResNet50 and DenseNet169 show considerably better reliability, typically misclassifying fewer than five samples in most classes, highlighting their stronger feature extraction capability.

The hybrid architectures further reduce these class-wise errors by leveraging complementary feature representations. The DenseNet169 + MobileNetV2 hybrid achieves the fewest misclassifications overall, with notable improvements in the boron and healthy classes, confirming its superior generalization ability observed in previous evaluations. Although the ResNet50 + MobileNetV2 hybrid also reduces errors compared to individual models, it shows slightly higher misclassification levels—particularly in the zinc category—indicating comparatively weaker constructive collaboration between the fused backbones. Representative examples of correct and incorrect predictions are illustrated in Figure 4.9; the misclassified cases highlight the

inherent difficulty in differentiating between mild deficiencies and visually healthy leaves.

Table 4.7: Wrong predictions per class by Models

Models	Samples predicted wrongly per class										
MobileNetV2	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>15</td> </tr> <tr> <td>Potassium</td> <td>10</td> </tr> <tr> <td>Healthy</td> <td>3</td> </tr> <tr> <td>Boron</td> <td>2</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	15	Potassium	10	Healthy	3	Boron	2
Class	Wrong Predictions										
Zinc	15										
Potassium	10										
Healthy	3										
Boron	2										
EfficientB0	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>1</td> </tr> <tr> <td>Potassium</td> <td>10</td> </tr> <tr> <td>Healthy</td> <td>85</td> </tr> <tr> <td>Boron</td> <td>1</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	1	Potassium	10	Healthy	85	Boron	1
Class	Wrong Predictions										
Zinc	1										
Potassium	10										
Healthy	85										
Boron	1										
VGG16	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>11</td> </tr> <tr> <td>Potassium</td> <td>3</td> </tr> <tr> <td>Healthy</td> <td>8</td> </tr> <tr> <td>Boron</td> <td>6</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	11	Potassium	3	Healthy	8	Boron	6
Class	Wrong Predictions										
Zinc	11										
Potassium	3										
Healthy	8										
Boron	6										
ResNet50	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>5</td> </tr> <tr> <td>Potassium</td> <td>4</td> </tr> <tr> <td>Healthy</td> <td>6</td> </tr> <tr> <td>Boron</td> <td>7</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	5	Potassium	4	Healthy	6	Boron	7
Class	Wrong Predictions										
Zinc	5										
Potassium	4										
Healthy	6										
Boron	7										
DenseNet169	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>4</td> </tr> <tr> <td>Potassium</td> <td>6</td> </tr> <tr> <td>Healthy</td> <td>2</td> </tr> <tr> <td>Boron</td> <td>2</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	4	Potassium	6	Healthy	2	Boron	2
Class	Wrong Predictions										
Zinc	4										
Potassium	6										
Healthy	2										
Boron	2										
InceptionV3	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>9</td> </tr> <tr> <td>Potassium</td> <td>5</td> </tr> <tr> <td>Healthy</td> <td>7</td> </tr> <tr> <td>Boron</td> <td>3</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	9	Potassium	5	Healthy	7	Boron	3
Class	Wrong Predictions										
Zinc	9										
Potassium	5										
Healthy	7										
Boron	3										
Xception	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>15</td> </tr> <tr> <td>Potassium</td> <td>30</td> </tr> <tr> <td>Healthy</td> <td>40</td> </tr> <tr> <td>Boron</td> <td>20</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	15	Potassium	30	Healthy	40	Boron	20
Class	Wrong Predictions										
Zinc	15										
Potassium	30										
Healthy	40										
Boron	20										
Hybrid (DenseNet169 + MobileNetV2)	Fallacies on testing data <table border="1"> <thead> <tr> <th>Class</th> <th>Wrong Predictions</th> </tr> </thead> <tbody> <tr> <td>Zinc</td> <td>8</td> </tr> <tr> <td>Potassium</td> <td>8</td> </tr> <tr> <td>Healthy</td> <td>2</td> </tr> <tr> <td>Boron</td> <td>5</td> </tr> </tbody> </table>	Class	Wrong Predictions	Zinc	8	Potassium	8	Healthy	2	Boron	5
Class	Wrong Predictions										
Zinc	8										
Potassium	8										
Healthy	2										
Boron	5										



4.4.4 Overall Performance Evaluation

Finally, all the models are compared to identify the best-performing models. While DenseNet169 achieved the highest standalone accuracy, precision, recall, and F1-score, excel for large-scale and real-time deployment. In contrast, the proposed DenseNet169 + MobileNetV2 hybrid delivered a competitive performance—achieving 93.21% accuracy, 93.06% precision, 93.09% recall, and a 93.04% F1-score. The capability to extract different features efficiently since exhibited by hybrid model during validation, makes it potential model for deployment in the field. Although the ResNet50 + MobileNetV2 hybrid also performed reasonably well, it did not exhibit the same level of constructive collaboration or balanced feature integration. Overall, the substantial reduction in fallacies achieved by the DenseNet169 + MobileNetV2 hybrid model further underscores its robustness and suitability for reliable real-world deployment in micronutrient deficiency detection. These findings highlight that the fusion between DenseNet169’s deep feature extraction and MobileNetV2’s lightweight representations outperform other hybrids in terms of efficiency, versatility, and practical applicability. However, the key advantage of the hybrid model is that complementary data patterns can be extracted from individual models that may not be observed by single models. Therefore, the rich feature representations of DenseNet169 concatenated with the lightweight feature representations of MobileNetV2 with the anticipation of improved performance of nutrient-deficiency classification. In this study, the hybrid model achieved the highest validation accuracy but lower testing accuracy compared to DenseNet169. Several factors can contribute to lesser performance of hybrid model[161].

- Limited feature diversity:** The utility of hybrid models depends on diverse features extracted by individual models. In the proposed study, base models shared similarity in the process of features extraction they depended upon. Eventually, the both models learnt overlapping visual patterns and therefore, MobileNetV2 failed to provide additional complementary features information.

Therefore, the hybrid model performance is comparable or marginally worse than individual models.

- **Overfitting:** The hybrid model often improve generalization by feature fusion of complementary features. However, the increased complexity of the model leads to mild overfitting and lower performance despite strong validation performance.
- **Feature-fusion configuration:** The choice and method of concatenation of two individual model influence largely the results. If the procedure is not suitable for specific dataset and task, it may not lead to improved performance compared to individual base models.
- **Dataset characteristics:** The imbalanced or data size also play a significant role. Since it may exhibit challenge to hybrid model to efficiently leverage the diversity of base models. In such conditions, individual models competitive in extracting unique patterns and performs superior.

Future research could further examine the alternative feature fusion techniques, more diverse individual models or contemplating other ways can potentially strengthen the performance of hybrid models.

4.4.5 Paired t-test

The difference between the 16 paired metric values of the two hybrid models from category-wise performance mentioned in Table 4.6 has been used to calculate a paired t-test [161]. The following formula has been used to determine the performance difference for each pair:

$$\text{diff} = X_i - Y_i \quad (4.11)$$

where X_i and Y_i represent performance metric values of two models

The standard deviation of differences (SD) and the mean of the difference (m_d) are computed. The standard error (E) is given as:

$$E = SD/\sqrt{16} \quad (4.12)$$

The t-statistic is determined as:

$$t = m_d/E \quad (4.13)$$

Since there are 16 paired observations, the degrees of freedom (df) are

$$df = \text{number of paired metric value} - 1 = 15.$$

The two hybrid models differed statistically significantly with $t(15) = 2.13$ and $p = 0.049$ according to a paired t-test. The null hypothesis that both classifiers perform similarly is rejected because of this outcome since p is less than the significance level. However, Hybrid 1 (DenseNet169 + MobileNetV2) performs much better than Hybrid 2 (ResNet50 + MobileNetV2) because Hybrid 1 attained a higher mean accuracy throughout the investigated categories.

4.4.6 Best Model Selection and Comparison with Existing Studies

Compared to other models, as shown in Table 4.8, the suggested hybrid model, DenseNet169 + MobileNetV2, displays a good balance between computational efficiency and performance. With an F1-score of 93.04%, precision of 93.06%, recall of 93.09%, and validation and testing accuracy of 95.10% and 93.21%, respectively, it keeps competitive classification performance while drastically lowering model complexity.

The suggested hybrid model offers competitive performance (95.10% accuracy, 93.04% F1-score) with significantly lower complexity (15.1M parameters) than InceptionV3 + DenseNet169 (Muthusamy et al., 2024), which achieved 98.62% validation accuracy using 35.5M parameters. This makes it more feasible for real-time and resource-limited applications. Similarly, VGG16 [139] reported metrics that were almost ideal, but its large number of parameters (138M) makes it inefficient for implementation.

While less sophisticated, traditional methods such as Random Forest [138] have poorer accuracy (91.64%) and F1-score (89.3%). In a similar vein, ConvNext-Tiny[60] outperforms the suggested model in terms of accuracy (87.89%) and complexity (28.6M parameters). Given the circumstances, the hybrid DenseNet169 + MobileNetV2 model that provides the perfect balance between computational cost and accuracy.

To sum up, the suggested DenseNet169 + MobileNetV2 hybrid provides the best possible balance between efficiency and accuracy. It is perfect for real-world implementation in intelligent agricultural systems since it significantly lowers the number of parameters and processing requirements while delivering high-performance metrics comparable to those of state-of-the-art models. All analyses consistently demonstrate that the DenseNet169 + MobileNetV2 hybrid is the most reliable and

computationally efficient model, making it best suited for practical agricultural field deployment.

Table 4.8: Comparison with other studies

Author, Year	Model	Complexity	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Muthusamy, S., et al. (2024)[162]	InceptionV3+ Dense169 (Heavy)	Total Parameters- 35,530,088	98.62 (Validation)	99.12	98.37	93
Dabalos, J. T., et.al. (2017)[138]	Random Forest	Low (5-10 MB)	100 training, 91.64 (Cross- validated)	90.5	88.5	89.3
R. Guerrero, etal. (2021)[139]	VGG16	Total Parameters- 138,357,544	98.61 (Validation)	100	100	100
K. A. M. Han, et.al. (2023)[140]	ConvNext- Tiny	Total Parameters- 28,592,840	87.89 (Overall accuracy)	87.5	85	88
Proposed work	Dense169+ MobileNetV2	Total parameters- 15,105,540	95.10 (Validation) 93.21 (Testing)	93.06	93.09	93.04

4.4.7 Severity Estimation

A comprehensive image-processing method for assessing the extent of deficiencies after categorization in banana leaves is presented in this section. The affected area, convex hull, intensity, and then intermediate severity value (ISV) are calculated based on these methods for boron, potassium, and zinc deficits. Prior to class-specific segmentation using predetermined HSV thresholds, images undergo preprocessing in the HSV color space. Whereas potassium and zinc are extracted using intensity and lesion area ratio, boron is extracted using shape factor and yellow area ratio. The ISV is obtained from weighted combinations of these features (w_1 , w_2). The calculated value is then mapped to mild, moderate, or severe severity levels using threshold ranges specific to each nutrient.

