DESIGN AND DEVELOPMENT OF AUTOMATIC SYSTEM FOR DETECTION OF DISEASES IN BANANA AND PAPAYA

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Computer Science and Engineering

by

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LOVELY PROFESSIONAL UNIVERSITY, PUNJAB

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DECLARATION

I, hereby declared that the presented work in the thesis entitled **“Design and Development of Automatic System for Detection of Diseases in Banana and Papaya”** in fulfillment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Deepak Prashar**, working as Professor, in the School of Computer Science and Engineering of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "**Design and Development of Automatic System for Detection of Diseases in Banana and Papaya**" submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the School of Computer Science and Engineering, is a research work carried out by **Harjeet Kaur, 41900199**, is bonafide record of 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.

Name of supervisor: **Dr. Deepak Prashar**

Designation: **Professor**

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ABSTRACT

This study presents an innovative ensemble method based on deep learning to detect diseases in banana and papaya plants. In order to improve the agricultural productivity and ensuring food security it is crucial to detect disease in plants. By facilitating efficient and timely disease control, crop yields can be increased consequently decreasing economic losses and fostering sustainable agricultural practices. In the present work an ensembled model, integrating YOLOv8 and EfficientNet models is proposed to increase the classification accuracy to 96.3% by exploiting the capabilities of both the models. The dataset used for the research comprises of high resolution images of different parts of the plants collected through sources including field visits, lab and internet. Model is made to be robust by effectively applying pre-processing techniques like image cleaning and data augmentation. YOLOv8 and EfficientNet are used for feature extraction and representation respectively for special object detection. Later on bounding box matching mechanism and majority voting strategy based on confidence score are manipulated. Experimental results are surpassing the results produced by both the models individually by exhibiting the overall precision of 96.3% and a recall of 96.3%. Compared to existing studies, the proposed method significantly improves classification performance while maintaining real-time efficiency. Key strengths include reduced false positives, better generalization, and robustness across diverse environmental conditions. The model's real-world applications span disease monitoring and precision agriculture, offering a scalable solution for disease detection. An effective and precise approach for plant disease detection is provided by this research, which contributes to the area of precision agriculture. The implementation of ensembled model has the potential to enhance crop yields, reduce economic losses, and promote sustainable farming practices through timely disease management.

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Harjeet Kaur

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ABBREVIATIONS

AI - Artificial Intelligence

DL - Deep Learning

DNN - Deep Neural Network

ANN - Artificial Neural Network

CNN - Convolution Neural Network

RNN - Recurrent Neural Network

BP - Back Propagation

GAN - Generative Adversarial Network

ReLU - Rectified Linear Unit

YOLO - You Only Look Once

ML - Machine Learning

NN - Neural Network

SVM - Support Vector Machine

DSLR - Digital Single-Lens Reflex

HE - Histogram Equalization

SGD - Stochastic Gradient Descent

ELU - Exponential Linear Unit

MSE - Mean Squared Error

DFL - Distribution Focal Loss

NAS - Neural Architecture Search

FP - Final Prediction

TP - True Positive

TN - True Negative

FP - False Positive

FN - False Negative

UI - User Interface

IoT - Internet of Things

Chapter – 1

INTRODUCTION

Agriculture has a significant impact on world's economy. With the continuous expansion of human population, pressure on agricultural system is increasing to meet the requirements. In today's world also, there are many countries which rely on old, traditional ways of farming which sometimes leads to insufficient production of grains or low quality crops. Precise, accurate and fast decision making systems are required for better field work which can be achieved with the use of modern machinery and automated robots in agricultural fields. Many researchers are working on combining technology with farming to improve productivity with minimum adverse effects on environment. Problems associated with conventional agriculture system and different approaches to solve them, from databases to decision support systems, are suggested in different works [1]. Systems those make use of Artificial Intelligence (AI) are becoming more popular choice because of evident accuracy and robustness. AI techniques can solve complex problems with better accuracy and preciseness than other techniques.

1.1 SMART FARMING

Idea of Smart Farming revolves around the use of technology in agricultural fields with clear cut objectives of improved quality and quantity of crops. Use of technology and data-driven solutions to maximize many aspects of agricultural practice is known as smart farming. The objective of smart farming is to improve efficiency, production, and sustainability in agricultural operations. This strategy entails applying AI and ML algorithms to both farm product management and field farming procedures [2]. Several agricultural sectors can benefit from the application of DL techniques. Smart farming has the potential for higher productivity, decreased environmental impact, and improved sustainability in the field of agriculture. Through the adoption of technology, farmers may effectively negotiate the intricate aspects of contemporary agriculture, resulting in improved efficiency. This enables a more resilient and adaptable approach to food production, especially in response to ever-changing global issues. Advantages of smart farming comprise enhanced efficiency, reduced resource usage, minimized environmental impact, improved crop yields, and better overall farm management. The use of smart farming techniques is anticipated to be essential in tackling the problems facing contemporary agriculture as technology develops. Smart farming is leading the way in the changing agricultural scene, bringing about a new era of accuracy, efficiency, and environmental responsibility [3].

1.1.1 Role of AI in Agriculture

Agriculture, the fundamental pillar of worldwide food supply, confronts unparalleled challenges in the 21st century. The challenges of climate change, population increase, limited resources, and the necessity for sustainable practices necessitate the development of creative solutions to guarantee food security and enhance efficiency in agriculture. Thanks to its numerous and inventive uses, AI has great promise for revolutionizing the agricultural industry. There are five major areas where the use of AI solutions can benefit agriculture or farming [4].

- Crop Supervisory Activities
- Monitoring of Field Conditions
- Insect Control
- Managing Livestock
- Climate Prediction

Crop Supervisory Activities

Crop Supervisory Activities includes estimating productivity, counting fruit, detecting crop disease, distinguishing weeds from crops, recognizing a plant species, and measuring crop quality. Stakeholders interested in further cost calculation are crucial for everyone, including the government, consumers, and farmers. This must serve as the foundation for comprehensive marketing, purchasing, and sales strategy. Fruit counting is used not just in robotic harvesting, but also in yield predictions. Manual labor in these fields is both tiring and time-consuming. Crop management with AI and Deep Learning can yield accurate outcomes [5]. Pattern recognition and image categorization can be used to identify disease in crop.

Monitoring of Field Conditions

Monitoring of Field Conditions involves managing both water and soil resources. Artificial intelligence and deep learning can be used in fields to detect soil issues and deficiencies. Soil health inspection is critical for producing quality crops. Smart irrigation, which makes better use of water resources, also employs AI approaches.

Managing Livestock

Managing Livestock is divided into two categories: livestock production and animal welfare. Smart farming approaches can assist monitor individual animals' requirements and health. As a result, their food can be modified to be more nutrient dense, protecting them from harmful diseases and improving herd health.

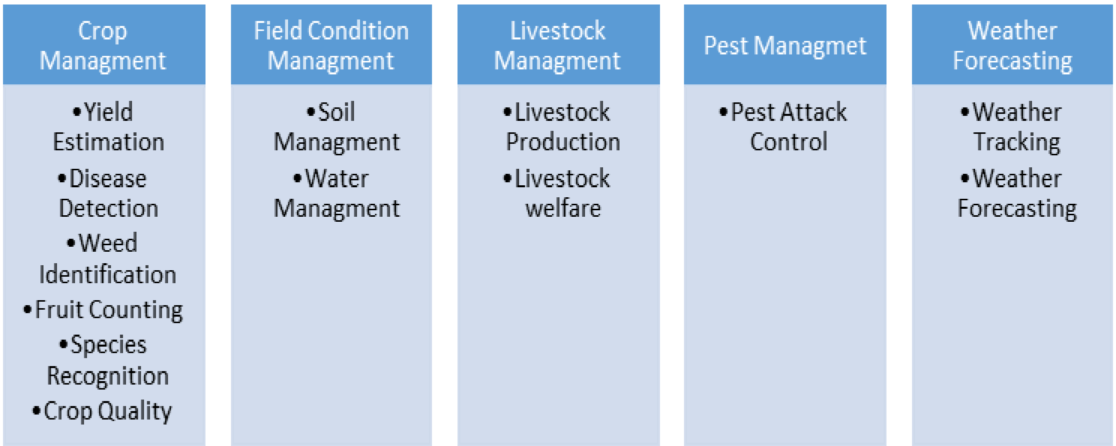
Insect Control

Pests are always a problem for farmers since crop-eating insects such as grasshoppers and locusts destroy their crops. However, artificial intelligence provides growers with a weapon against cereal-hungry bugs. Farmers make poor selections when selecting insecticides and fertilizers for pest control. However, precision agriculture allows farmers to measure variation within the field and adjust their techniques accordingly. It leads to improved pest management.

Climate Prediction

Weather and rainfall have a significant impact on the harvesting process. Continuous monitoring of weather conditions is essential, especially during crop harvesting. Farmers rely on their own expertise and intuition to predict weather conditions. Deep learning solutions in this are benefiting farmers.

AI plays an important role in agriculture by overcoming challenges and introducing a new era of intelligent and data-driven farming. AI offers solutions that improve farming efficiency and productivity while also supporting sustainable and environmentally responsible practices. AI introduces some options like Precision agriculture, automated machinery, and predictive analytics [6]. The integration of AI and agriculture provides a promising answer for meeting the needs of a fast-growing global population while also ensuring the long-term viability of our food systems in the face of a changing agricultural environment. Figure 1.1 exhibits the summary of use of different AI solutions in smart farming.



Crop Managment	Field Condition Managment	Livestock Managment	Pest Managmet	Weather Forecasting
• Yield Estimation • Disease Detection • Weed Identification • Fruit Counting • Species Recognition • Crop Quality	• Soil Managment • Water Managment	• Livestock Production • Livestock welfare	• Pest Attack Control	• Weather Tracking • Weather Forecasting

Figure 1.1: Areas for implementing AI solutions in Smart Farming

1.2 DEEP LEARNING (DL)

The way the human brain analyses information and finds patterns in order to make judgments is replicated by DL This technology has evolved as an important technology in medical diagnosis, text, speech, and facial recognition, internet security, mobile and wearable devices, agricultural, and manufacturing applications that require accurate decision making.

Artificial neural networks are used in the ML branch known as DL. It is capable to identifying intricate links and patterns in data. It is not necessary to explicitly program everything in deep learning. It has grown in popularity in recent years as computing power has improved and massive datasets have become more accessible. Mainly because deep neural networks (DNNs), another name for artificial neural networks (ANNs), are the foundation of it [7]. These neural networks, which are designed to learn from enormous volumes of data, are modelled after the structure and operation of organic neurons in the human brain.

1.2.1 Artificial Neural Networks

Neurons, which are layers of linked nodes that work together to analyse and learn from input data, make up an artificial neural network, or ANN. Figure 1.2 illustrates the components of a fully linked deep neural network, which include an input layer and one or more hidden layers connected sequentially. The input layer or the neurons in the layer above send information to each individual neuron. The weighted nature of these connections optimizes the impact of the inputs from the preceding layer by giving each input a specific weight. Afterwards, when the model is trained, these weights are adjusted to enhance its functionality [8]. The output of one neuron feeds into the input of neurons in the network's subsequent layer, and so on, until the output of the network is provided by the last layer. By applying a series of nonlinear modifications to the input data, the layers of the neural network enable the network to learn intricate representations of the data.