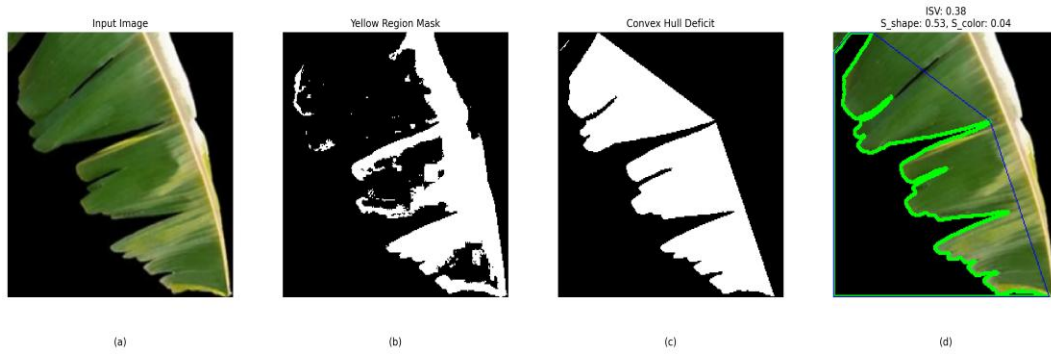


Figure 4.10: Boron deficiency severity estimation in banana leaf. (a) Input leaf image; (b) Yellow region mask obtained by HSV thresholding; (c) Convex hull deficit showing structural deformation; (d) Final overlay with leaf contour (green) and convex hull (blue), showing severity score

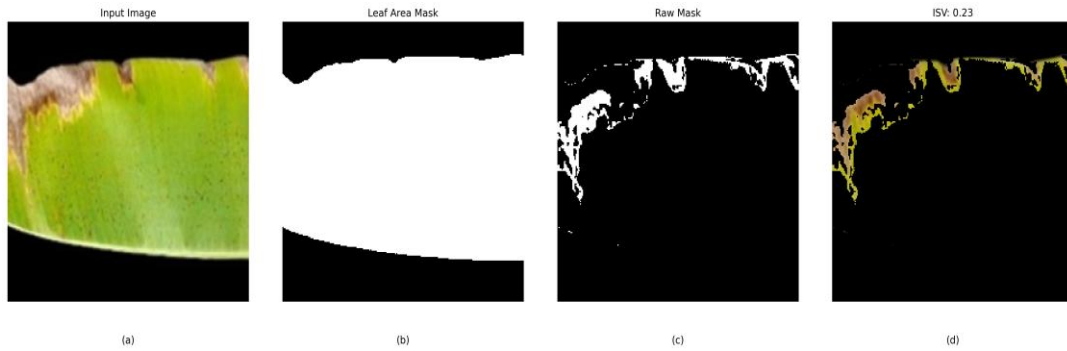


Figure 4.11: Potassium deficiency detection in banana leaves. (a) Original image; (b) Leaf mask after segmentation; (c) Potassium-deficient regions identified using HSV thresholding; (d) Segmented result showing affected areas overlaid on the original image with 0.23 ISV

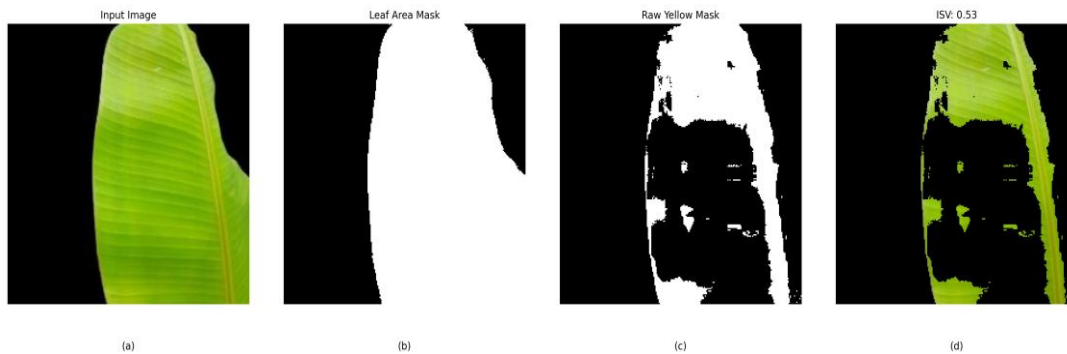


Figure 4.12: Zinc deficiency segmentation in banana leaf. (a) Input image; (b) Initial yellow region mask based on HSV thresholds; (c) Cleaned binary mask after morphological operations; (d) Final segmented overlay with ISV (Intermediate Severity Value) of 0.53.

The workflow is visually illustrated in Figure 4.10, which displays the original RGB input image in the first panel for the boron deficiency. One of the primary signs of boron shortage, chlorosis, is indicated by yellow areas in the second panel, which are

highlighted by a binary mask. Using HSV thresholding, these yellow pixels are retrieved, paying particular attention to hue and value ranges that differentiate healthy green areas from stress signs. The overlay of the retrieved contours, as depicted in the third panel, and the severity metrics are displayed in the last panel. Here, the following is combined to get the Intermediate Severity Value (ISV): S-color (0.04) is the normalized brightness (intensity) from the V channel in areas impacted by yellow, and S-shape (0.53) is the percentage of the convex hull area lost because of margin cuts or tears. An ISV of 0.38 denotes a moderate level of insufficiency, characterised by noticeable shape and color deterioration. Thus, this multimodal severity estimation integrates both geometric changes and visual symptoms to determine the value of zinc deficiency.

Figure 4.11 illustrates a multi-stage processing pipeline to evaluate potassium (K) deficit in banana leaves. Marginal yellowing and browning, two signs of potassium insufficiency, are clearly concentrated near the leaf margins in the first panel, which displays the original input image. The leaf area mask, shown in the second panel, separates the complete leaf from the background to allow for an accurate determination of the impacted areas. The raw mask, which is displayed in the third panel, highlights the potassium-deficient areas using HSV-based color thresholding that is concentrated on the yellow and brown tones that are commonly linked to K shortage. With an Intermediate Severity Value (ISV) of 0.23, the segmented areas are superimposed over the original image in the final panel. The figure represents a mild case of potassium insufficiency and is based on the percentage of the affected region as well as the degree of discoloration. Given the importance of potassium in physiological processes, including stomatal control and enzyme activation, such early detection is essential. By detecting mild signs early on, targeted fertilization can be used to reduce stress and yield loss.

A visual investigation of zinc (Zn) deficiency in a banana leaf using an image-based severity assessment pipeline is shown step by step in Figure 4.12. The input image, which is displayed in the first panel, clearly displays interveinal chlorosis and other typical signs of zinc deficiency, particularly in the central section of the leaf. The leaf area mask, which separates the full leaf from the background, is shown in the second

panel. The raw yellow mask, the third panel, uses HSV thresholding to identify yellowish discoloration linked to zinc stress, highlighting the chlorotic areas. These impacted areas are superimposed on the original image in the last panel, where an Intermediate Severity Value (ISV) of 0.53 is determined. To measure severity, this figure combines the brightness of the impacted leaf areas with the percentage of the damaged leaf area. With an ISV of 0.53, a significant zinc shortage is indicated, indicating active nutritional stress that affects growth and photosynthesis.

Furthermore, to better classify banana leaf images into high severity (HS), moderate severity (MS), and low severity (LS) for boron (B), potassium (K), and zinc (Zn) deficiencies, different combinations of weights w_1 and w_2 have been tested in the Intermediate Severity Value (ISV) computation, as shown in Table 4.9. The distribution of predictions (33 HS, 31 MS, 36 LS) among 100 photos has been balanced for boron when form features ($w_1=0.7$) are given a greater weight and color ($w_2=0.3$) is given a lower weight. In potassium, the lesion has a significant impact on the severity estimate, as seen by the higher number of HS, MS, and LS classifications (9 HS, 106 MS, 95 LS) from 210 pictures when the lesion area ratio ($w_2=0.7$) is prioritized over mean intensity ($w_1=0.3$). For zinc, a modest preference for mean intensity ($w_1=0.6$) over area ratio ($w_2=0.4$) resulted in a preponderance of MS predictions (134 HS, 232 MS, 34 LS) out of 400 pictures. According to these findings, different nutrients have different ideal weighting schemes, which reflect variations in the relative significance of lesion area, shape, color, and intensity in precisely forecasting the severity of nutrient deficiencies.

Table 4.9: Values of weights w_1 and w_2 to calculate ISV for B, K and Zn

Weights to calculate ISV	Images Predicted HS	Images Predicted MS	Images Predicted LS	Total Number of Images for each class
$w_1=0.7$ for shape, $w_2=0.3$ for color in boron	33	31	36	100
$w_1=0.3$ for mean intensity, $w_2=0.7$ for area	9	106	95	210

ratio in potassium				
w1= 0.6 for mean intensity, w2= 0.4 for area ratio in zinc	134	232	34	400

4.4.8 Pixel-Level Segmentation Validation

To quantitatively validate the precision of the proposed HSV-based segmentation for nutrient deficiency severity estimation, Intersection over Union (IoU) and Dice coefficients [163] have been computed between the predicted binary masks and corresponding manually annotated ground-truth masks for representative samples of each deficiency category. The IoU quantifies the degree of spatial overlap, while the Dice coefficient measures similarity between the two masks. High values indicate accurate localization of deficiency-affected regions, confirming the reliability of the segmentation process.

$$\text{IoU} = \frac{|\text{PM} \cap \text{GT}|}{|\text{PM} \cup \text{GT}|} \quad (4.14)$$

$$\text{Dice} = \frac{2|\text{PM} \cap \text{GT}|}{|\text{PM}| + |\text{GT}|} \quad (4.15)$$

where PM and GT denote predicted and ground-truth binary masks, respectively.

Table 4.10: IOU and Dice Coefficient for different nutrient deficiencies.

Deficiency	IOU	Dice coefficient
Boron	0.87	0.93
Potassium	0.30	0.46
Zinc	0.69	0.82

The quantitative results in Table 4.10 reveal strong agreement between predicted and ground-truth regions for boron and zinc deficiencies, achieving IoU scores of 0.87 and 0.69, respectively.

The relatively lower IoU for potassium (0.30) is attributed to the irregular, diffuse nature of potassium-deficient areas, which makes precise boundary detection challenging under field illumination variations. Nonetheless, the overall mean IoU

(0.62) and Dice (0.74) values indicate reliable segmentation performance suitable for subsequent severity quantification.

Table 4.11: Fertilizer Recommendation based on severity

Nutrient	Severity	Fertilizer Type	Recommended Dose & Application
Boron (B)	Mild	Borax ($\text{Na}_2\text{B}_4\text{O}_7 \cdot 10\text{H}_2\text{O}$)	Foliar spray @ 0.1% concentration (1g per liter) once at 30 Days after Planting (DAP)
	Moderate	Borax or Solubor	0.2% foliar spray at 30 and 45 DAP
	High	Solubor (20% B)	Soil application: 1.5–2 kg/ha or Foliar 0.3% every 20 days until symptoms reduce
Potassium (K)	Mild	Muriate of Potash (MOP: KCl)	40–50 g/plant split into 2–3 applications per crop cycle
	Moderate	MOP + Organic Mulch	60–80 g/plant, plus FYM to improve uptake
	High	MOP or SOP(K_2SO_4)	100–120 g/plant in 3–4 splits + biofertilizer (Potash Mobilizing Bacteria)
Zinc (Zn)	Mild	Zinc Sulphate (ZnSO_4)	Foliar spray of 0.25% ZnSO_4 at 15 and 45 DAP
	Moderate	Zinc Sulphate (ZnSO_4)	Foliar spray of 0.5% ZnSO_4 at 15 and 30 DAP
	High	Zinc Sulphate (ZnSO_4)	Foliar spray of 0.5% ZnSO_4 at 30 and 45 DAP; Repeat every 15–20 days

4.4.9 Fertilizer Recommendation Based on Level of Severity

The recommendations for banana plant fertilizers [164] shown in Table 4.11, are heavily impacted by underlying soil factors, including soil pH, organic carbon (OC), and electrical conductivity (EC), rather than just the degree of symptoms of nutrient shortage seen in leaves. Once the degree of deficiency has been classified as mild, moderate, or high (through image-based analysis), the parameters of the soil must be considered to customize the kind, dosage, and application technique of fertilizer for optimal efficacy.

However, because of better retention and release, boron [159] is given at lower dosages or at less frequent intervals in organic-rich soils ($> 0.6\%$ OC). Similarly, potassium uptake is hindered by high EC soils (> 0.7 dS/m), which are prevalent in parts of Davangere or Hassan. To improve uptake under salt stress, potassium fertilizer (Kirla 2024) recommendations in these areas typically include higher doses, slow-release forms like SOP, and the addition of biofertilizers (e.g., Potash Mobilizing Bacteria).

For instance, even when zinc is administered through soil, its availability drastically decreases in alkaline soils ($\text{pH} > 7.5$). Zinc sulphate (ZnSO_4) [158] used topically, is more beneficial in these situations, particularly in moderate to severe deficiencies. Low organic carbon ($< 0.5\%$) soils also have trouble holding onto micronutrients like boron. Foliar sprays, as opposed to soil application, are the best way to immediately prevent the shortage.

On the other hand, normal fertilizer doses for mild or severe deficiencies are frequently enough if the soil has low EC (< 0.5 dS/m), moderate OC, and a balanced pH (6.5–7.2), like in sections of Shimoga. As a result, the final fertilizer recommendation needs to be adjusted considering the local soil fertility levels as well as the severity of the discovered deficiencies. This integrated strategy reduces toxicity or waste, guarantees effective nutrient delivery, and encourages sustainable banana farming.

For automated nutrient-deficiency diagnosis and severity estimation in banana crops, the suggested NutriSense-TL framework offers a cohesive, end-to-end solution. Because of its better generalization, smoother convergence, and lower complexity, the DenseNet169 + MobileNetV2 hybrid model is ideal for real-time deployment. While the fertilizer recommendation component guarantees accurate nutrient

supplementation, the severity estimation module uses HSV-based lesion identification to deliver interpretable data. The methodology goes beyond traditional classification-only methods by combining hybrid deep-learning architectures with pixel-level lesion quantification and soil-parameter analysis. In this way, the framework offers a useful, scalable, and field-ready decision-support tool for boosting banana crop productivity and fertilizer management.

4.5 Conclusion

In this study, a multilayer AI-driven framework has been presented to identify and treat nutritional shortages in banana crops, specifically boron, potassium, and zinc. An input layer, perceptive modules, intelligent learning components, and cloud computing support comprise the framework's tiered architecture. DenseNet169 and MobileNetV2 are the most successful deep learning models at the Intelligent and Edge Layer, respectively, after an exhaustive simulation of seven transfer learning models. DenseNet169 has the highest independent test accuracy of 95.87%, whereas MobileNetV2 has the least complexity while achieving an accuracy of 91.15%. Furthermore, by utilizing complementary feature representations, hybrid models MobileNetV2 plus DenseNet169 showed improved generalization, achieving faster convergence and lower loss.

In addition, accurate quantification of nutritional shortage levels has been made possible by integrating the methodology with severity estimation for each deficiency. Furthermore, prescribed fertilizer recommendations are created based on soil parameters, guaranteeing accurate supplementation, reducing unnecessary fertilizer consumption, and fostering long-term productivity. This creates a real-time, scalable crop monitoring system with a multilayer framework that also integrates cloud support for scalable deployment and storage with edge computing for preprocessing and lightweight inference. Furthermore, the proposed framework could be scaled up to incorporate additional macro and micronutrients, developing into a complete nutrient management system. In addition, an extension of this kind can be increased in agriculture, encourage better decision-making, and reinforce its function in precision agriculture, which maximizes crop productivity.

However, judicious use of fertilizers is crucial for the effective use of natural resources in modern farming practices. The primary objective of the precision agriculture framework is to maximize yield using optimal resources. Several research efforts have been noted in this direction, but they concentrate on a minimum amount of water at the expense of a lower yield. Therefore, an automated framework with a reinforcement learning agent has been presented in the forthcoming chapter that guarantees effective resource utilization with no compromise to crop production.

Chapter 5

Adaptive Irrigation for Yield Stability and Stress Minimization for Banana Cultivation

Banana is a crop that requires 4.5 to 6 mm of water daily, and the annual water requirement lies [165] between 1800 and 2200 mm/year for the full growth season. Apparently, it is considered a highly sensitive crop to the amount of water present in its root zone. The major challenge in the banana plantation is to find a balance between the requirement and the actual water content of the soil to get an optimum yield. Throughout the lifecycle of the banana, from vegetation to flowering to development and fruiting, an adequate supply is important. Water stress, as well as waterlogging, negatively impacts the size and count of the fruit. The consistent and accurate amount of water to be supplied should be the major goal of the water management system.

Currently, the efficient scheduling of the water requirements of the banana plantation is a non-trivial task. In addition, the depleting groundwater poses another huge challenge to fulfilling the demand. Conventional irrigation mechanisms are dependent on fixed schedules and fixed rules, e.g., considering evapotranspiration solely. Moreover, factors such as variation in climate, water scarcity, and soil factors are not considered. Irrigation based on assumptions about environmental parameters frequently leads to unnecessary water wastage. As a result, advanced irrigation mechanisms are pivotal, as they can provide sufficient water to the fields depending on forecast weather conditions, soil moisture, and growth stage.

In this direction, the latest advancements of AI-driven approaches [166] can be leveraged to efficiently irrigate the fields. Trending technologies, IoT, and RL algorithms are the key players in this unexplored environment for picking the right move. Traditional ML, DL, and CNN algorithms have been trained on historical data and determine the water requirements daily. ML and DL calculate soil moisture patterns and, accordingly, determine the water demand for crops. While CNN analyses drones and satellite images to predict water stress of crops, overirrigated fields, and the fraction of irrigated land. Nevertheless, there is no long-term prediction based on climate variability, no learning from past outcomes, and no strategy to maximize production.

Existing approaches do not adapt to the dynamic behaviour of the environment. However, reinforcement learning is a promising method wherein an agent continuously interacts with the various real-time sensor data and weather patterns to formulate the final irrigation policy [129]

In this study, one of the RL approaches, which is Proximal Policy Optimization (PPO), has been leveraged[167]. It gets trained with collected data and considers physical parameters of fields such as area and water flow rate. The potential of this approach lies in learning from the convergence of weighted rewards or penalties, periodic irrigation schedules, water optimization, and yield under soil moisture constraints. The focus of this research is enumerated as follows:

1. To design an AI-driven irrigation framework by incorporating climatic data, sensor data, crop growth, evapotranspiration, and soil moisture content.
2. Multi-seed evaluation of PPO-based adaptive irrigation policy convergence and stability.
3. Comparative analysis of water usage and yield-proxy preservation against fixed-schedule baselines.

The proposed research is segregated into different sections. The recent advancements and significant contributions are summarized in Section 5.2. The proposed framework is illustrated in Section 5.3, and the complete framework is explained in Section 5.4. The results are presented in Section 5.5 with detailed graphs and enumerated tables. Finally, Section 5.6 includes the inferred conclusions of the experiment and sheds light on future opportunities.

5.1 Background

Since an adequate amount of water availability to plants is quite essential for the desired growth, as well as to get an optimum yield of the crop. Over-watering or poor drainage can cause stagnation of water, resulting in rotting of roots and outbreak of diseases. Several research studies have contributed to this direction to optimize the irrigation amount and time to benefit the yield while reducing the usage of resources. To automate the irrigation, several approaches have been developed by scholars that leverage AI-

based frameworks. ML, DL, and RL algorithms have been utilized to determine the accurate amount of water needed. Further, this section highlights the major additions by the intellectuals to automate the field operations. Thus, farmers can operate the systems from remote locations.

Amongst the state-of-the-art works, a method [97] that irrigates rice fields based on deep Q-learning in Nanchang, China. The weather forecast and meteorological data from 2012 to 2019 were collected from nearby stations, which were used to train the model. Markov decision process is employed, wherein environmental parameters such as rainfall, stage of the crop, soil moisture, and evapotranspiration define the state. Afterwards, actions are taken discretely, and rewards are given weights by balancing water utilization with yield. With continuous interactions of an agent with its surroundings while considering state, actions, and reward, the optimized policy gets formulated that decides when to irrigate the fields. This DQN-based irrigation strategy is compared with flood irrigation, where it outshines in terms of decreasing water by 23 mm, reducing drainage by 21 mm, and reducing the irrigation timing, but at the cost of the yield factor. This demonstrates the robustness of DQN in uncertain weather forecasts and water-scarce areas.

A recent investigation [168] also highlights the utilization of various machine learning models to predict water requirements. Firstly, sensors are used to collect data from the ground using sensors. Data gathered from root depth sensor, soil moisture, inclinometer, humidity, temperature, and water levelling sensors are used to train a hybrid ensemble model. It consists of KNN, Gradient Boosted Trees (GBT), and Long Short-Term Memory (LSTM). KNN extracts feature of the root, GBT performs regression as well as classification, while LSTM makes time series predictions. Spearman's rank correlation is further employed to determine how the estimated value is correlated with the actual value of water irrigation. The framework predicts 12-hour to 4-day water requirements of the fields, at the same time automating the irrigation control. Field experiments have been conducted on banana plantations in India. This ensemble approach achieved water savings of 31.14% in 2020 and up to 50.1% in 2021. Thus, hybrid learning is effective for adaptive irrigation optimization.

Research work [169] demonstrates a hybrid IoT, machine learning, and reinforcement learning-based precision irrigation framework targeted to optimize the water needs of banana cultivation. The system utilizes a multi-layer architecture where the data-transferring and collection layer consists of soil sensors, water level, temperature, root moisture, humidity, and land-slope sensors, i.e., an inclinometer. Wireless sensor nodes collect the ground data, whereas Zigbee is used to transmit local data. The second layer, an intelligent decision layer, is utilized to process data. The third layer is a user application. The framework executes KNN to extract the nearest features. Further, the ML agents interact with the environment using an RL approach. The agent formulates the best action after observing the states and actions taken. The experiments are conducted on data from Kanyakumari district, India. The framework displays a 10 to 24 percent reduction in water usage compared to traditional irrigation methods. It outlines the RL-driven methods for long-term optimization of water supply to banana fields.