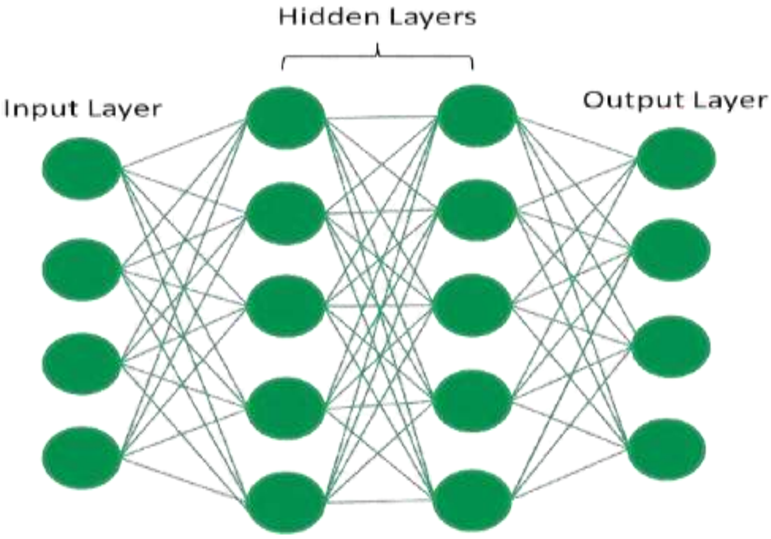


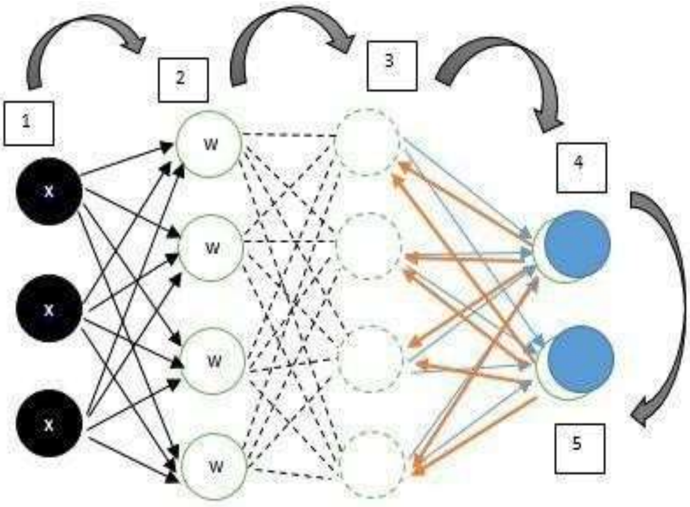
Figure 1.2: Components of Artificial Neural Network

1.3 DEEP LEARNING ALGORITHMS

Convolution neural networks (CNN), recurrent neural networks (RNN), feed forward neural networks with back propagation (BP), and generative adversarial networks (GAN) are popular deep learning techniques. There are several uses for these deep learning algorithms in the agricultural industry.

1.3.1 Feed Forward Neural Network and Backpropagation

A supervised learning methodology for multilayer networks in the field of artificial neural networks is called feed-forward back propagation. Figure 1.3 depicts how the entire model is built from many layers, including clear input and output layers as well as multiple hidden ones. Internal weights of input signals are modified several times based on deviations in produced and predicted output [9]. Errors are minimized to an acceptable degree.



1. Input Layer
2. Weights
3. Hidden Layers
4. Output Layer
5. Back propagation for adjusting weight following computation mistake

Figure 1.3: Simple Feed-Forward network with Back-propagation

1.3.2 Convolutional Neural Network (CNN)

Neuron connection patterns seen in human brains serve as an inspiration for CNN models [10]. Convolution networks are deep learning techniques that use image inputs. Networks are intended to provide learnable weights for various detectable objects in image input. The image is flattened to create an array, and the number in the image is calculated by considering the value of each pixel as a feature. This is called a weight matrix, and it functions similarly to a filter. Weight may be removing edges or a specific colour. A convolutional network consists of three layers: convolutional, optional pooling, and output. The number of trainable parameters decreases as the image size increases. That is why a pooling layer is inserted between two convolutional layers to reduce the spatial size of the image as depicted in figure 1.4.

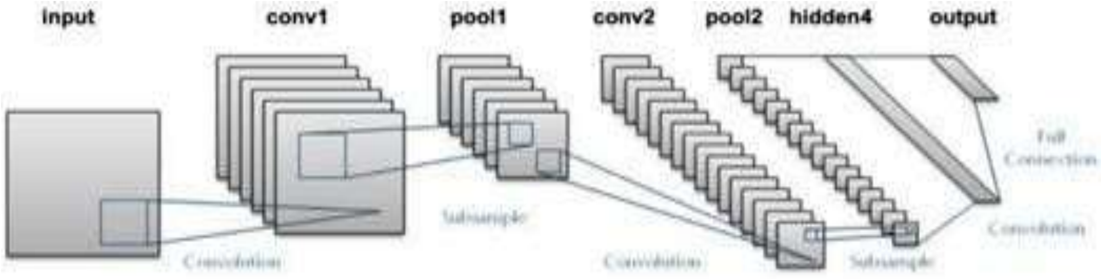


Figure 1.4: Convolutional Neural Network

Essential Elements of Convolutional Neural Networks

- **Convolutional layers:** The fundamental components of convolutional neural networks (CNNs) are convolutional layers. Convolution operations are used to transform input data, allowing the network to learn features such as edges, textures, and patterns on its own. Convolution is the process of methodically sliding a compact filter (kernel) across input data to retrieve localized properties.

- **Pooling layer:** Convolutional layers provide feature maps with a higher spatial dimensionality, which is reduced by pooling layers. A common pooling method that preserves the most crucial data from a particular region of the feature map is called max pooling. This contributes to reduced processing cost and ensures translation invariance.

- **Activation Functions:** Rectified Linear Unit (ReLU) and other non-linear activation functions allow non-linear operations, which introduce non-linearity into the network. For example, ReLU replaces negative values with zeros, allowing the network to reflect complex linkages in the data.

- **Fully Connected Layers:** Fully connected layers are frequently used at the end of Convolutional Neural Network (CNN) architecture. They produce predictions using the high-level properties obtained from convolutional and pooling layers. These layers connect each neuron to every neuron in the layers preceding and following it.

Essential Principles in Convolutional Neural Network Operation:

- Local receptive fields allude to the fact that each neuron in a CNN is connected to a small subset of the input data. This enables the network to focus on local patterns while gradually acquiring global features.
- Weight sharing is an important principle in convolutional neural networks (CNNs). Convolutional layers use a consistent set of weights for the filters throughout the input, allowing the network to recognize the same characteristic regardless of its position.
- Convolutional layers generate feature maps. They correctly discover and represent various properties in the provided data. Several feature maps are generated, each corresponding to a separate learned feature.
- Striding is the movement of the convolutional filter over the input data. Using a stride value greater than one in the convolution process results in the exclusion of some pixels, reducing the size of the resulting feature maps.

Utilizations of CNN:

CNNs are very good in image classification. They accomplish this by gaining hierarchical representations of information, which enables them to reliably recognize objects in images.

- **Object Detection:** CNNs can precisely locate and recognize distinct objects in an image. To detect objects efficiently, architectures such as YOLO (You Only Look Once) and Faster R-CNN make use of CNNs. Image segmentation uses CNNs to classify individual pixels inside an image. This is particularly useful in medical imaging and the development of driverless vehicles.
- **Facial identification:** CNNs have effectively been used for facial identification, leading to progress in biometric authentication systems. Convolutional Neural Networks have become essential in computer vision, showcasing their capacity to autonomously acquire and derive significant characteristics from visual data, ultimately resulting in cutting-edge performance across various applications.

- **Face identification:** CNNs have been successfully employed for facial recognition, resulting in advancements in biometric systems.

Convolutional Neural Networks have proven indispensable in computer vision, demonstrating their ability to autonomously acquire and extract significant properties from visual data, resulting in cutting-edge performance across a wide range of applications.

1.3.3 Recurrent Neural Networks (RNNs)

As the name suggests, recurrent neural networks feed the output from the previous phase into the current stage [11]. All input and output are independent of one another in conventional neural networks. On the other hand, it is frequently required to recall the prior state. For instance, words placed before a phrase must indicate what word comes next. The hidden layer in RNN helps to fulfil this memory need. RNN differs from previous algorithms mainly in that it uses a hidden layer to remember the state.

1.3.4 Generative Adversarial Networks (GAN)

Another potent family of neural networks under the umbrella of unsupervised learning is called generative adversarial networks. It is generative because it generates data using probabilistic models. Because instruction is given in unfavourable circumstances, it is hostile. For training, it also makes use of deep neural network techniques [12]. A discriminator plus a generator make up a GAN. To prevent discrimination, the generator generates fake samples of visual or audio data. As the discriminator is in charge of differentiating between authentic and fraudulent samples. Neural networks called Discriminator and Generator compete with one another throughout the training phase. Every time the procedure is repeated, the discriminator and generator perform better because of their increased loop efficiency.

1.4 COMPUTER VISION

Within artificial intelligence (AI), computer vision is the study of how computers can intercept and extract information from images and videos in a manner similar to that of humans. It entails creating algorithms and approaches for extracting meaningful information from visual inputs and making sense of the visual environment. The following are a few essential elements as shown in figure 1.5 also that Computer Vision aims to recognize in photographs:

- **Object Detection:** Detecting and locating objects.
- **Object Recognition:** Recognize and position things in images.
- **Object Classification:** Identifying the object's broad category in a image.
- **Object Segmentation:** Identifying pixels that belong to a specific item.

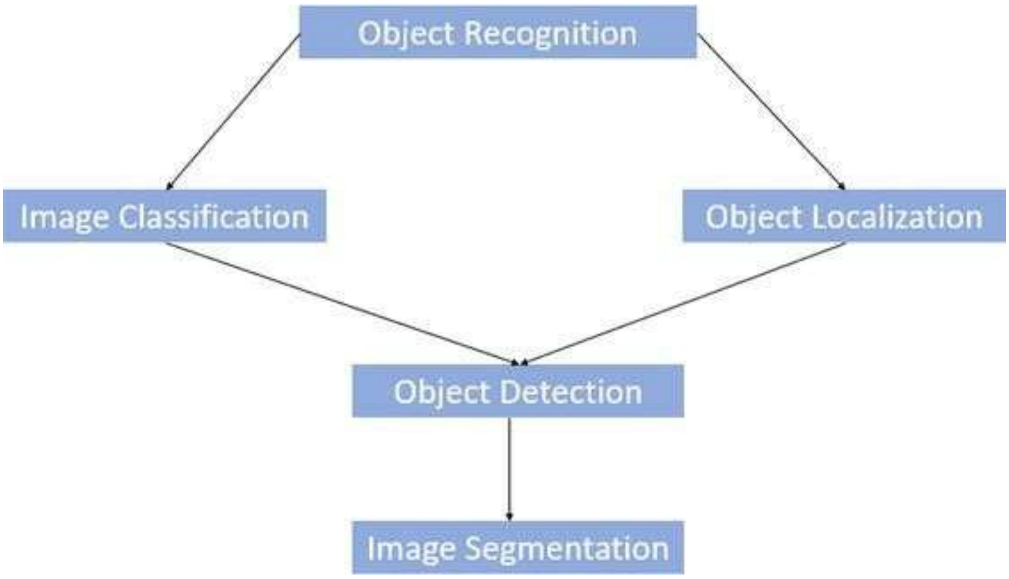


Figure 1.5: Domains of Computer Vision

1.4.1 Object Detection and Recognition

The process of recognizing items in images and movies is known as object recognition. It is a crucial use for ml and dl. To identify the content of an image like people do is the aim of this discipline. CNN are among the most widely used techniques for object recognition. For many different object identification tasks, including image classification, this method is extensively used in the majority of state-of-the-art neural networks. The probability of each class is output by this CNN network after receiving an image as input. The output probabilities of the other classes are insignificant or low if the item is not present in the image. If it is, its output likelihood is high. In contrast to machine learning, deep learning eliminates the necessity for feature extraction from data [13].