Further, the study evaluates the irrigation water requirements (IWR) and irrigation scheduling [170] of major crops - wheat, cotton, sugarcane, and banana in the Shaheed Benazirabad district of Sindh, Pakistan, using agro-climatic data and the FAO CROPWAT 8.0 model. By integrating long-term climate parameters such as temperature, rainfall, humidity, wind speed, and sunshine hours with standardized crop and soil data, the study estimates reference evapotranspiration (ET_o), effective rainfall, crop water requirements (ET_c), and gross irrigation demand. The results indicate that crops with longer growing cycles and exposure to hot seasons, particularly sugarcane and banana, exhibit substantially higher water requirements compared to short-duration crops like wheat. These findings highlight widespread over-irrigation practices driven by limited farmer awareness and outdated scheduling methods. Overall, the paper demonstrates that CROPWAT is an effective decision-support tool for scientific irrigation planning and water resource management in arid and semi-arid regions.

Another research work proposed a model [171] to schedule irrigation of banana-specific smallholder fields of Magdalena, Colombia. A soil-water balance approach is employed by considering site-specific climate data, soil moisture content, and crop coefficient. The model generates advisories to farmers through SMS-based communication for

weekly irrigation recommendations. This study also reports the reluctant behaviour of farmers towards the adoption of technology. Since the model considers the feedback from farmers related to irrigation against the suggested amount of irrigation. The model reveals the poor correlation between actual irrigation and the estimated amount of irrigation. Despite the accurate recommendations, fields get over irrigated that leads to leaching of nutrients. The efforts are required to practically implement water management.

Table 5.1: Comparison of the proposed work with the existing research

Author	Crop	Methodology	Key Findings	Limitations
Chen et al., 2021[97]	Rice	Reinforcement Learning for irrigation, modelled as a Markov Decision Process.	RL adapts irrigation decisions dynamically to weather and soil variability. Achieves significant water savings without reducing crop yield	Tested primarily on rice; crop-specific transferability not validated
Vianny et al., 2022 [168]	Banana	IoT-based precision irrigation system integrated with a hybrid machine learning model (KNN + GBT + LSTM + Spearman correlation)	31.14% water optimization (2020); 50.1% optimization (2021); improved R ² and reduced RMSE compared to existing models	Tested on limited geographic locations; performance is sensitive to climate variability and sensor noise.
Angelin Blessy et al. (2022) [169]	Banana cultivation	IoT sensors, KNN, Reinforcement Learning	Adaptive, data-driven irrigation scheduling using RL for banana crops	Limited discussion on large-scale deployment and long-term field validation
Solangi et al. (2022) [170]	Wheat, Cotton, Sugarcane, Banana	FAO CROPWAT 8.0	Provides region-specific irrigation scheduling to	Based on 5 years of climatic data, broader

			reduce over- irrigation	temporal validation is recommended
Zubelzu et al. (2023) [171]	Banana	Soil–water balance model, SMS-based advisory	Demonstrated the potential of tailored irrigation scheduling	Moderate to poor farmer adoption; KC uncertainty;
Kelly et al., 2024[172]	Maize	Aquacrop-gym +DRL	DRL approaches outperform optimized heuristics	DRL is sensitive to rainfall variability, high computational and data demand, and inconsistent superiority over optimized heuristics
Proposed Work	Banana	NASAPOWER+IOT Sensor+PPO	Automated irrigation	Yield Improvement

One more study utilized Aquacrop-OSPy [172], a crop simulation model, to report the maize crop behaviour under water stress in the United States. DRL has been employed and trained for 70 years of local climate parameters with restricted water usage, along with some heuristic approaches based on fixed rules of soil moisture. Both methods have also been validated for 30 years of data generated from LARS-WG, which is a synthetic weather generator. Results from this open-source Python framework show that DRL lags in performance when rainfall variation is high. But it performs effectively when rainfall is zero and strict water utilization rules are implemented. Thus, DRL appears as a solution for farmers in rain-scarce regions.

The findings, enumerated in Table 5.1, demonstrate that considerable benchmarks have been achieved in the irrigation strategies through crop models, IoT-based data collection centres, machine learning, deep learning, reinforcement learning, and data-driven decision-support systems. Aquacrop, CROPWAT, and soil-water balance models provide experimentally accurate irrigation volumes. Still, they consider uniform growth of crops, the coefficients of crop values are fixed, and site-specific assumptions are

taken for granted. They are limited to static conditions and not adapted to the dynamic variability of the environment, space, and time. IoT-based ML frameworks offer increased accuracy with improved monitoring of the fields, but they need large datasets, wide sensor networking, and have not been validated across wider agro-climatic zones. DL and RL models performed well under certain situations, but not in all scenarios. Results showed that under certain constraints, fixed rules outperformed these advanced techniques for irrigation scheduling. Moreover, studies have hardly focused on perennial crops, less popular crops, challenges faced by farmers in adopting the technology, and yield improvement. Therefore, there is a great need for irrigation frameworks that can be practically deployable, scalable, and, most importantly, along with water, yield should also be taken as a prime factor.

5.2 Proposed Framework

This section presents an intelligent irrigation framework[173]that consists of data collection, edge processing, cloud processing, AI modules, developed logic for actions involving on-field physical constraints, authorized execution only, and actual valve or pump operations in a single frame (Figure 5.1). The detailed description of the proposed framework has been provided below:

5.2.1 Data Collection Layer

The Internet of Agricultural Things (IoAT) deploys sensors in the field that continuously collect ground data, including temperature, humidity, soil moisture, pressure, and solar radiation intensity. In parallel, satellites perform remote sensing by providing spatiotemporal data including solar radiation, rainfall forecasts, wind speed, and corrected precipitation. These heterogeneous data sources are stamped with location and time to preserve the context at the collection centre. The quality of these data sources is crucial for the overall performance of data-driven modules.

5.2.2 Edge Processing Layer

The edge processing layer fetches data from the collection layer to carry out preprocessing. Data filtering, noise removal, and integrating satellite data with sensor data are accomplished. Only the pre-processed data is forwarded to the succeeding layers to reduce redundant data, bandwidth, and latency.

5.2.3 Cloud Storage Layer

This layer serves as the core repository of the framework. It acquires pre-processed data from the edge layer along with data recorded by sensors, weather stations, and irrigation logs while maintaining privacy. The maintained databases by this layer are employed to train AI-based models and obtain inferences.

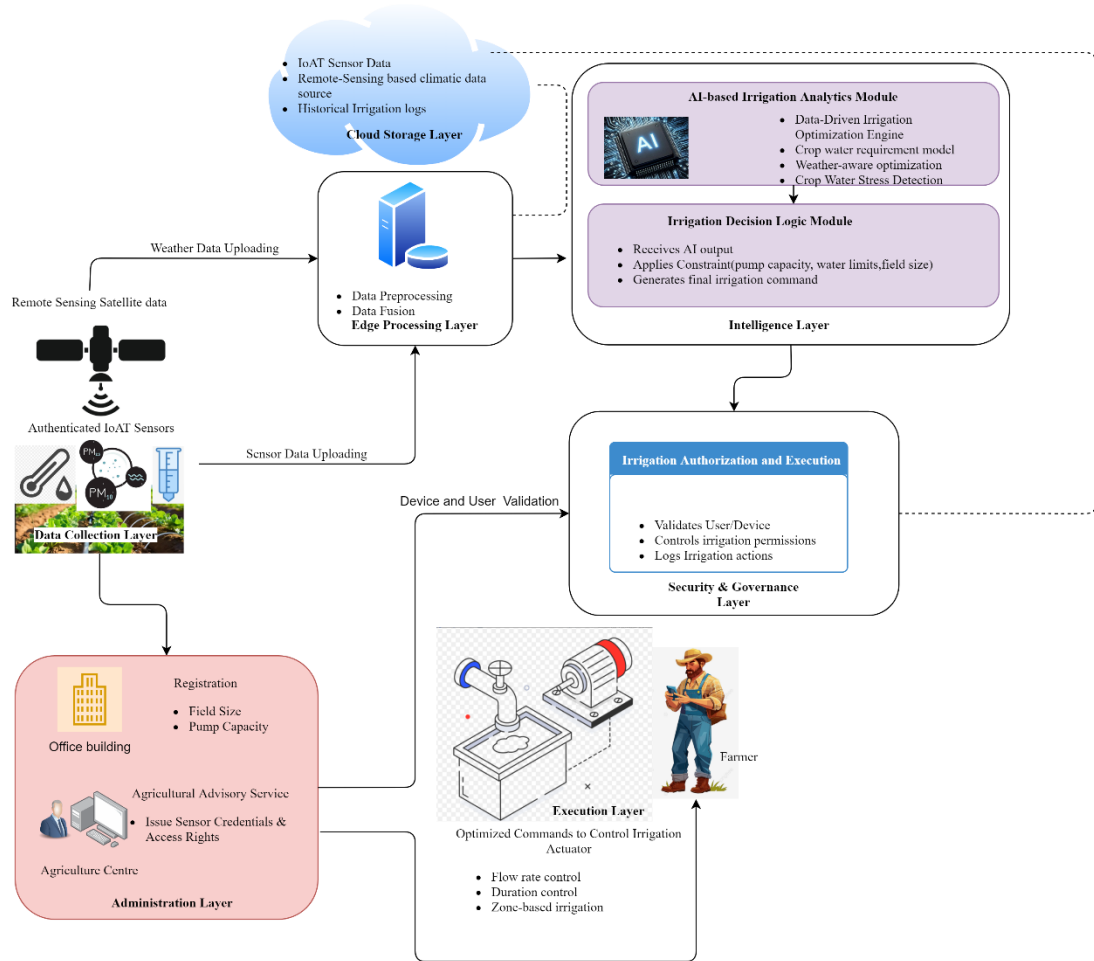


Figure 5.1: Layered architecture of the proposed intelligent IoAT-based irrigation framework

5.2.4 Intelligent Layer

The intelligent layer is the computational core of the framework that operates in two modes. In the AI-based irrigation analytics module, AI algorithms are trained with

structured datasets. During analysis, crop stage, crop type, root depth, and soil type are provided to AI algorithms to predict evapotranspiration ET_c . The irrigation decision logic module finally decides the irrigation amount after considering operational restrictions, including water flow, pump capacity, and field size, along with the output of the AI module. The final recommendation is passed on to the security and governance layer for access control.

5.2.5 Security and Governance Layer

The security and governance layer receives irrigation commands derived from the intelligent layer before the actual execution. It authenticates the user and ensures authorised users such as administrators, agriculturists, and experts have access to the suggested irrigation commands.

5.2.6 Execution Layer

The execution layer operates the actuators after receiving authorized irrigation commands. It regulates motor valves to control water flow rate and operation duration in designated irrigation zones. Information, such as irrigation actions and motor runs, is fed back to the cloud layer for auditing later.

5.2.7 Administration Layer

The administration layer acts as an interface for management. Farmers get registered at agricultural centres with their field profiles, such as area, soil type, crop, and pump capacity. Advisory committees and agricultural experts issue recommendations and alarms to avoid yield loss and water wastage.