Object Localization: When an item is detected in an image, this method identifies it with a bounding box. The bounding box's location in the format (position, height, and width) is returned after a image is received as input.

Object detection methods combine image categorization and object localization. Upon receiving an image as input, it produces one or more bounding boxes, each labeled with the class name. These algorithms are capable of handling items that reappear often as well as multi-class categorization and location.

1.4.2 Image Classification

Using any measure (probability, loss, accuracy, etc.), image classification takes a image as input and outputs the image's categorization label. For instance, a image of a cat may be assigned the class label "cat," yet a image of a dog may very well be assigned the class label "dog."

1.4.3 Image Segmentation

A subset of object detection called "image segmentation" uses pixel-wise masks created specifically for each object in the image to determine if the object is there. Because it may help us comprehend the geometry of each object in the image, this method is more detailed than bounding box creation. Rather than generating bounding boxes, segmentation helps to determine which pixels make up that object. Several sectors, such as satellite imaging and medical image processing, can benefit from this degree of granularity. In recent times, several novel methods for segmenting images have been created. Among the most well-known is Mask R-CNN, which was created in 2017. Two primary types of segmentation exist:

- **Instance Segmentation:** Multiple instances of the same class are considered independent segments, which mean that objects of the same class are processed differently. As a result, even if the objects are from the same class, they are all coloured differently.

- **Semantic Segmentation:** Because all items of the same class belong to the same categorization, they are all color-coded the same way.

1.5 ENSEMBLE LEARNING AND TECHNIQUES

A machine learning method called ensemble learning combines many different models to produce a more potent and precise prediction model. Ensemble learning aims to improve performance, reduce mistakes, and boost the overall dependability of forecasts; this leads to improved scores on various data processing computing approaches. Using the strengths of many models, assembling is a potent tactic that enhances prediction resilience and accuracy overall. The selection of bagging or boosting, base model choice is determined by the data's properties and the machine learning task's specific goals. As time has gone by, there have been various kinds of ensemble procedures evolved to making people's models generalize with improved ability [14]. A learning method called ensemble learning blends many ML models. In machine learning, individual models are prone to underperformance. Stated differently, their forecast accuracy is usually poor. Several models are combined to get a better performing model in order to solve this problem. Weak learners are the individual models that are constructed. Because of their high bias or variation, they are referred to as poor learners. Due to a large bias or variance, weak learners are unable to learn properly and perform badly. Figure 1.6 (a) and (b) defines high bias and high variance.

The result of insufficiently effective data learning is a high-bias model. It has nothing to do with how the data are distributed. Future estimates will be inaccurate since they are not based on the facts.

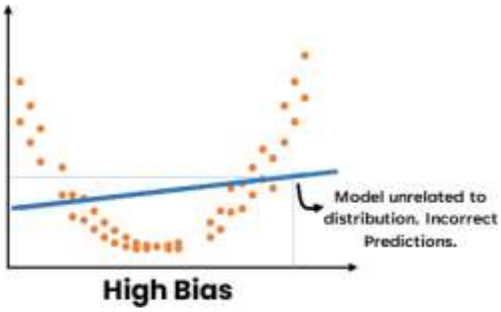


Figure 1.6 (a): High Bias model

A high variance model is caused by overfitting the training data. It learns the specifics of the data so well that its predictions become untrustworthy when confronted with new cases.

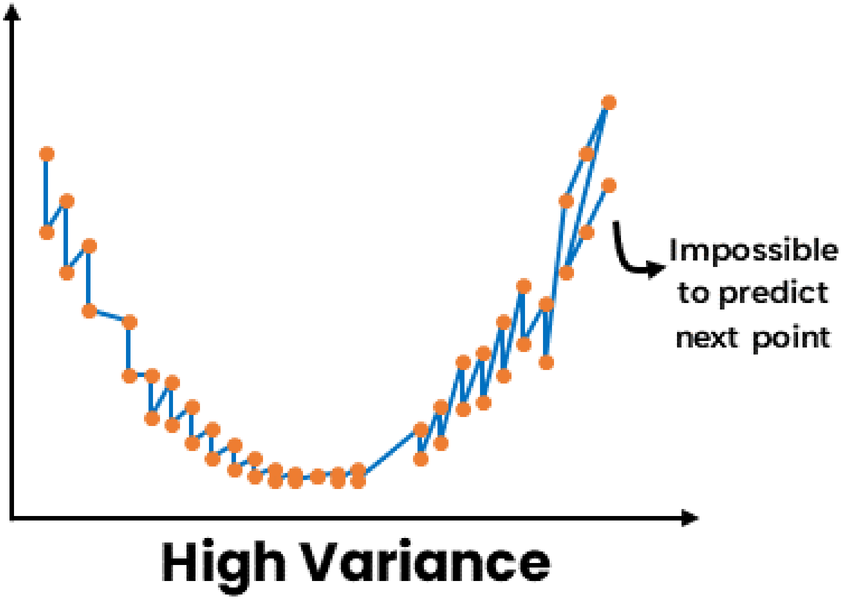


Figure 1.6 (b):High Variance Model

Consequently, models with large variance or strong bias are unable to generalize sufficiently. Weak learners will thus either fail to generalize at all or make incorrect generalizations. Therefore, it is not possible to rely solely on the predictions made by poor learners. An overfit model has high variance and low bias, whereas an underfit model has high bias and low variance, according to the bias-variance trade-off. Bias and variance are out of balance in both situations. Both the bias and the variance need to be small for there to be balance. By reducing bias or variance, ensemble learning aims to achieve a trade-off between the two variables. If is a poor model with high bias and low variance, it aims to minimize bias [15].

The aim of ensemble learning is to reduce a weak model that has a big variance and low bias. This process yields a model that is low in volatility and bias and much more balanced. Consequently, the finished model is referred as a strong learner. Compared to the poor learners, this model will be easier to generalize. As a result, it will be competent at making projections as depicted in Figure 1.7.

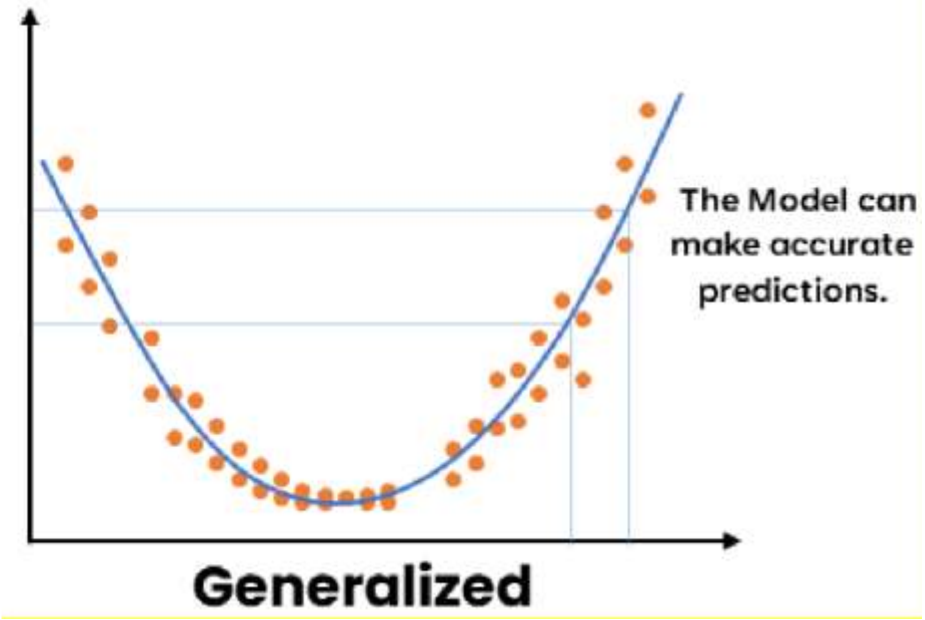


Figure 1.7: Generalized Model

Ensemble learning makes models better by:

- Reducing the random fluctuations typical of weak, high-variance models.
- Minimizing the fixed errors common in weak, high-bias models.
- Increasing the already high precision of strong models.

One way to lessen the unpredictability of weak learners is by bagging. The purpose of boosting is to mitigate the prejudices of subpar pupils. Strong learners can get greater accuracy overall via stacking. Three well-known ensemble learning techniques that can enhance machine learning include bagging, boosting, and stacking. The technique of fitting several decision trees to different samples of the same dataset and averaging the predictions is known as bagging. The act of fitting many models to the same data and figuring out how to combine predictions is called stacking. Boosting creates a weighted average by gradually adding ensemble members to adjust earlier model predictions.

1.5.1 Bagging Ensemble Learning

By modifying training data, bootstrap aggregation, sometimes referred to as bagging, is an ensemble learning technique that seeks to identify a diverse group of ensemble members. Bootstrap Aggregating is shortened to Bagging. As the name suggests, aggregation and bootstrapping are the two key elements of bagging. This often means training each model on a different sample of the same training dataset using a single machine learning technique, which is nearly invariably an unpruned decision tree. The projections of the ensemble members are then combined using basic statistics such as average and voting.

Ensemble variety is ensured by both the employment of a relatively weak classifier whose decision limits change greatly with regard to relatively modest perturbations in the training data and by the differences within the bootstrapped copies on which each classifier is trained. To train ensemble members, the method depends on how each dataset sample is created. A distinct dataset sample is given to each model. Random selections are made from the dataset for examples (rows), but with replacement. Bagging generates different base learners by utilizing the bootstrap distribution. Stated differently, it generates data subsets for base learner training via bootstrap sampling.

A row that is chosen is sent back to the training dataset so that it may be chosen again from that same training dataset. For a given training dataset, this means that a row of data may be selected zero, one, or many times. This is a bootstrap sample. It is a widely used statistical technique for determining a dataset's statistical value [16]. Creating many bootstrap samples, estimating a statistical number, and calculating the mean of the estimates yields a higher overall estimate of the desired quantity than just estimating from the dataset.

In the same way, it is possible to generate, estimate, and forecast multiple training datasets. Rather to fitting a single model directly to the training dataset, averaging the predictions made by the models frequently produces superior results. The bagging steps shown in figure 1.8 are as follows:

- From the training dataset, create bootstrap samples.
- Fit decision trees without pruning to every sample.
- Predictions can be easily voted on or averaged.

To sum up, bagging adds to the diversity of training data that is used to fit each member of the ensemble, producing skilled yet unique models.

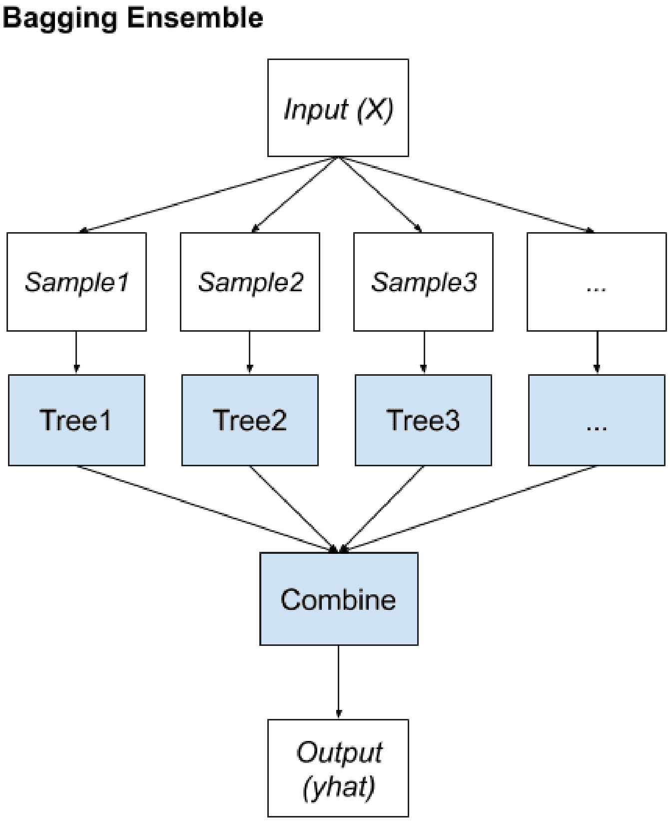


Figure 1.8: Bagging Ensemble Learning

This method underpins popular ensemble algorithms such as:

- Bagged Decision Trees (canonical bagging)
- Random Forest
- Extra Trees

Reducing Variance with Bagging

To mix low variance learners with strong learners, bagging is applied. The goal of bagging is to produce a model that is less variable than each of the individual weak models. Because they are the entire same sort, these weak learners are homogenous. Bootstrap aggregating is another term for bagging. It consists of two steps: aggregation and bootstrapping.

Bootstrapping

Bootstrapping works by generating many smaller datasets ('bootstraps') from the main data, which can include the same data point multiple times. These bootstraps are used to instruct specific weak learners.

Aggregating

Each weak learner works separately, producing a unique prediction. To make a final conclusion, these predictions are aggregated, either by determining the most frequent forecast (max voting) or by calculating the average value.

Max Voting

Max voting is a popular technique for classification tasks where predictions from multiple models are combined. Like counting votes in an election, the most frequently occurring prediction is declared the winner, representing the ensemble's final decision.

Averaging

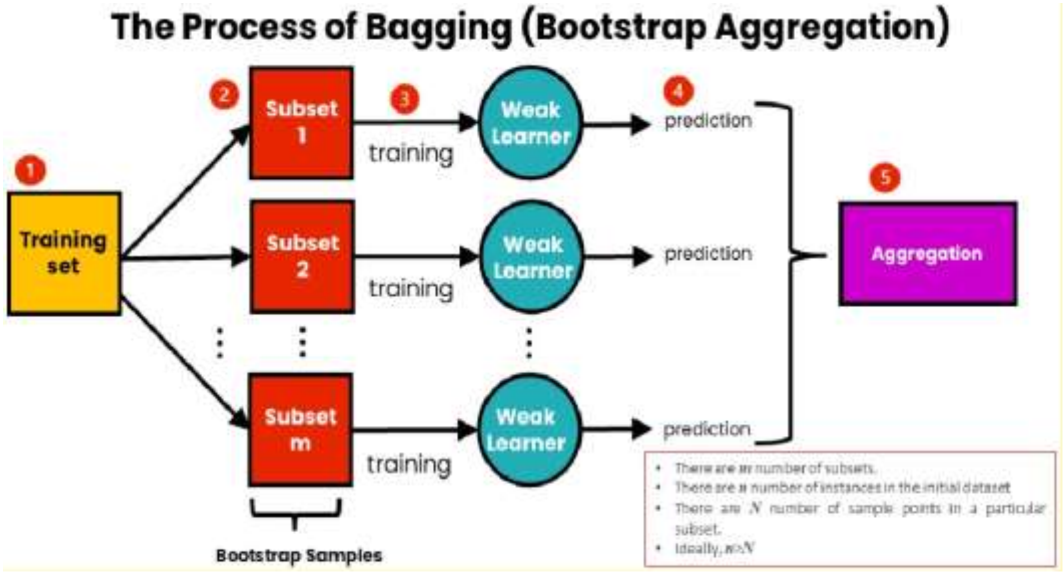
Regression problems are the usual purpose for it. That means taking the forecasts and averaging them. The aggregate that is produced is the combined model's overall forecast.

Steps of Bagging

The steps of bagging as in figure 1.9 are as follows:

1. Initial training dataset has n instances.
2. The training set is divided into m subsets. An N-point subset of the original dataset for each subgroup is chosen. Replacement is used to choose every subset. This implies that several samples can be taken from a single data point.
3. Training of each data group's weak learners happens separately. Because these models are homogeneous, they belong to the same kind.
4. A prediction is given by every model.

5. A single prediction is created by combining all of the projections. Either maximum voting or average is used for this.



- There are m number of subsets.
- There are n number of instances in the initial dataset
- There are N number of sample points in a particular subset.
- Ideally, $n>N$

Figure 1.9: The process of Bagging

1.5.2 Stacking Ensemble Learning

A general technique that teaches a learner to combine separate learners is called stacked generalization or stacking. First-level learners are individuals, while second-level learners, also known as meta-learners, are those who combine learning. The phrase "level-0 model" refers to ensemble members in stacking, whereas "level-1 model" refers to the model used to integrate forecasts. Although two levels is the most common model hierarchy, there is always room for extra layers. One may have three or five level-1 models in place of a single level-1 model, in addition to a single level-2 model that combines level-1 model predictions to produce a forecast.

Arguably, the most popular meta-learning technique is stacking. This approach uses a meta-learner to try to identify which classifiers are trustworthy and which are not. Although a linear model, such as logistic regression for binary classification or linear regression for regression, is frequently employed, any machine learning model may be used to aggregate the predictions. In order to learn how to harness the variety of forecasts, this encourages the model's complexity to be limited to basic models and lower-level ensemble member models. Trainable combiners may be used to determine which classifiers are most likely to perform well in a given area of the feature space and then combine them accordingly [3].

The essential components of stacking as shown in figure 1.10 are summed up as follows:

- The training dataset remained unchanged.
- Every member of the ensemble employs distinct machine learning algorithms.
- To improve prediction combinations, a machine learning model is used.

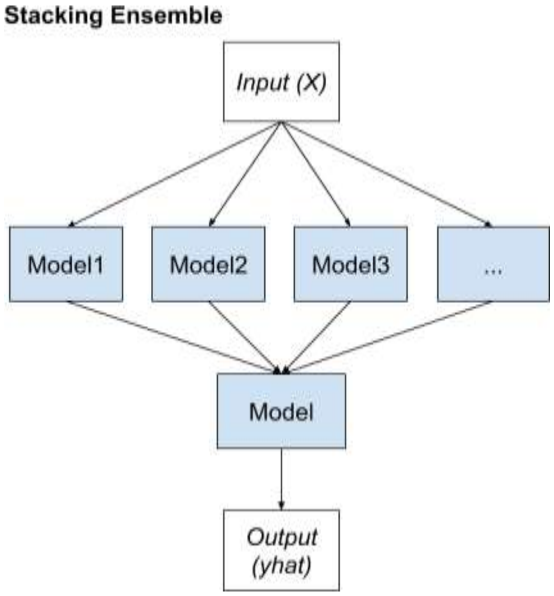


Figure 1.10: Stacking Ensemble

This method is the foundation for many prominent ensemble algorithms, such as

- Stacked Models (canonical stacking)
- Blending
- Super Ensemble

Enhancing Model Precision by Stacking

To improve the prediction accuracy of strong learners, stacking is used. Combining many heterogeneous strong learners into a single robust model is the aim of stacking. In the following respects, stacking differs from bagging and boosting [17]:

- Brings together strong learners.
- Combines several models.
- The procedure entails creating a metamodel. A model constructed from a new dataset is called a metamodel.

On a first dataset, distinct heterogeneous models are trained. One new dataset is created using the predictions from these models. The metamodel, which generates the final forecast, is trained using this new collection of data. Additionally, weighted averaging is added to the forecast. It may contain bagged or boosted models as stacking combines strong learners.

Steps of Stacking

The steps of Stacking as depicted in figure 1.11 are as follows:

1. Train m algorithms with initial training data.
2. Build a fresh training set based on each algorithm's output.
3. Created a meta-model algorithm with the new training set.
4. The final prediction is created using the meta-model results. Use weighted averaging to combine the data.

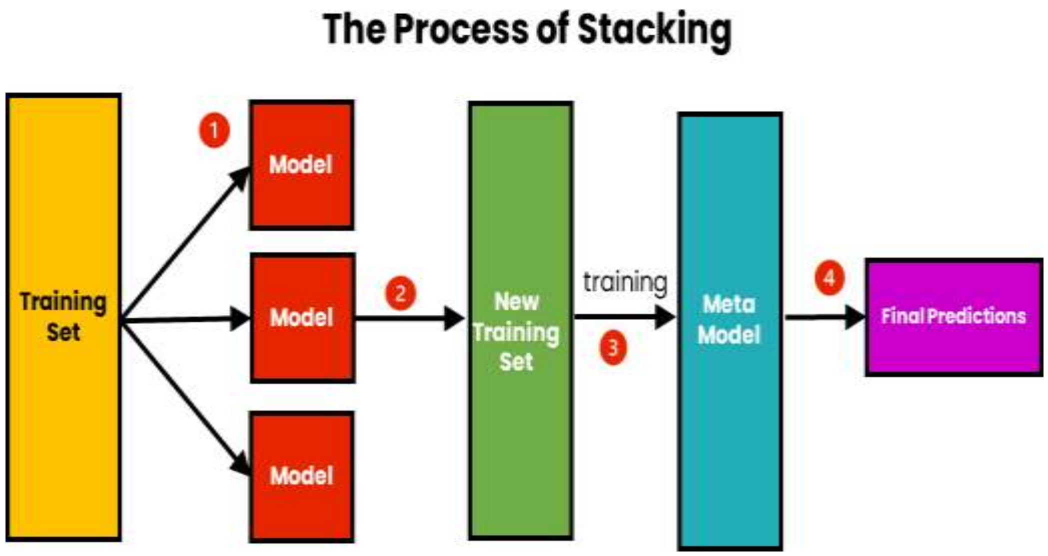


Figure 1.11: The process of Stacking

1.5.3 Boosting Ensemble Learning

In order to draw attention to instances where earlier fit models on the training dataset failed, an ensemble technique known as "boosting" tries to modify the training data. In boosting, each consecutive classifier's training dataset focuses more on cases misclassified by preceding classifiers. One crucial aspect of boosting ensembles is their capacity to correct prediction mistakes. The models are fitted and presented to the group in the following order: the first model's predictions are attempted to be corrected by the second model, the second model's predictions are corrected by the third, and so on as shown in figure 1.12.