Following the irrigation schedules, soil factors and environmental conditions are recorded and fed back to the cloud storage layer. This helps to improve subsequent irrigation decisions in the dynamic environment by retraining AI models. Thus, the framework employs a closed-loop, multisource data integration method for scalable PPO-based irrigation control.

5.3 Methodology

This section dives into the detailed methodology being adopted to irrigate the banana fields automatically [174] as presented in Figure 5.2. The approach integrates data from multiple sources, creates an environment to train an agent, and formulates the optimized

irrigation policy. The detailed description of data, deep reinforcement-based proximity policy optimization and training based on state, action, reward, and observations have been discussed in the following subsections.

5.3.1 Dataset Description

This study assesses banana crop dynamics over one complete growth cycle, that is, from July 2022 to March 2023. Since an IoT-enabled field dataset has been collected from the Space Data Science Laboratory, IIT Dharwad, Karnataka, India[175]. The on-field sensor nodes deployed inside a banana cultivation regularly monitor soil and various atmospheric parameters with a 5-minute gap over approximately eight months, encompassing multiple critical growth stages of the banana plant. The recorded parameters in the data and their significance are enumerated in Table 5.2. The data has been automatically timestamped through the network of an embedded data acquisition system.

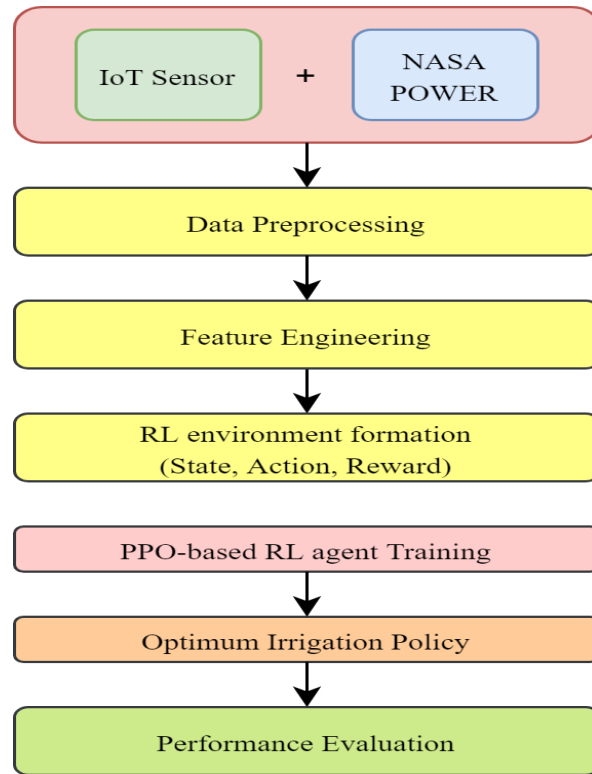


Figure 5.2: The proposed methodology

Table 5.2: IoT sensors and their description

Sensor	Parameter Measured	Role
PMS5003	Air particulate concentration	Environmental stress indicator
Soil Moisture	Soil moisture index	Primary irrigation state variable
BH1750/LDR	Light intensity (lux)	Evapotranspiration & growth factor
DHT22	Relative humidity (%) and Ambient temperature (°C)	Crop stress & water demand
BMP280	Atmospheric pressure (Pa)	Weather trend indicator

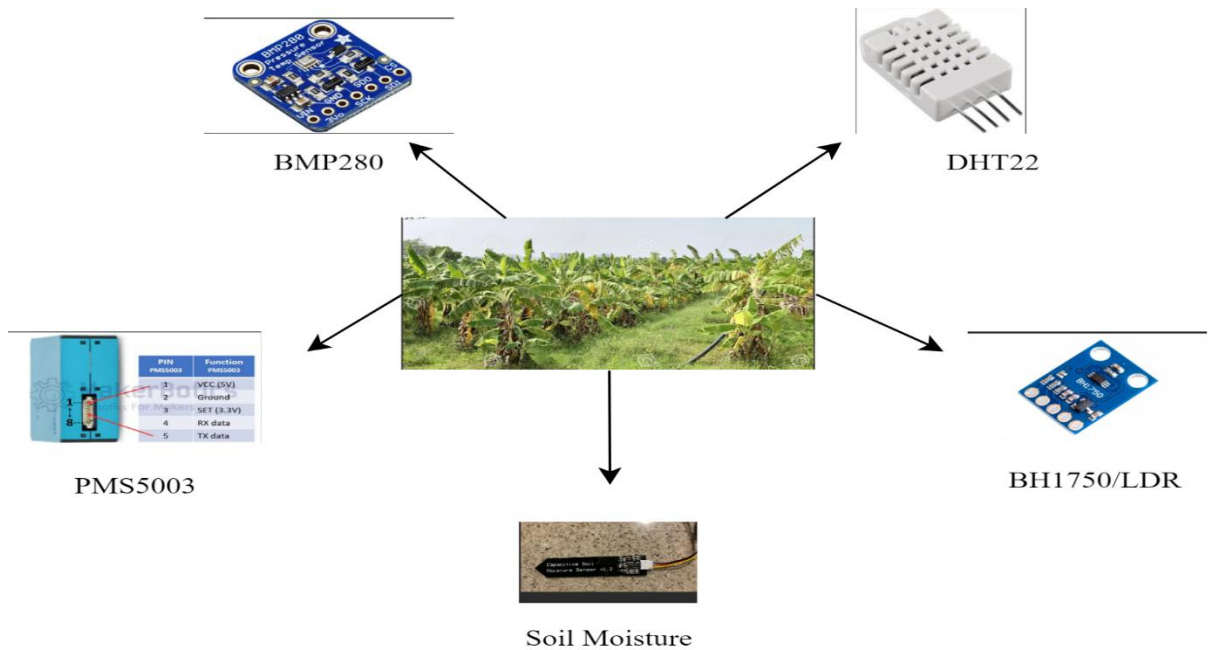


Figure 5.3: IoT Sensors deployed on banana fields

Figure 5.3 demonstrates the IoT sensors being installed in the banana field. Soil moisture (SM) based on capacitance is the primary irrigation indicator that captures water in the root zone of the crop, which is also supported by auxiliary moisture feedback (AM). Ambient temperature (TEMP) and relative humidity (HUMD) are measured by the DHT22 sensor. Light intensity (LUM) has been measured with a Light Dependent Resistor (LDR). Atmospheric pressure (PRES) has been determined by BMP280. Particulate matter concentrations (PM1, PM2, PM3) are measured by PMS5003. The measured factors characterize the field microclimate, radiation environment, and ambient stress conditions influencing evapotranspiration and crop

water demand. Collectively, these measurements enabled a comprehensive representation of soil–atmospheric interactions relevant to precision irrigation and water stress assessment.

To supplement the field-deployed IoT sensors data, NASAPOWER weather data [176] has been obtained for the same location at latitude 15.4589 and longitude 74.9950. NASA POWER provides a daily meteorological database from satellite observations across the Earth. The gathered variables include air temperature at 2 m height, relative humidity again at 2m distance from the earth, wind speed also at 2m height, precipitation in the air, and solar radiation, which are downward of shortwaves of the whole sky as depicted in Figure 5.4. These factors determine evapotranspiration, rainfall forecast, and soil-water demand. These values are significant for increasing the reliability of irrigation models under different climate situations.

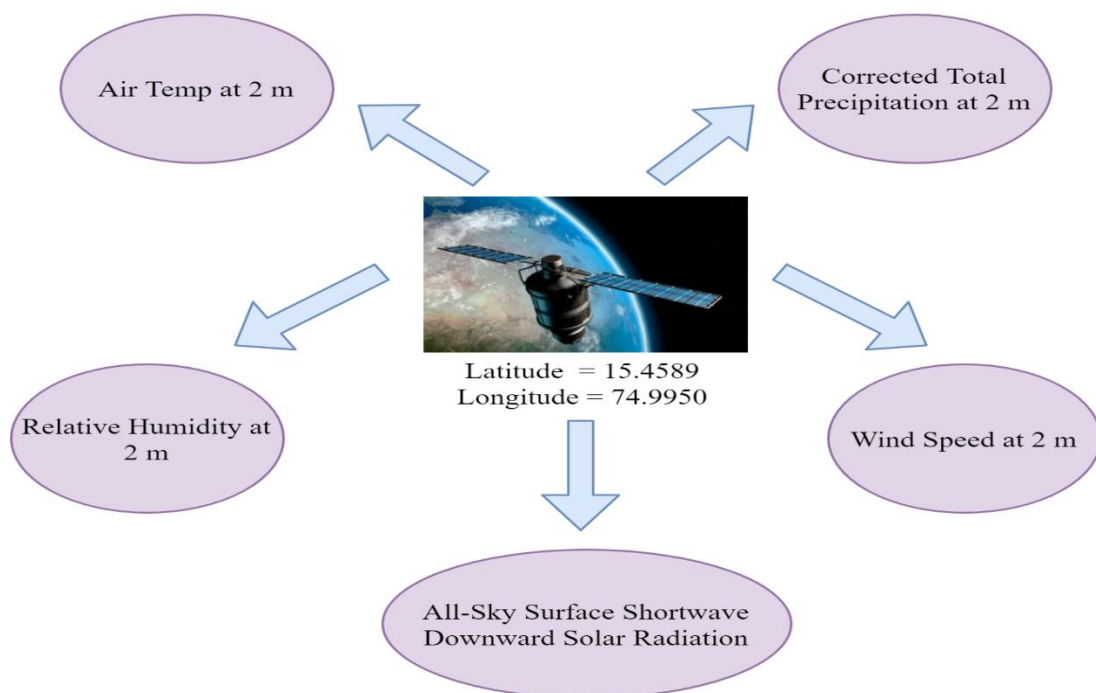


Figure 5.4: Data collected from a satellite

Thereafter, field-based sensor data is cleaned by maintaining uniform time and date formats while removing invalid timestamps. Also, field sensors log readings every 5 minutes, so the daily mean is calculated for each parameter to integrate data with satellite-observed data. In the NASAPOWER weather dataset, missing values are replaced with NULL by removing irrelevant characters. The day of the year is converted

into properly formatted timestamps that are in the same format as a field-based dataset. The pre-processed IoT dataset is synchronized with satellite data to generate a merged dataset in a unified daily dataset. After integration, 224 days of data have been prepared with all soil and environmental parameters. These variables form the state space for reinforcement learning, including the observed site-specific soil factors and region-specific atmosphere parameters.

The field parameters, such as flow rate, have been considered 0.8 m³/hr per drip irrigation line. Thus, the analysis period has covered the most sensitive stages of banana, including vegetation, flowering, and bunch development. These stages have maximum impact on the yield and are highly influenced by water availability. The approximately eight-month data provide sufficient time coverage to optimize irrigation for maximum production of the cash crop.