This often involves using what are called as weak learners in boosting, which are very basic decision trees that only make one or a few decisions. Simple voting or averaging is used to combine the predictions of the weaker learners, and each participant's input is weighted according to their performance or competency. The objective is to construct a "strong learner" out of a group of specially designed "weak learners.". It is an iterative process that builds a strong classifier from a set of weak classifiers that can all hardly beat guesswork, with the goal of achieving arbitrarily low training error.

The learning algorithm is modified to give individual instances (rows of data) varying attention depending on whether the members of the previously recruited ensemble correctly or incorrectly anticipated them. The training dataset stays intact. To indicate how much attention a learning algorithm should pay when learning the model, for instance, the rows of data might be weighted [18].

The key principles of boosting are summarized below:

- More attention to training data on unusual examples.
- Iteratively add ensemble members to enhance earlier model predictions.
- Use a weighted average to combine forecasts from several models.

Theoretically, it was originally suggested that several weak learners may be integrated into strong learners, and numerous algorithms were created, albeit with mixed results. Boosting wasn't established as an effective ensemble method until the development of the Adaptive Boosting (AdaBoost) algorithm. A class of algorithms known as "boosting" is capable of turning weak learners into strong learners. Since AdaBoost, several boosting techniques have been developed, some of which, like stochastic gradient boosting, may rank among the best algorithms for structured data classification and regression. Lastly, this technique is the foundation of several widely used ensemble algorithms, such as:

- AdaBoost (canonical boosting)
- Gradient Boosting Machines
- Stochastic Gradient Boosting (XGBoost and similar)

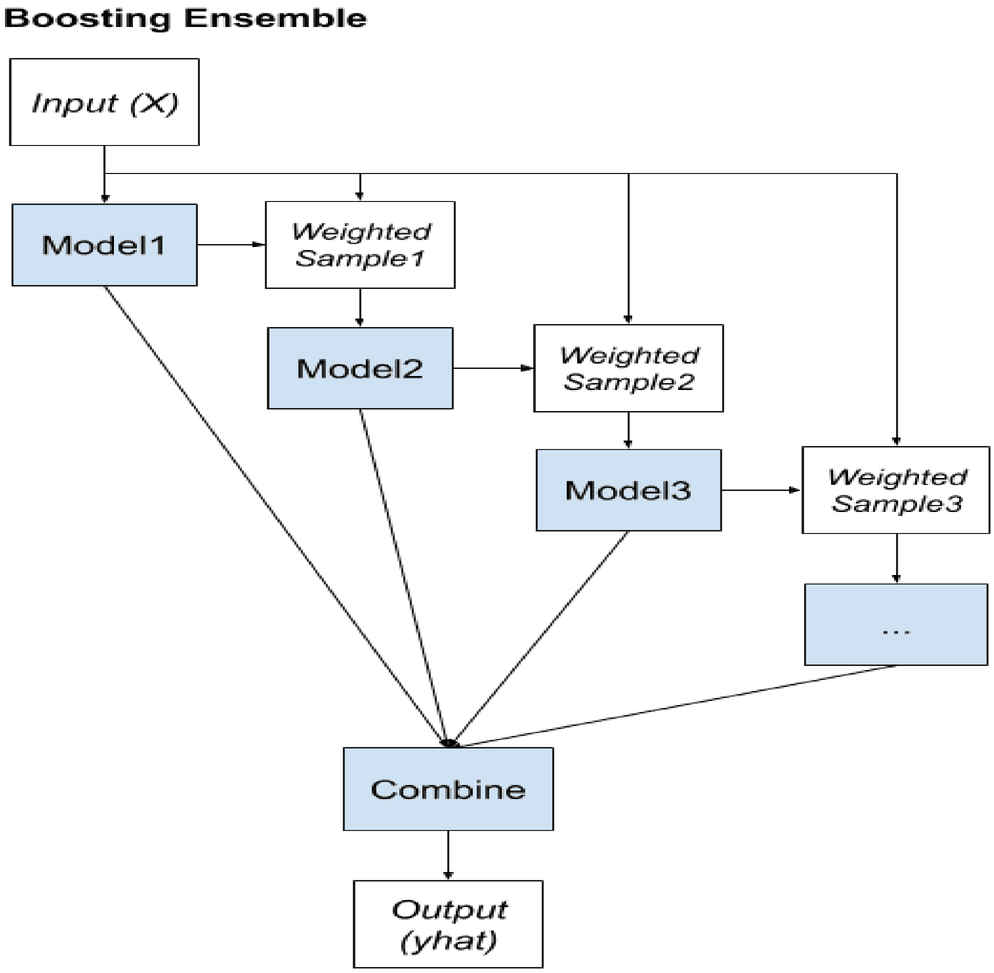


Figure 1.12: Boosting Ensemble

Reducing Bias by Boosting

To combine weak learners with a big bias boosting is used. The goal of boosting is to produce a model with less bias than the individual models. The weak students are all the same, just as in bagging. Training weak learners progressively is the process of boosting. Every subsequent student in the series builds upon the mistakes made by the earlier learners. A portion of the original dataset is first chosen. The first model is trained on this data and then generates predictions. Samples can be correctly or incorrectly predicted. Samples with inaccurate predictions are used to train the subsequent model. This enables subsequent models to address the shortcomings of earlier models. Unlike bagging, which gathers prediction results at the end, boosting gathers them at each stage [19]. Weighted average is used to combine them. Assigning different weights to each model according to its prediction power is the process of weighted averaging. To put it another way, it gives the model with the best predictive potential priority. This is thus because the most crucial learner is the one who can forecast the most [20].

Steps of Boosting

Boosting works as shown in 1.13 with the following steps:

1. From the initial training dataset, choose m subgroups.
2. The first subgroup should be used to train the weak learner.
3. The training data are used to test the trained weak learner. The testing procedure will cause certain data points to be projected incorrectly.
4. Each incorrectly predicted data point is added to the second subgroup and modified.
5. Using the modified subset, train and evaluate the second weak learner.
6. Continue until all subgroups have been finished.
7. This concludes the prediction. The total prediction output does not need to be determined because it has already been gathered at every stage.

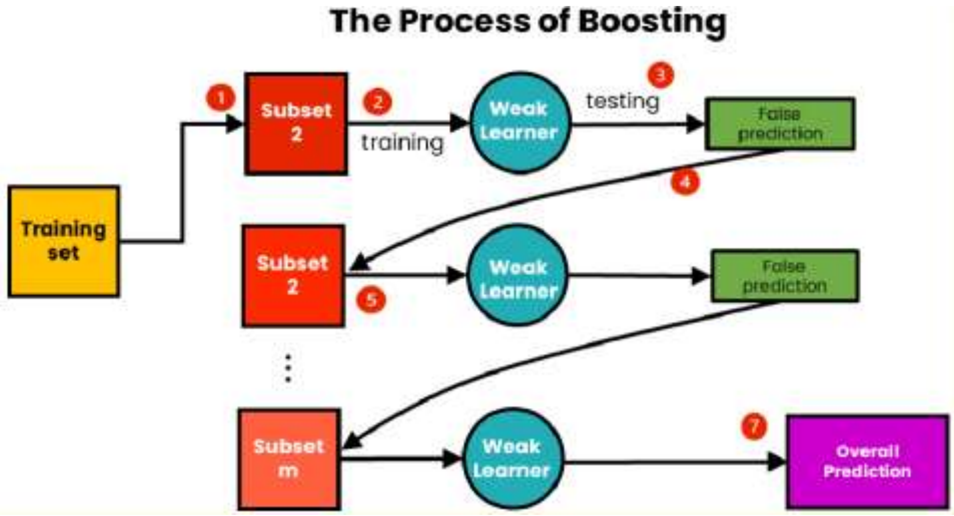


Figure 1.13: The process of Boosting

1.5.4 Applicability of Ensemble Learning Techniques

	Bagging	Boosting	Stacking
Purpose	Reduce Variance	Reduce Bias	Improve Accuracy
Base Learner Types	Homogeneous	Homogeneous	Heterogeneous
Base Learner Training	Parallel	Sequential	Meta Model
Aggregation	Max Voting, Averaging	Weighted Averaging	Weighted Averaging

Figure 1.14: Applicability of Bagging, Boosting, and Stacking

Bagging is used to reduce overfitting or variance in a model, whereas boosting is used to reduce underfitting or bias. Stacking, on the other hand, is useful for improving forecast accuracy. For homogenous weak learners, both bagging and boosting are effective. With a range of strong learners, stacking is effective. These three approaches can be used to solve regression or classification issues. Figure 1.14

summarizes this. The vulnerability of boosting to variation or overfitting is one of its drawbacks. For variance reduction, it is therefore not advised to boost. Boosting reduces variance less effectively than bagging. The converse is true, however. Bagging is not recommended for reducing bias or underfitting [21]. This is because bagging increases the likelihood of bias and does not help to lessen prejudice. The advantage of stacked models over bagging or boosting is higher prediction accuracy [22]. However, because they incorporate bagged or boosted models, they need a significant amount of time and computer resources. If faster results are required then stacking is avoided but for excellent accuracy, stacking is the best option.

1.6 MAJOR CONTRIBUTION OF THE WORK

The key contributions of this research work are outlined below:

1. Comprehensive Literature Review

A detailed and structured literature review was conducted to analyse current research efforts in plant disease detection using deep learning. The review revealed that most existing models are trained on limited datasets captured in controlled environments with uniform backgrounds, primarily focusing on leaf images. These models often struggle to generalize well in real-world farming conditions, where variations in lighting, background, and plant parts (such as stems or fruits) are common. Additionally, few studies have explored practical implementation or deployment in field-ready tools, highlighting the need for more holistic and usable solutions.

2. Development of a Custom Dataset

To address the shortcomings in existing datasets, a custom image dataset was developed consisting of high-resolution images of Banana and Papaya plants affected by various diseases. The dataset includes diseased images of different plant parts such as leaves, stems, and fruits, representing real-world farming conditions. It ensures sufficient intra-class variance and inter-class distinction to train deep learning models effectively. The dataset has been made publicly available on Kaggle, allowing other researchers to reuse and build upon this work, thereby contributing to the broader research community.

3. Use of Cutting-edge Technology

The research introduces an ensemble model combining YOLOv8 and EfficientNet, capitalizing on the strengths of both architectures. YOLOv8, known for its high-speed and accurate object detection, is used to locate disease-affected regions in images. EfficientNet, with its balanced depth, width, and resolution scaling, is employed to classify the disease accurately. This fusion enables both precise localization and reliable classification, ensuring the system performs robustly in diverse image conditions.

4. Improved Accuracy and Precision

The proposed ensemble model demonstrated significant improvements in key performance indicators such as accuracy, precision, recall, and F1-score, when compared to individual baseline models. The improved classification and localization capability reduces false positives and false negatives, which is critical in real-world agricultural applications where wrong diagnosis can lead to ineffective treatments and financial losses for farmers.

5. Increased Usability through Mobile Application

To ensure practical applicability of the research, a mobile application named PlantScan was conceptualized and developed. The app is designed to be intuitive and easy to use for farmers, allowing them to upload plant images directly from their mobile phones and receive instant diagnostic feedback. The mobile interface is user-friendly, even for users with minimal technical knowledge, and contributes significantly to making advanced AI solutions accessible to non-experts.