5.3.2 Feature Engineering

After the dataset preparation, raw parameters have been converted into useful factors for model training. The derived factors interpret better water stress and can optimize the rewards. To accomplish this, reference evapotranspiration has been calculated by the standard method suggested by the Food and Agriculture Organization [177] and normalized. It is used to determine how much water is lost by a plant to the atmosphere from a well-irrigated surface. The equation is Penman–Monteith [178] which uses climatic parameters, given as:

$$ET_0 = \frac{0.408\Delta R_n + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1+0.34u_2)} \quad (5.1)$$

ET_0 is measured in mm/day, where T = air temperature; R_n = net radiation; u_2 = wind speed; e_s, e_a = saturation & actual vapor pressure; Δ = slope of vapor pressure curve; γ = psychrometric constant

Furthermore, to determine the crop water requirement of a specific crop at a certain stage, the banana crop coefficient is utilized. The crop coefficient encompasses all the phenological details of the crop at some specific stage. To calculate the water demand of a banana at a specific stage with its canopy, the average Kc [179] has been assigned as follows in Table 5.3.

Table 5.3: Crop Coefficient for banana at different stages

Growth Stage	Duration (Days)	Kc Range
Initial (Establishment)	0–60	0.5–0.6
Vegetative Growth	61–150	0.8–1.0
Flowering & Bunch Formation	151–240	1.1–1.2
Maturity	>240	0.9–1.0

Now, the water requirement can be computed with the following equation:

$$ET_c = ET_0 \times K_c \quad (5.2)$$

This formula guarantees that optimum water would be recommended according to the crop, avoiding water stress and overwatering during critical stages.

Furthermore, soil moisture has been normalized between the wilting point, i.e., minimum soil water, and the field capacity, i.e., maximum soil water. Normalized soil moisture value ensures neural networks have better stability.

$$SM_{frac} = \frac{SM - WP}{FC - WP} \quad (5.3)$$

Root zone depth is 600 mm, which supports total water available (TAW) given as follows:

$$TAW = (FC - WP) * 600mm \quad (5.4)$$

5.3.3 RL Environmental Design

In standard reinforcement learning, the agent interacts continuously with the environment. At each time interval, the agent observes the state and acts accordingly. The action taken brings a reward in return. With its observation, the agent transitions to the next state. Figure 5.5 depicts the algorithm wherein the state vector is fed to a PPO [97]. The RL agent gets trained in the OpenAI Gymnasium. The RL environment is customized by deciding state vector parameters, irrigation actions, reward function, a soil-water model, and termination of the episode. The algorithm integrates crop evapotranspiration, soil moisture balance dynamics, and operational irrigation conditions using the Markov Decision Process (MDP).

Firstly, the state space vector is defined as:

$$S_t = \{sm_{frac}, ET_c, P_c, SR, DOY\} \quad (5.5)$$

where sm_{frac} represents water available in the root zone of the plant, ET_c is crop evaporation, P_c is corrected precipitation, SR indicates solar radiation, and DOY is the date of the year.

The normalized soil moisture directly points to water availability since affected by irrigation immediately. Evapotranspiration indicates the water depleted from the soil as well as the plants. Corrected precipitation takes care of uncertainty in the environment. It saves water in case rain is expected. Solar radiation is directly proportional to evapotranspiration, which helps to predict future depletion of soil moisture. The date of the year decodes the stage of the banana crop since water needs depend on the season and level of growth. Thus, the state vector encompasses soil-atmosphere-crop interactions that govern the water requirements. It satisfies the Markov decision property.

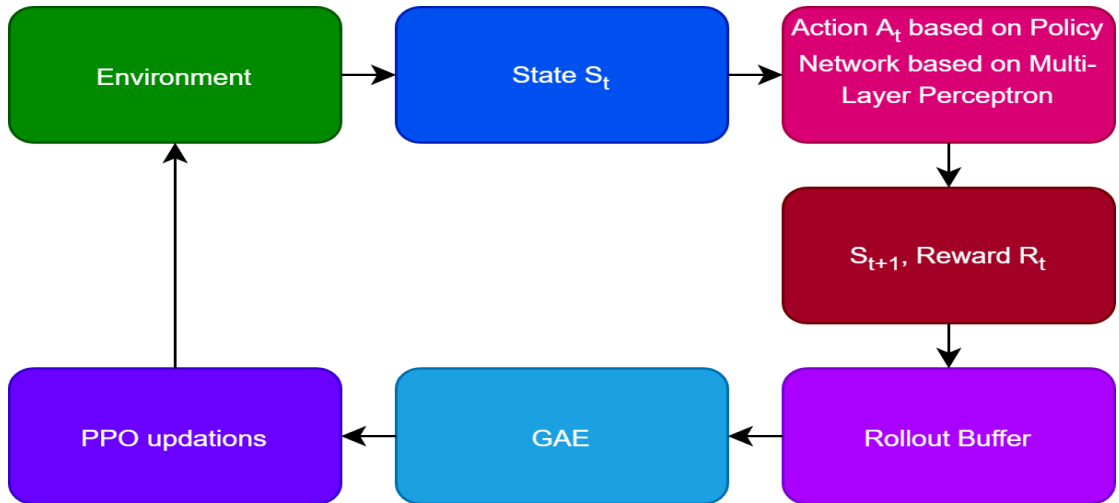


Figure 5.5: The PPO algorithm

Action Space irrigates the field continuously for a duration of 0 to 3 hours, which can be represented as follows:

$$a_t \in [0,3] \text{ hours/day} \quad (5.6)$$

The upper limit has been set to 3 hours per day per plant with a flow rate of $0.8m^3$ per hour for the drip line. The physical constraints of prolonged operation that would spike the soil moisture are avoided. It explores the maximum irrigation intensity[178].

The multi-objective reward is further designed to consider crop yield protection and efficient water utilization, along with the required soil moisture. The reward equation considers moisture tracking, rainfall utilization, water stress, and water use. The moisture tracking punishes the agent in case of deviation from the target soil moisture. The rainfall utilization promotes the use of rain instead of over-irrigating the fields. The stage-sensitive stress factor increases the penalization if soil moisture deviates from the target during the yield-affecting stages. Finally, the agent gets strict punishment, provided soil moisture falls below a critical value where a crop dies.

The moisture tracking reward is defined as:

$$R_m = \max[0, \min(1, 1 - \frac{SM - SM_t}{SM_{\max} - SM_{\min}})] \quad (5.7)$$

where SM and SM_t denote the current and target soil moisture, and $SM_{\min}$ and $SM_{\max}$ represent the minimum and maximum values of soil moisture, respectively, used to normalize the difference.

The agent gets a maximum reward when soil moisture is near the target, which is 1, and a minimum reward of 0 when soil moisture is far from the target, as depicted by Eq. 5.7.

Further, the rainfall utilization reward mentioned in Eq. 5.9 considers the effective use of rainfall so that soil moisture does not exceed the maximum limit. The agent gets rewards if the rainfall, in addition to the current moisture, does not exceed the field capacity. Conversely, the agent gets minimum rewards if irrigation wastes water by over-irrigating the field, letting the soil moisture rise above the field's capacity of the field. This supports water-efficient strategies and explores the soil's physical capacity to hold water. If soil moisture reaches the maximum, a proportional penalty is applied that ensures smooth reward decay and stabilizes the policy optimization.

The updated soil moisture after rainfall is given as:

$$SM' = SM + \frac{P_c}{D_r} \quad (5.8)$$

Where SM is the current soil moisture, P_c is the rainfall in mm/day, and D_r is the root zone depth

$$R_r = \begin{cases} 1, & SM' \leq SM_{\max} \\ \frac{SM_{\max}}{SM'}, & SM' > SM_{\max} \end{cases} \quad (5.9)$$

Moreover, the yield protection reward punishes the agent if soil moisture falls below the target, and this penalty is high if the crop is in its critical stage, that effects the maximum yield that is fruiting, as given by Eq. 5.11. It includes soil moisture along with the significance of yield.

$$Stress_t = \max(0, SM_t - SM) \quad (5.10)$$

$$R_s = e\left(-\frac{K_{c,t}}{K_{c,\max}} \cdot Stress_t\right) \quad (5.11)$$

Where SM_t is target soil moisture, SM is soil moisture at time t , K_c is the crop coefficient at a particular stage of the crop, and $K_{c,\max}$ is the highest value of crop coefficient, which is 1.15.

The water-use penalty penalizes the agent if more irrigation is scheduled, and if soil moisture falls below a critical value, then again, more punishment is imposed to avoid the stress on crops given by Eq. 5.12. Beta value is a trade-off knob between yield and water stress decided based on experimentation.

$$R_w = e(-\beta I_t) \quad (5.12)$$

Where I_t is the irrigation depth in mm/day and β , the water-use penalty coefficient is taken as .08

Also, a hard penalty is imposed if soil moisture falls below a critical value as a safety measure by Eq. 5.13. It prevents excessive water stress to reduce yield loss.

$$R_t = \begin{cases} -1 & \text{if } SM < SM_t - \lambda \\ \text{Reward}, & \text{otherwise} \end{cases} \quad (5.13)$$

Where λ is the critical soil moisture value

Finally, the total weighted reward is given by Eq. 5.14, assigning different weights to different factors after the trial-and-error method.

$$R_t = 0.25R_m + 0.20R_r + 0.40R_s + 0.15R_w \quad (5.14)$$

Furthermore, the next state equation is given by the equation 5.15. The next soil moisture state depends on the current soil moisture, irrigation action, crop evapotranspiration, and rainfall. After the irrigation, the updated soil moisture utilizes the soil water balance model for the next timestep. It considers the dynamics of the environment to formulate the irrigation policies by reducing the yield loss. Thus, this state transition equation concerns agronomically safer limits by maintaining the required soil moisture.

$$SM_{t+1} = f(SM_t, I_t, ET_c(t), R_t) \quad (5.15)$$

Where SM_t = current soil moisture, I_t = irrigation applied, ET_c = crop evapotranspiration, R_t = rainfall

Finally, the episode gets terminated if soil moisture goes below the wilting point, represented by equation 5.16. The crop goes into irreversible crop stress and dies.

$$SM_t + 1 \leq W_p \quad (5.16)$$

Algorithm 5.1 PPO-Based Irrigation Control System

Input: Initial Soil Moisture SM, Training timestep, Random seed=5 to train PPO 5 different times

Initialize the Policy Network $\Pi(s_t|a_t)$ that decides irrigation and gives value to the current state $V(s_t)$

For each seed $s=1$ to 5 do

- A. Observe the state vector
- B. Select irrigation action using policy
- C. Apply irrigation to a depth of I_t
- D. Update Soil Moisture
- E. Compute reward
- F. Store transition S_{t+1}

Rollout Buffer

- A. Compute Generalized Advantage Estimation

- B. Update Policy Π
- C. Update Value Network

Output: Trained irrigation policy Π

5.3.4 PPO Training

The PPO algorithm is implemented in Stable-Baselines, and a Multilayer Perceptron (MLP) policy network has been utilized to train the irrigation agent due to its stability and effectiveness in continuous closed-loop problems. The agent interacts with the custom OpenAI Gym-compatible irrigation environment and observes daily data from sensors and NASAPOWER. Data is pre-processed, merged, and used to compute evapotranspiration specific to the crop. The state vectors are constructed and fed to the PPO agent, which takes an action to irrigate the fields. Thereafter, the agent transitions to the next state after accessing the current soil moisture, irrigation action, evapotranspiration, and rainfall. The reward is also allocated to the agent as per performance after the evaluation of soil moisture tracking, rainfall utilization, yield protection, and efficient utilization of water. Accordingly, the agent transitions to the next state. The agent has been trained rigorously by interacting with the surroundings for several timesteps. The rollout trajectory of sequences is recorded as the collection of experiences. Further, Generalized Advantage Estimation (GAE) is calculated to compare how much better the action is compared to the average. The policy is framed for a particular action to be taken in a specific state repeatedly.

Table 5.4 enumerates the list of all the tuned hyperparameters; the agent interacts with the environment for 300000 steps per run. The rollout size is finalized, where the irrigation policy gets updated after 2048 irrigation decisions. The total episode length is 224 days, the full growth season of the crop. The learning rate has been set to 0.0003, the batch size to 64, and the clipping range to 0.2, which is a 20 percent change. The discount factor (γ) is 0.99, and GAE λ is 0.95. The policy gets updated using the trajectory of rollout, which stores the current state, action taken, reward received, and next state to compute GAE. The policy gets updated iteratively in a closed-loop manner using the PPO clipped surrogate objective. The model has been trained for five different random seeds to ensure reliability. The performance metrics have been averaged across all five runs. The complete algorithm is elaborated in Algorithm 5.1.

Table 5.4: List of hyperparameters

Parameter	Value	Meaning
Algorithm	PPO	Stable policy optimization
Policy	MLP	Neural network policy
Learning rate	3e-4	Policy updates step size
Rollout steps	2048	Steps per policy update
Batch size	64	Mini-batch size
Clip range	0.2	PPO trust region
Total steps	300,000	Training horizon
Seeds	5	Robustness

Additionally, stability has been further confirmed by the training diagnostics generated during PPO optimization. The clip fraction of 0.035 has shown little clipping during optimization, while the approximate KL divergence (Kullback–Leibler divergence) of 0.0048 stayed low, indicating regulated policy updates. The value function correctly predicted expected returns, as seen by the explained variance of 0.999. Stable policy and value network optimization are shown by the final training loss of 0.116, value loss of 0.357, and minor policy gradient loss of -0.000798 . Overall, the findings show that the PPO-based irrigation scheduling policy converges reliably.

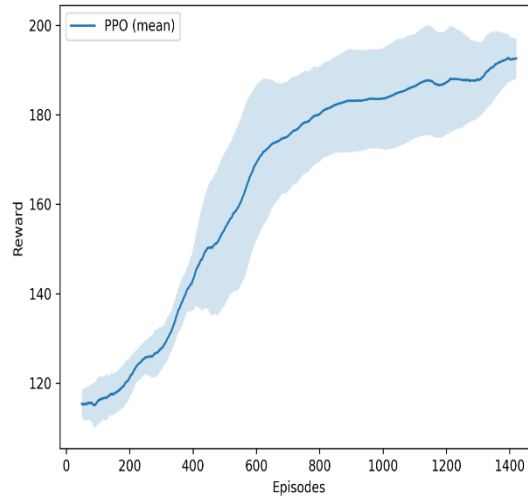


Figure 5.6: Training Convergence Curve

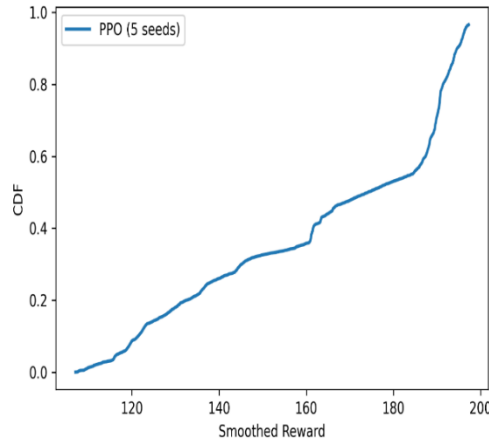


Figure 5.7: CDF of PPO

The training performance has been evaluated across five independent training seeds for the irrigation controller based on Proximal Policy Optimization. Figure 5.6 illustrates the convergence behavior of the agent, where the mean episode reward increases steadily from approximately 115 to about 192 over the training period. The shaded region represents the variability across different seeds, which gradually narrows as training progresses. The reward curve stabilizes after 900 to 1000 episodes. This indicates stable policy learning and reduced variance. The agent successfully converges to a successful irrigation policy. To evaluate the strength further, the cumulative distribution function (CDF) is generated as shown in Figure 5.7. The CDF represents the steep rise of reward from low 110 to high 195. This curve suggests low variability across runs and a reliable decision policy.

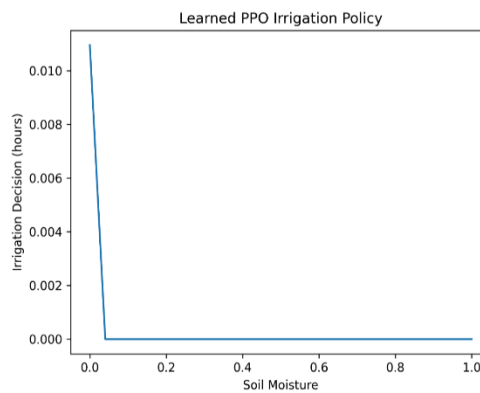


Figure 5.8: Policy Behaviour

Further, the behaviour of the learned policy is demonstrated in Figure 5.8. The agent triggers the irrigation immediately after the soil moisture falls below the critical threshold. Conversely, no irrigation is applied if soil moisture rises above the threshold. The agent has successfully learnt to prevent excessive water or water stress while maintaining adequate soil moisture.

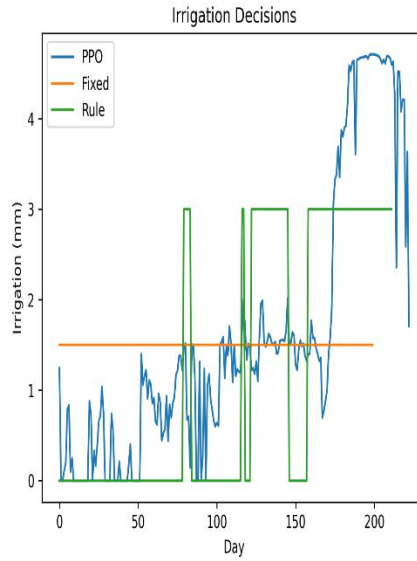


Figure 5.9: Irrigation Schedules

Furthermore, the irrigation decisions are compared with fixed and rule-based irrigation strategies, as shown in Figure 5.9. The fixed irrigation strategy applies a constant 1.5 mm of water throughout the crop life cycle, irrespective of environmental conditions or the state of the crop. In contrast, rule-based irrigation initiates irrigation only when soil moisture falls below a certain threshold. However, the PPO agent adapts to environmental parameters and current soil moisture. Accordingly, a variable amount of irrigation is applied to the crop as per water demand.

Figure 5.10 depicts the soil moisture dynamics for different irrigation strategies. The Proximal Policy Optimization (PPO)-based controller showcases superior moisture regulation by keeping soil moisture within a comparatively steady range during the growing season. It demonstrate soil moisture levels rise roughly 0.35–0.40 during the early growth stage for all three techniques. However, as the session progresses, the evapotranspiration increases, and the operation mode of strategies becomes noticeable.

The PPO method maintains sufficient soil moisture mostly between 0.22 and 0.35. The irrigation gets modified in response to plunging soil moisture and environmental factors. The fixed irrigation approach applies consistent irrigation regardless of the state of the soil, leading to both excessive and insufficient moisture. Also, the rule-based approach shows greater fluctuations, although it partially controls soil moisture by initiating irrigation below a threshold. It is also observed that towards the end of the season, water demand increases, and soil moisture decreases for all techniques. However, the PPO controller maintains more regulated variations and avoids protracted moisture deficits, demonstrating its capability for stable soil moisture management.

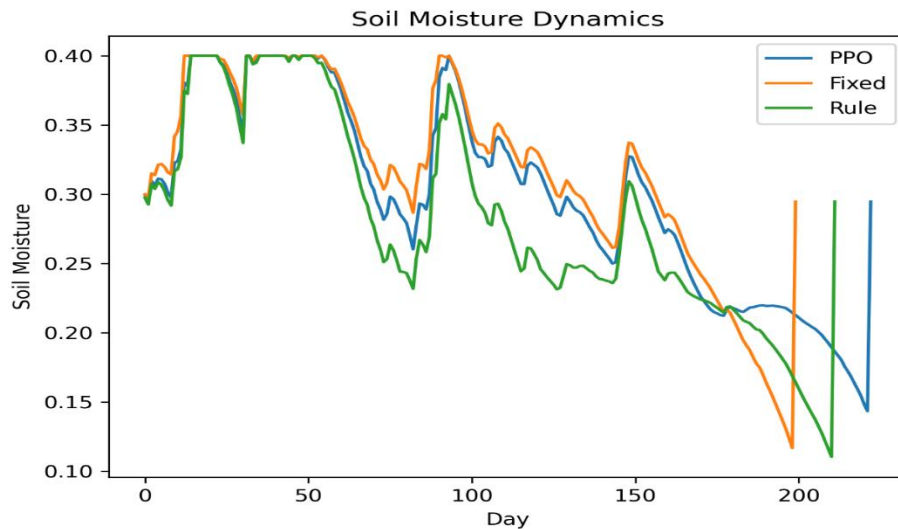


Figure 5.10: Soil Moisture Regulation

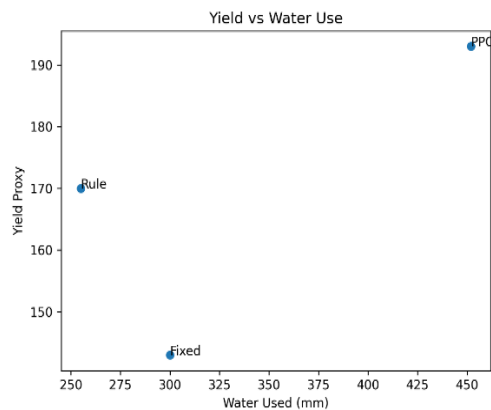


Figure 5.11: Yield vs water used plot

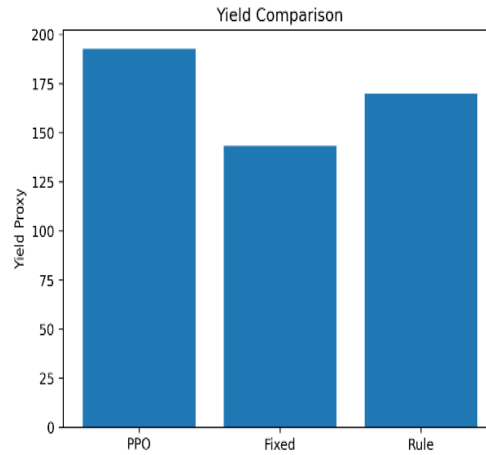


Figure 5.12: Yield comparison Plot

For crop productivity, a yield proxy is calculated as the cumulative reward obtained over the irrigation season. The reward function incorporates soil moisture tracking, crop stress penalties, and irrigation efficiency, allowing the reinforcement learning agent to learn irrigation strategies that maximize crop performance while minimizing water stress. Figure 5.11 depicts that the PPO controller prioritizes maintaining optimal soil moisture in the field, which improves crop productivity. While the rule-based strategy conserves water, it cannot produce optimum yield since irrigation amounts have not been dynamically adjusted. Figure 5.12 compares the yield from three methods. The PPO irrigation policy significantly improves crop yield compared with conventional strategies. The fixed schedule fails to match crop water demand, leading to lower productivity. Rule-based irrigation performs better than fixed scheduling but still lacks the adaptability of PPO.