6. Model Deployment in PlantScan App

The trained ensemble model was successfully deployed into the PlantScan mobile application, enabling real-time disease detection for Banana and Papaya plants. The application supports multilingual functionality in English, Hindi, and Punjabi, catering to the linguistic diversity of Indian farmers. It is optimized for use in low-bandwidth rural areas, ensuring that farmers can benefit from it even in regions with limited internet connectivity. This deployment bridges the gap between academic research and real-world agricultural practice, empowering farmers with actionable information at their fingertips.

Incorporating YOLOv8 and EfficientNet into an ensemble model for detecting banana and papaya trees is a big step forward in agricultural technology. This study not only enhances the precision and effectiveness of plant detection, but it also shows that this technology can be applied to other aspects of precision agriculture. It emphasizes the importance of innovative technology in dealing with the evolving challenges of current farming techniques.

1.6.1 Gap Analysis

After reviewing the literature as discussed in last section, certain gaps in current research have been identified. These have been highlighted for consideration in future research in the field of plant disease detection.

1. Real-time data acquisition is necessary for plant disease identification, rather than relying on images taken in controlled environments with the same background.
2. Current study focuses on plant leaves, although diseases can also affect other parts of a plant or tree.
3. Experiments are often conducted on a small data collection. A large dataset is essential for optimal learning.
4. The disease identification procedure should be speedier and easier for end users.
5. Only few studies have integrated AI approaches for identifying plant diseases.
6. In very limited works deployment of the model is done

1.6.2 Problem Formulation

Plant diseases cause significant output and economic losses in the global agricultural business. It is critical for sustainable agriculture to monitor plant health and detect diseases early. The review conducted in this context and reported in Chapter 2 emphasizes the importance of developing a rapid, cost-effective, and dependable system to promote agricultural improvements. After reviewing several models and frameworks available in this industry, it was determined that to produce faster and more reliable disease detection findings, the integration of intelligent methodologies is necessary. In this case, a hybrid system that combines deep learning algorithms will be useful.

As a result, the proposed project would focus on designing and developing ensembled model for the detection of plant diseases. To be more particular, design and develop an automatic system for detecting diseases in banana and papaya.

1.6.3 Objectives

Different plant disease detection approaches are investigated to conduct a comparative analysis of existing algorithms and lay a solid foundation for identifying the strategies to be employed in this effort. The findings will be used to create an ensembled model of deep learning algorithms that addresses the observed limitations in plant disease detection.

The work will be assessed for precision and performance. To fill the gaps and solve the problems highlighted in the previous section, the work intends to achieve the following:

1) To collect and preprocess the images of various parts of Banana and Papaya plants including stem, leaf, cut fruit.

2) To design and develop a system for disease detection in Banana and Papaya using Deep learning techniques.

3) To compare the proposed system with already existing systems.

4) To develop a mobile application for the proposed system for commercial use.

1.7 OUTLINE OF THE THESIS

This thesis presents a comprehensive study on the application of deep learning and ensemble learning techniques for disease detection in papaya and banana, within the context of smart farming. The work begins with an introduction to smart agricultural practices, emphasizing the role of artificial intelligence, particularly deep learning, in automating disease diagnosis. It discusses how ensemble learning can further enhance model performance and reliability, setting the stage for the research problem and objectives.

The second chapter provides an extensive literature review, organized in two major parts: one focusing on the techniques used in existing studies for disease detection in papaya and banana, and the other on the datasets available for these crops. This dual perspective helps identify gaps in current methodologies and limitations in dataset availability. Building upon these insights, the third chapter introduces a curated and augmented dataset specifically developed for this research. It documents the diseases considered and describes the preprocessing and augmentation techniques used to enhance data diversity and quality.

The subsequent chapter explores deep learning models applied for disease detection, including YOLOv3, YOLOv8, ResNet50, and EfficientNet. A novel ensemble method combining YOLOv8 and EfficientNet is proposed to improve detection accuracy and generalization. The fifth chapter presents a detailed comparison between the proposed ensemble model and existing approaches, based on evaluation metrics such as precision, recall, and F1-score, and interprets the findings in relation to real-world agricultural challenges. Further extending the practical impact of this work, a mobile application named PlantScan is developed, which allows real-time disease detection in banana and papaya using Android smartphones. The final chapter concludes the research, summarizing its contributions and highlighting future research directions such as expanding the model to other crops and enabling real-time edge deployment.

Chapter – 2

LITERATURE REVIEW

Tropical fruits like bananas and papayas are hugely important to the world economy since they are both eaten regularly and exported by numerous countries. Nevertheless, a number of diseases pose serious threats to these crops, reducing their quality and output. Manual visual examination by seasoned farmers or agricultural specialists is a common but laborious and error-prone approach to disease identification and control in the past. A new era in disease identification has begun in agriculture, thanks to deep learning techniques, which could lead to better, more scalable solutions. Deep learning, a branch of machine learning algorithms that draws inspiration from the way the human brain works, has been making waves in recent years, and offering impressive results in domains like computer vision. In this section, how convolutional neural networks (CNNs) and other deep learning methods may be used to identify banana and papaya plant diseases are explained. Work goes over the ways in which precise and early identification may reduce the impact of these diseases on crops and help them stay healthy and productive. Apart from this, the current literature and research on disease detection in agricultural settings using deep learning, pointing out its advantages, disadvantages, and potential for development are also presented. In addition, light on the creation of disease-specific datasets for bananas and papayas, which are crucial for developing and testing deep learning models is also provided.

2.1 REVIEW METHODOLOGY

An exhaustive review of the strategies used to identify and diagnose diseases affecting banana and papaya crops using deep learning techniques is presented in the chapter on disease detection in these important crops using deep learning. Systematically several factors necessary to understanding and using deep learning models in agricultural disease detection as part of review approach are also examined. In the first part of the chapter, the economic relevance and worldwide impact of diseases on crop productivity and food security are highlighted, and the necessity of disease detection in papaya and banana farming is explained. The literature continues by explaining the theory behind deep learning, giving the reader grounding in neural networks, CNNs, and other important designs.

Methodologically, the work assesses the methods used to acquire datasets and preprocess them in order to build deep learning models for diseases detection. To guarantee the models' resilience and generalizability, this covers topics like dataset augmentation, labelling techniques, and tactics to reduce class imbalance. In addition, CNNs, RNNs, and variations thereof are some of the deep learning architectures covered in this chapter, as are their applications in diseases detection. It assesses their accuracy, efficiency, and scalability to provide the best designs for disease detection in papaya and banana crops.

Questions of model interpretability, dataset availability, and computing resources are among those covered in the technique review that pertain to deep learning-based diseases diagnosis. It sheds light on these problems, suggests ways forward for study, and suggests solutions that might make deep learning more useful in agricultural disease control [23]. A thorough and organized examination of the approaches used for disease detection in bananas and papayas using deep learning is presented in the chapter review methodology. It provides useful information for academics, farmers, and policymakers who are trying to figure out how to use cutting-edge innovation to make crops healthier and farming more sustainable.

2.2 LITERATURE REVIEW BASED ON DISEASE DETECTION

Significant production losses and economic damages to agricultural businesses worldwide are caused by plant diseases, which constitute a danger to global food security. To reduce these losses, it is essential to have efficient disease detection systems in place so that management methods may be implemented promptly. Visual examination, genetic analysis, and remote sensing are just a few of the ways that have been used to identify plant diseases throughout the years. The significance of literature review in the advancement of plant disease detection methods is highlighted in this chapter, which offers an overview of various strategies. Abiotic variables, such as environmental stresses and nutritional deficits, and biotic factors, such fungus, bacteria, viruses, and nematodes, can both cause plant diseases. Leaf spots, withering, necrosis, and stunted development are some of the ways these diseases can show themselves. The fast spread of plant diseases, if not controlled, can cause farmers and agricultural companies to suffer enormous economic losses due to crop failures, lower yields, and reduced productivity [24].

When diseases are identified quickly, it becomes much easier to control and manage outbreaks, which in turn increases agricultural output and ensures food security. To minimize production losses and ensure food supply stability, farmers should employ disease management measures such chemical treatments, crop rotations, and resistant crop types upon early detection. Visual examination and symptom recognition by trained agronomists and plant pathologists used to be the main methods for plant disease diagnosis in the past. There are more advanced and precise detecting methods available now, but this methodology is still often utilized. Plant diseases can be identified using traditional approaches such as eye examination, laboratory procedures (such as culture-based methods), and field surveys. One way to visually evaluate plants for signs of diseases is to look for abnormalities like discolored leaves, lesions, or abnormal shapes. The individual pathogens responsible for diseases can be identified and characterized by laboratory procedures, such as cultivating pathogens from affected plant tissues. Researchers conduct field surveys to measure the frequency and severity of diseases by methodically sampling and monitoring plants in agricultural fields [25].

Molecular biology, imaging, sensor-based systems, and remote sensing have all contributed to the development of new methods for detecting plant diseases in the last several years. Molecular methods, such as nucleic acid sequencing and polymerase chain reaction (PCR), allow for the precise and quick identification of infectious diseases by analyzing their genetic markers. Imaging methods include thermal imaging, hyperspectral imaging, and multispectral imaging enable the rapid and non-destructive identification of disease signs in the canopy or leaves [26]. Technologies that rely on sensors, such as the electronic nose (E-Nose) and biosensors can identify biochemical markers and volatile organic chemicals linked to plant diseases. In order to track the spread of diseases over vast agricultural regions, researchers are turning to remote sensing technologies like satellite photography and UAVs.

2.2.1 Traditional Methods for Plant Disease Detection

The viability of agriculture and the world's food supply are seriously jeopardised by plant diseases. It is imperative that researchers, legislators, and farmers all work together to identify and control these diseases. Visual examination and symptom recognition were the mainstays of plant disease diagnosis in the past, with the help of laboratory-based approaches including culture-based procedures and field surveys [27]. Old approaches are still essential for plant disease control despite the rise of contemporary technology. This is because old methods are simple, inexpensive, and easy to obtain.

- **Visual Inspection and Symptom Recognition:** The use of one's eyes is among the first and most basic ways to identify plant diseases. Leaf stains, withering, browning, and abnormalities are some of the telltale signs that farmers and agronomists depend on. In many cases, these signs point to particular diseases or environmental stresses that are harming the plants. A good early warning strategy for possible epidemics is visual examination, which permits quick evaluation of disease prevalence across vast agricultural regions.

- **Laboratory Techniques: Culture-based Methods:** approaches based on culture isolation and culture of pathogenic organisms from plant tissues or environmental samples are used in culture-based approaches. The agents that cause plant diseases can be identified and characterized using this method. Colony morphology, biochemical testing, and molecular assays are common methods for species identification, together with plating samples on nutritional medium.

- **Field Surveys and Epidemiological Studies:** Assessing the occurrence, distribution, and dynamics of plant diseases in agricultural environments involves rigorous monitoring and data collecting through field surveys and epidemiological research. Researchers in this research often gather plant samples or data on the environment from various sites and times using sampling techniques like systematic transects or random sampling.

Visual examination, culture-based approaches, and field surveys are still important parts of plant health management systems for detecting diseases. Early identification, diagnosis, and monitoring of plant diseases are greatly aided by these approaches, despite their limitations such as subjectivity, time limits, and resource needs [28]. In order to create effective and long-lasting disease control strategies, it will be crucial to combine old approaches with modern technology, especially when agricultural systems encounter more changes and new obstacles.

2.2.2 Modern Techniques for Plant Disease Detection

When it comes to guaranteeing food security on a worldwide scale, modern techniques for plant disease detection are crucial. These techniques allow for the early and precise diagnosis of plant diseases. The intricate dynamics of plant diseases are becoming more difficult to manage using just conventional approaches, what with the rise of new pathogens, shifting weather patterns, and other environmental concerns. As a result, there has been a major change in attitude towards using cutting-edge technology that can diagnose diseases more efficiently and with greater sensitivity [29]. This chapter gives a synopsis of the many current methods used to diagnose plant diseases, touching on their underlying concepts, practical applications, and recent developments.

Plant pathologists can now directly identify and characterize diseases at the genetic level with Biochemical methods and molecular technology, which has completely changed the discipline. One of the most important tools in molecular diagnostics, the Polymerase Chain Reaction (PCR) allows for the amplification of certain DNA sequences, which makes it possible to identify extremely low amounts of infectious agent DNA [30]. This technique has found extensive use in the identification of several plant diseases, including bacteria, viruses, and fungi. Furthermore, for diagnostics in resource-limited field settings, Loop-mediated Isothermal Amplification (LAMP) provides a quick and inexpensive alternative to polymerase chain reaction (PCR). Additionally, high-throughput sequencing of plant pathogen genomes has been made possible by developments in nucleic acid sequencing technology, which has allowed for comprehensive genomic analysis and surveillance activities.

One more potent weapon in the contemporary toolbox for plant disease detection tools are imaging techniques. Acquiring spectral data over hundreds of small spectral bands enables hyperspectral imaging to identify minor alterations in plant physiology linked to disease stress. Agricultural fields may be screened non-destructively and with high throughput using hyperspectral imaging, which analyses the distinct spectral fingerprints of sick plants [31]. In a similar vein, multispectral imaging provides a more realistic and economical alternative for disease identification in industrial agricultural operations by capturing data over a reduced number of predetermined spectral bands. In addition, when it comes to abiotic stressors like temperature changes, thermal imaging—which relies on measuring infrared radiation generated by plants—can provide important information about plant stress responses and disease development.

The use of sensor-based technology allows for the early diagnosis of plant diseases through real-time monitoring. This enables prompt intervention and mitigation measures. Using arrays of chemical sensors, E-Nose and E-Tongue mimic the human olfactory and gustatory systems, respectively, to identify plant diseases by detecting volatile organic compounds (VOCs) and other indicators. These handheld, non-invasive tools have demonstrated potential in identifying a wide range of plant diseases, such as nematodes, fungus, and bacteria. The use of biological recognition components like enzymes or antibodies in biosensors allows for very sensitive and selective detection of target biomolecules or pathogens [32]. Quick, on-site detection is possible with biosensors when they connect with microfluidic platforms or wearable devices for diagnostics in the field.

Agricultural landscapes may be observed from above using remote sensing technologies, which allow for widespread monitoring of crop health and disease outbreaks. Global vegetation dynamics and disease prevalence can be better understood with the use of satellite images captured by Earth-observing satellites in orbit around the planet. Early warning signals of disease stress and the geographical distribution of infections in agricultural regions can be assessed by analysing multispectral or hyperspectral satellite data. Similarly, UAVs with remote sensing payloads like thermal sensors or multispectral cameras provide a versatile and economical platform for tracking crop health and disease outbreaks in specific areas. In order to characterise disease dynamics at the microscale in detail, satellite and UAV-based platforms supplement data collected by ground-based remote sensing devices planted in fields or orchards.

Agricultural systems can now monitor and manage plant health with new capabilities thanks to modern approaches for disease detection in plants. These techniques include a varied array of instruments and procedures. Researchers and practitioners may improve plant disease detection, diagnosis, and mitigation efforts by using molecular biology, imaging, sensor-based technologies, and remote sensing. This will have a positive effect on world food production. The future of agricultural systems and their ability to withstand new diseases and environmental stresses depends on ability to keep innovating and incorporating these cutting-edge methods [33].

2.2.3 Advancements in Artificial Intelligence and Machine Learning for Plant Disease Detection

Technological developments in AI and ML have had a profound impact on several sectors, including farming. The use of artificial intelligence and machine learning to identify plant diseases has seen a dramatic uptick in academic interest in the last several years. There is hope that these technologies will help farmers overcome the difficulties they have when trying to detect and control crop diseases. This chapter delves deeply into the state-of-the-art in artificial intelligence and machine learning as it pertains to plant disease detection, including its uses, advantages, disadvantages, and potential future developments. Machine learning (ML) and artificial intelligence (AI) include a wide range of computational approaches that allow computers to learn from data, spot patterns, and make judgements or predictions without human intervention. Crop monitoring, yield prediction, and pest control are just a few of the many agricultural concerns that are seeing increased use of these technologies. To help farmers improve their yields and implement precision agriculture methods, AI-powered systems compile data from a variety of sources, including satellite images, weather predictions, and sensor networks [34].

When compared to more conventional approaches, there are various benefits of using AI and ML for plant disease diagnosis. In image identification and classification, for example, AI systems can reliably detect signs of diseases in crops or plant leaves. A subset of deep learning algorithms known as Convolutional Neural Networks (CNNs) has achieved outstanding results in this area, learning important properties from images automatically and accurately differentiating between damaged and healthy plants. The creation of models for the prediction of diseases is another very significant application. Artificial intelligence systems can study past data on environmental variables, crop health, and disease incidence to predict when certain crops or locations would experience disease outbreaks. By using these models for prediction, farmers may administer fungicides, change irrigation schedules, or adopt crop rotation policies to proactively manage diseases.

AI-powered decision support systems are currently in development to aid farmers in the diagnosis and treatment of plant diseases. These systems compile information from various sources, such as sensors, field observations, and disease databases, to generate recommendations that are specific to each crop variety, growing environment, and disease pressures. Through the integration of domain knowledge and advanced analytics, these systems enable farmers to make well-informed decisions and optimize.

Farmers rely highly on their personal instincts and experience to identify the diseases in plants. Consultation with any agricultural expert or pathologist also results in time consumption and inconsistent results. Experience and expertise of the person observing the plant, which is prone to human errors, effects the accuracy of the assessment. Moreover, if disease not detected at early stage may lead to delayed interventions and increase spread of disease. Conventional techniques of ML (Machine Learning) like SVM (Support Vector Machine), k-NN (Neural Network), Decision trees have been extensively used for identification of diseases but they need handcrafted feature extraction because of which generalization across different environmental conditions becomes limited. Samajpati & Degadwala in 2016 [35] used Random Forest in a hybrid approach for classification of diseases in fruits. As per their observation hybrid machine learning models enhance classification accuracy in contrast to traditional machine learning models requiring feature engineering which limits scalability. Accuracy of 88.3% was achieved by them but in large scale applications the model was not observed to be much flexible because of dependency on hand crafted features.

In a study, authors probed convolution neural network (CNN) based models for detecting diseases in fruits. Their results supported the use of deep learning in comparison to traditional machine learning techniques for enhancing the accuracy of classification. Although the high accuracy of 92.4% was reported by the work but it was lacking real time feasibility which restricted its use in field application [36].

Mukti [37] in 2019 made use of transfer learning in conjunction with ResNet50 for the detection of plant diseases. As per their findings feature extraction and classification accuracy can be improved using pre-trained models. Researchers were able to achieve the accuracy of 94.1% but the system was less adaptable to real time dynamic environments of agriculture, new disease variants and required large scaled datasets for efficient performance.

Behera et al in 2020 [38] made use of machine learning and transfer learning to identify the level of maturity of papaya fruit. They concluded that the generalization can be improved using transfer learning specifically in case of maturity classification and disease identification. Accuracy achieved out of the experiment is 90.8%. Proposed model of their work could not include object detection model and required large and diverse dataset, limiting its capability to correctly locate infected region. Vijayan et al. [39] proposed the use of ensembled learning approach using multiple convolution neural networks for classifying the diseases in plants. Misclassification rates are reduced and accuracy is improved using ensembled techniques. Real time dynamic identifications are limited in the work. Moreover, additional computational overhead was observed due to multiple model combinations. Researchers [40] made an optimized deep learning model for identification of diseases in paddy leaves. Achieved F1 Score out of this work is 93.5%. The model here also faced the same challenge of object detection in real life under dynamic conditions so could not be applied on large scale field applications. Study presented an automated deep learning centered disease detection system with a little faster and accurate classification of diseases. Her model achieved accuracy of 97% [41]. The major short coming of the work was lack of real time data. Vijayakumar & Vinothkanna [42] detected the ripe status of fruits using deep learning based models. Classification accuracy was improved with the use of CNN based model applied on papaya fruit. The study was made for checking the maturity levels in papaya fruits. Another CNN based classification model was explored by Hossen et al in 2021 [43] for detecting papaya diseases. F1 score of 91.2 was observed but like other models it was incorporating real time detection of objects so making it unsuitable for crucial real time monitoring.

Selvam, L in 2020[26], proposed a CNN design for the classification of ladyfinger plant leaf. Farms in several villages in India's Tiruvannamalai district, Tamil Nadu, provided the raw material for these photographs. Total collection was of 1088 images. Classification accuracy of 96% was attained using the suggested CNN design. Sujatha, R. and her companions [44] in 2021 compared the various machine learning and deep learning techniques for their ability to identify diseases in citrus plants. As per their observations deep learning approaches outperform machine learning methods by showing promising results. Abbas et. Al in 2021 [31] made use of transfer learning with C-GAN images of tomato plant for disease detection. The accuracy achieved came out to be more than 98%. The system was not using real time images for the detection. The work was carried on dataset available on plant village.

Table 2.1 presents the summary of related literature and current work going on in this field as discussed above.