The irrigation strategies have been evaluated using water consumption, yield, water stress days, and root mean square error of soil moisture, as illustrated in Table 5.5. PPO achieved the highest yield proxy of 196 with minimal crop stress of 1 day, although it has consumed higher irrigation water of 452 mm. In comparison, the fixed irrigation strategy has produced a lower yield proxy of 143 and experienced significant crop stress for 15 days. The rule-based strategy reduced irrigation water to 255 mm but resulted in crop stress for 10 days. The PPO controller maintained stable soil moisture regulation with a Root Mean Square Error (RMSE) of 0.110, demonstrating effective irrigation

decision-making. The PPO controller applies higher irrigation volumes to maintain soil moisture within an optimal range, resulting in improved yield and minimal crop stress compared to fixed and rule-based irrigation strategies.

Table 5.5: Evaluation Parameters

Method	Water (mm)	Yield	Stress Days	RMSE
PPO	452	196	1	0.110
Fixed	300	143	15	0.124
Rule	255	170	10	0.104

5.4 Conclusion

In this proposed work, an automated framework to irrigate the fields has been proposed. By considering farm conditions, AI-driven techniques can generate commands that can be controlled by the farmer to decide. The registered farms would get advice from an expert. Moreover, irrigation logs would be stored in the cloud for future predictions and improvements. The deployment of this model also considers the field size and other hardware constraints.

Further, a novel approach by integrating field data with satellite weather data is used to train an RL agent to irrigate for maximum yield and minimum water stress for the banana crop. PPO, an RL-based technique, has been optimized and evaluated against fixed and threshold-based irrigation. The reward has been framed for optimal soil moisture, minimum water use, and stable irrigation decisions. The fundamental concept is to protect the crop first, then save the water. The results display that the PPO agent learns to dynamically irrigate the fields as per the soil moisture needs to produce maximum fruit. The proposed method achieves maximum yield and minimum stress days. Although the higher irrigation volumes are being consumed by the PPO-based method, this extra water usage has contributed to improved crop health and reduced stress conditions. This highlights a trade-off between water efficiency and yield optimization.

Chapter 6

Conclusion and Future Prospects

The trends in precision agriculture increasingly aim to advance agricultural methods, incorporating Artificial Intelligence techniques. The methodologies aim to develop intelligent frameworks to maximize production by tackling plant diseases, providing sufficient nutrients, and supplying adequate water to the fields with optimal resource utilization.

As a result, the present dissertation effectively addresses the critical challenges in banana crop management. This objective has been achieved by enhancing models' performance through feature extraction and parameter tuning. The proposed frameworks ensure timely and accurate decisions through modular and scalable approaches. The dissertation also emphasizes image processing by incorporating environmental parameters. Moreover, this section also recommends significant motivating future extensions of the dissertation.

6.1 Summary of major contributions

This section outlines the main inferences obtained from extensive simulations to develop smart framework solutions for banana cultivation practices, as detailed in earlier chapters.

1. A detailed scientometric analysis of AI technologies in agricultural practices has been conducted. The data obtained from Scopus, from 2015 to 2024, have been analysed and visualized using VOSviewer and Bibliometrix software. The presented research concluded that India excels in the field, contributing 874 research documents, a substantial portion of the global total of 1,938. Based on link strength, China has secured the top position in countries' collaboration with 56 links and a total link strength of 1,080, while India follows closely in second place with 56 links and a total link strength of 871. The leading institution, funding researchers with the highest number of publications, is ICAR. Science of the Total Environment stands out as the most prominent journal for disseminating findings globally. The notable emerging research topic has been outlined. The field of plant disease detection, addressing nutrient

deficiencies, analysing soil content, and optimizing irrigation schedules is explored further to leverage the effectiveness of AI in agriculture.

2. Intelligent computational methods that identify diseases at an early stage and evaluate severity can greatly enhance plant health. In this context, the current study proposes an innovative framework for intelligent detection and severity of banana diseases. A hybrid sampling technique, SMOTE-ENN, is applied for the first time to address unbalanced classes while removing noisy and potentially mislabelled data. Four modified CNN models-CNN1, CNN2, CNN3, and CNN4 with a varied number of layers, filter size, and number of neurons have been evaluated. The CNN2 model with five convolutional layers outperforms other CNN models with an accuracy of 96.86 percent. The CNN2 model has also been evaluated with 96.4% sensitivity, 98.92 % specificity, 97.31 % precision, and 96.74 % F1 score. The ROC–AUC analysis demonstrated that CNN2 has excellent discriminative capability with an AUC value of 1. Furthermore, the time and space complexities of the models have been analysed and compared to modern baselines to assess computational efficiency. The CNN2 model contains 220,964 parameters, a compact model size of 863.14 KB, and a computational cost of 2,100 MFLOPs, making it computationally resource-efficient compared to EfficientNetB0, ResNet50, VGG16, and Vision Transformer. Following established agricultural norms, the severity percentage is then used to assign a severity grade- low, moderate, high, and very high of the classified disease and suggest a suitable amount of fungicides. The proposed CNN-based integrated framework facilitates timely interventions, reduces excessive fungicide usage, and supports sustainable banana cultivation.

3. This work further introduces NutriSense-TL, an intelligent framework that integrates nutrient-deficiency classification, pixel-level severity estimation, and soil-based fertilizer prescription. Seven pre-trained models have been evaluated with DenseNet169, achieving the highest standalone accuracy of 95.87%. To improve generalization and reduce computational load, two hybrid models have been created by concatenating MobileNetV2 with DenseNet169 and ResNet50. The DenseNet169 + MobileNetV2 hybrid achieved the best balance of accuracy 93.21%, smoother convergence, lower validation loss, and reduced misclassification. Additional metrics,

precision 93.06 %, recall 93.09 %, and F1 score 93.04%, have also been determined. The space complexity, when compared with existing literature, is minimal, that is, 15,105,540 parameters for the proposed hybrid model. Following classification, severity has been quantified using HSV thresholding, lesion intensity measurements, and contour-based features to compute the Intermediate Severity Value (ISV). HSV-based segmentation is validated with an IoU of 0.87 for boron, 0.30 for potassium, and 0.69 for zinc. Soil parameters (pH, Organic Carbon, and Electrical Conductivity) are also incorporated to generate precise fertilizer recommendations. The framework is a reliable decision-support system and helps farmers optimize fertilizer use and boost crop yield.

4. Furthermore, a reinforcement learning-based intelligent irrigation model has also been proposed to optimise crop yield. For intelligent decision-making, the PPO agent has been trained to automatically irrigate the banana fields using data from NASA POWER and IoT sensors. The agent is rewarded based on soil moisture value, rainfall utilization, water stress, and irrigation actions. The proposed PPO-based irrigation scheduling framework exhibits consistent and robust convergence, with the mean episode reward rising from around 115 to 192, stabilizing after between 900 and 1000 episodes. Stable policy optimization is validated by low mean KL divergence (0.0048), mean clip fraction (0.035), and high explained variance (0.9992) of the strategy-aware model, with models generating similar irrigation decisions across multiple training runs, as indicated by a low CDF standard deviation. RMSE for soil moisture, minimum for the proposed model, 0.110, suggesting better irrigation decisions. The stress day is a minimum of 1 day, while the maximum yield proxy of 196 with water consumption of 452 mm has been achieved with the designed model.

6.2 Future Recommendations

This section also highlights the recommendations that are associated with the presented research work, which are described as follows:

1. The designed frameworks incorporate heterogeneous data sources, including images, soil parameters, weather stations data, and IoT sensors measured parameters. Hence, the proposed frameworks can be extended to distinct crop varieties, different climatic conditions, and soil factors.

2. The presented models illustrate generalizability and versatility in correspondence to various disease patterns, multiple nutrient deficiencies, irrigation to diverse field conditions, and a variety of cropping systems. Therefore, this framework acts as a fundamental framework for designing further intelligent systems for precision agriculture.

3. It designs a system with multiple components that can be extended to other applications in agriculture pest management, weed management, and agricultural economics in terms of marketing, pricing, and supply chain. It can be made more flexible by wisely selecting feature sets and learning models.

6.3 Future Scope

The smart agricultural methodologies proposed for precision agricultural models can be further enhanced for future work. In this context, some of the initiatives have been delineated below:

1. Future work can focus more on increasing the value of the evaluation parameter of the classification algorithms. At the same time, spatial and temporal complexity should be reduced. In addition, segmentation techniques along with severity quantification can be further explored in varying illumination under natural conditions to achieve higher accuracy.

2. Integration of real-time as well as multi-season datasets from sensors and satellites with advisories from experts can be explored for futuristic models that can facilitate real-time actions for farmers.

3. The reinforcement-based learning can be further optimized for irrigation by formulating a multi-objective reward formulation, by focusing more on energy efficiency and water conservation, with no compromise of yield. While irrigation schedules are required to be validated by farmers or agronomists by considering specifications of irrigation systems.

4. The proposed methodologies can be extended to other economically important and herbal crops, such as dragon fruit, black turmeric, ashwagandha, and cassava, by

modifying various models and incorporating morphological attributes specific to each crop.

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List of Publications

International Journals

- Hardeep Kaur, Bhanu Priya, Kuldeep Singh, 2025. *Harnessing Artificial Intelligence for Sustainable Agriculture: A Comprehensive Scientometric Review*. Recent Advances in Food, Nutrition & Agriculture. DOI: 10.2174/012772574X355955250212112211.
- Hardeep Kaur, Bhanu Priya, Kuldeep Singh, 2025. *CNNx: Optimizing Smart CNN Models for Efficient Banana Disease Detection*. Concurrency and Computation: Practice and Experience, Impact Factor: 1.5. DOI: 10.1002/cpe.70475.

International Conferences

- Hardeep Kaur, Bhanu Priya, Kuldeep Singh, 2024. *Strategies of Artificial Intelligence for Sustainable Farming*. Paper presented at the 6th International Conference on Intelligent Circuits and Systems (ICICS 2024), 26 October 2024, Lovely Professional University (LPU).
- Hardeep Kaur, Bhanu Priya, Kuldeep Singh, 2024. *Nutrient Deficiency Diagnosis of Banana Crop by Deep Ensemble Convolutional Neural Network*. Paper presented at the 7th International Ankara Multidisciplinary Studies Congress, 5–6 March 2024.
- Hardeep Kaur, Bhanu Priya, Kuldeep Singh, 2025. *Enhanced CNN Approach for Classification of Nutrient Deficiency in Banana Crop*. Research paper presented at DECAI 2025, a Scopus-indexed conference, Guru Nanak Dev University (GNDU), Amritsar.

Book Chapter

- Hardeep Kaur, Bhanu Priya, Kuldeep Singh, 2025. *Application of AI in Agriculture for Real-Time Insights*. Book chapter accepted for publication in Intelligence-Driven Automation Techniques, to be published by John Wiley & Sons Limited (Wiley) in collaboration with IEEE Press.