Table 2.1: Literature for disease detection using advanced AI and machine learning

Study & Year	Methodology	Findings	Performance Metrics	Limitations
Samajpati & Degadwala (2016) [35]	Hybrid approach using Random Forest for fruit disease classification.	Hybrid ML approaches improve disease classification accuracy.	Accuracy: 88.3%	Traditional ML models require feature engineering, which limits scalability.
Varma, E (2019) [36]	CNN-based models for detecting papaya leaf diseases.	Deep learning significantly improves disease classification compared to traditional ML techniques.	Accuracy: 92.4%	Limited real-time feasibility and lacks integration with detection models.
Mukti (2019) [37]	Transfer learning in conjunction with ResNet50	ResNet50, when used with transfer learning, can detect plant diseases with high accuracy	Accuracy: 94.1%	Limited real-world generalization where backgrounds, lighting, and occlusions vary
Behera et al. (2021) [38]	Machine learning and transfer learning for papaya fruit maturity classification.	Transfer learning improves model generalization for disease and maturity classification.	Accuracy: 90.8%	Requires large, diverse datasets and lacks object detection capabilities.
Vijayan, S (2025) [39]	Hybrid CNN model integrated with feature optimization techniques	hybrid feature-optimized CNN significantly improves rice disease prediction accuracy by combining deep features with optimized feature selection	Accuracy: 97.5%	Generalizability is limited because it was not validated on diverse, real-world field images or external datasets

Study & Year	Methodology	Findings	Performance Metrics	Limitations
Ramesh & Vydeki (2020) [5]	Optimized deep neural network for paddy leaf disease classification.	Improved classification accuracy using deep learning optimization techniques.	F1-score: 93.5%	Does not explore real-time object detection, limiting practical application.
Vijayakumar & Vinothkanna (2020) [42]	Deep learning-based approach for fruit ripeness detection.	CNN-based models improve classification of fruit ripeness stages.	Precision: 91.7%	Focuses on fruit maturity rather than disease detection, limiting applicability.
Hossen et al. (2020) [43]	Transfer learning with ResNet50 for plant disease detection.	Pre-trained deep learning models improve feature extraction and achieve high accuracy.	Accuracy: 94.1%	Requires large-scale datasets for effective performance and struggles with new disease variants.
Sujatha, R. et al [44]	Performance of deep learning vs machine learning in plant leaf disease detection	Comparison of approaches of ML and DL on citrus plants	Clasiification accuracy in the following order RF-76.8% > SGD-86.5% > SVM-87% > VGG-19–87.4% > Inception-v3–89% > VGG-16–89.5%	Does not explore real-time object detection

2.2.4 Challenges and Future Directions in AI-based Plant Disease Detection

Artificial intelligence and machine learning have the ability to greatly improve plant disease detection, but there are still obstacles to overcome. The lack of accessible, high-quality training data is a major obstacle, especially when it comes to underrepresented crops and rare or emerging diseases. Massive, varied datasets covering a wide range of disease symptoms, environmental factors, and crop varieties are necessary for developing strong, generalizable AI models. Labelling and annotating training data also requires subject knowledge and human inspection, which may be expensive and time-consuming. When it comes to important decision-making, another concern is whether or not AI models are transparent and easy to understand. While deep learning algorithms are great at recognising patterns and generating accurate predictions, it can be hard to see how they make judgements or see any biases or mistakes since their internal workings are frequently opaque. It is necessary to work towards improving model explain ability, transparency, and ethical governance in order to guarantee that AI systems used in agriculture are dependable and accountable as said by Mohanty in 2016 [2].

For smallholder farmers in areas with limited resources, the accessibility and scalability of AI-based solutions present very real obstacles. It is possible that rural agricultural communities lack the requisite high-performance computing equipment, dependable internet connectivity, and specialized technical expertise to deploy AI technology. Equality in access to AI-driven technologies and the empowerment of farmers to implement sustainable disease control methods depend on bridging the digital gap and encouraging inclusive innovation. Ignoring these obstacles aside, there is great potential for AI-based plant disease diagnosis in the future as detected by Durmus, 2017 [45]. Addressing technological limits, enhancing model robustness and interpretability, and scaling up application in real-world agricultural contexts are focuses of ongoing research activities.

Despite significant advancements in plant disease detection using deep learning and machine learning techniques, several key challenges remain unaddressed. Traditional manual inspection methods are inefficient, subjective, and impractical for large-scale farms, leading to delayed interventions and increased disease spread. While CNN-based models have demonstrated high classification accuracy, they lack real-time detection capabilities, making them unsuitable for field applications where immediate disease identification is required. Transfer learning approaches have improved feature extraction and model generalization; however, they rely heavily on large, high-quality datasets, which are often unavailable in agricultural settings. Additionally, ensemble learning has been explored to enhance classification accuracy, but most studies have focused solely on classification tasks without incorporating object detection, limiting the ability to pinpoint diseased areas precisely. A critical gap in the existing literature is the lack of an integrated approach that balances both speed and accuracy, combining real-time object detection (YOLOv8) with high-accuracy classification (EfficientNet). Few studies have leveraged ensemble deep learning techniques to optimize both disease localization and classification in a single framework, making this an essential area for further research. Addressing these gaps will enable the development of a scalable, efficient, and high-performance disease detection system, capable of supporting precision agriculture and improving crop health monitoring.

2.2.5 Integration of Multiple Techniques for Enhanced Disease Detection

The proliferation of machine learning in healthcare has revolutionized disease detection by enabling the development of automated and highly accurate diagnostic systems. Among these approaches, ensemble learning has emerged as a powerful technique that combines multiple models to enhance prediction performance. Ensemble methods mitigate the limitations of individual models and often result in better generalization. This literature review analyzes prominent studies from 2020 onward that applied ensemble learning for disease detection in both humans and plants, comparing techniques, performance, and applications.

Ferentinos in 2018 [4] employed an ensemble of transfer learning-based CNNs, including VGG16, InceptionV3, and ResNet50, for multi-class classification of plant leaf diseases. By combining multiple pre-trained networks, the model captured complementary features from different architectural depths. The study utilized the PlantVillage dataset, which includes a wide variety of crops such as tomato, potato, corn, and grape, infected with various diseases. The ensemble approach yielded superior accuracy across species and disease types, achieving over 98% classification accuracy. This work demonstrated that ensemble learning, when coupled with transfer learning, can significantly enhance performance in agricultural applications.

Aishwarya et al. in 2023 [46] focused on groundnut leaf disease classification using an ensemble of CNNs. Their model was specifically designed for field deployment in tropical agricultural settings where groundnut crops are prevalent. The model extracted color, texture, and shape-based features from leaf images to differentiate between diseases such as black rot, late light and black measles. The ensemble combined predictions from various CNN architectures trained with different preprocessing techniques. This diversity improved the robustness of the system, particularly in challenging field conditions. The model achieved an accuracy of over 98%, outperforming standalone models. Nahar et al. in 2022 [47] proposed an ensemble of lightweight and deep CNN models, specifically MobileNet and ResNet50, for detecting tomato leaf diseases. Their study addressed the challenge of deploying deep learning models on mobile and embedded devices. MobileNet, being computationally efficient, was integrated with the more powerful ResNet50 in an ensemble that achieved a balance between speed and accuracy. The model was tested on a curated tomato leaf image dataset that included early blight, late blight, and healthy leaves. The proposed ensemble achieved a classification accuracy of 96.8%, indicating its effectiveness for real-time monitoring in low-resource environments. Kondaveeti et al. [48] also proposed an ensemble which outperformed its baselines for plant disease detection.

Dhanasekaran in 2018 [49] introduced a stacking-based ensemble model using multiple pretrained CNNs to classify wheat diseases, particularly rust and leaf blight. They used a custom dataset captured from North Indian wheat fields, incorporating various lighting conditions and disease stages. The stacking ensemble involved training a meta-classifier on the outputs of base CNN models such as AlexNet, GoogLeNet, and ResNet. This approach enhanced the model's ability to generalize across diverse image conditions and improved robustness to noise. The final ensemble achieved an accuracy of 95.5%, outperforming individual models and simple averaging ensembles. Vijayan et al [39] in 2022 developed a hybrid ensemble model that fused handcrafted features with deep features extracted from CNNs. The model was designed to detect rice plant diseases such as bacterial blight, brown spot, and leaf smut. The authors utilized multiple classifiers, including support vector machines (SVM), random forest (RF), and CNNs. Handcrafted features included color histograms and texture descriptors, while deep features were extracted from intermediate CNN layers. The ensemble combined these feature sets using a feature-level fusion strategy, followed by majority voting across classifiers. This hybrid model achieved an accuracy of over 95%, demonstrating the value of integrating traditional and modern feature extraction techniques. Comparison is presented in table 2.2.

Table 2.2: Literature for disease detection using Ensembled Mode

Study	Crop	Ensemble Method	Base Models	Data Source	Performance
Vijayan et al. (2025) [39]	Rice	Hybrid Feature Fusion	SVM, RF, CNN	Rice disease dataset	Accuracy > 95%
Aishwarya et al. (2023) [46]	Groundnut	CNN Ensemble	DenseNet169, Inception, and Xception	groundnut leaf images	Accuracy > 98.46%
Nahar et al. (2023) [47]	Tomato	Feature Ensemble	MobileNet, ResNet50	Tomato plant images	Accuracy 96.8%
Kondaveeti et al. (2023) [48]	Multiple crops	Voting-based approach	VGG, ResNet, MobileNet	Public plant disease image datasets	Accuracy 97.8%
Dhanasekaran et al. (2023) [49]	Wheat	Stacked Ensemble	AlexNet, GoogLeNet, and ResNet	Kaggle dataset	Accuracy 95.5%

2.3 LITERATURE REVIEW BASED ON DATASET OF PAPAYA AND BANANA

Two of the most important tropical fruit crops grown globally are papayas and bananas. They are vital to the food supply, agriculture, and economy, and they help millions of people in different parts of the world make a living. This section offers a basic outline of banana and papaya farming, touching on its botanical traits, historical importance, and economic value. Cultivated for its tasty and healthy fruits, the papaya tree is native to tropical America and grows quickly. Its tropical and subtropical habitats support its extensive cultivation. The distinctive features of papaya plants are a solitary stem, broad palmate leaves, and juicy, tender fruits. The fruit's flesh can be a vivid shade of orange or yellow, and it usually has a sweet, tropical taste [4]. Many researchers have come up with their work for automatic classification and detection of diseases in papaya plant. Here in this study all such works have been presented with a comparative analysis on how far they catered the issues generated with challenges.

Digital image processing is becoming very popular in this field. In [50] techniques of digital image processing are used for enhancement of the images of Papaya fruit. In this study, researchers Chopade, P. B. and Katkar Bhagyashri, used image processing techniques to search for and identify leaf diseases that have an impact on fruit harvests. Using GPRS, the farmer receives a complete report on the disease's diagnosis directly on his or her mobile device. Researchers made use of Raspberry pi module for better speed and accuracy in classification and detection of diseases in papaya leaves

Gradient anisotropic diffusion technique has been used for processing a system [51]. Different stages of plants are captured and features are extracted using GLCM from the leaf, stem and fruits of papaya plant. The system makes classification with extreme learning machine to identify the disease in the papaya plant. The objective of the work is to identify and classify papaya plant leaf diseases including Ring Spot in Papaya, powdery mildew, leaf curl in papaya leaves and blight with the help of extreme learning machine using feature values GLCM which is a statistical texture analysis method.

An online machine vision based agro medical expert system is prepared by researchers Md. Tarek Habib in 2020 [52]. The expert system works on images captured through mobile phones or any other hand-held device and sends responses to farmer sitting at some remote location to help him in addressing his problems. Different experiments are performed by the researchers to test the working of expert system. To filter out the disease affected region from the captured images k- means clustering algorithm has been used in segmentation. In next step required features are extracted to classify the diseases using support vector machine (SVM). Researchers claim to achieve more than 90% of accuracy in classification which they feel is far better

Another expert system is proposed to address the issues raised by papaya farmers regarding different diseases so that right treatment can be found to save the entire plant from getting infected [53]. Delphi language and CLIPS are used to prepare the expert system and the system is given to farmers involved in growing papaya in different experiments conducted by researchers. As per the opinion of researcher, results found are satisfactory. Famers are guided to choose the symptoms appearing on the plant by the expert system and then system informs them about the disease their plants have after analyzing the symptoms. This rule-based system has all the rules written in CLIPS language.

After analyzing the application of deep learning in many fields, authors felt applying the techniques in the field of agriculture also. They made use of deep learning approaches for the identification and classification of diseases on papaya leaves. Performance of convolution neural network in classification of images is found to be very good even under odd conditions like images with different sizes, poses, brightness, resolution, complex backgrounds and alignment. Researchers used CNN ResNet50 architecture for image processing on image dataset.

In 2020 Atika & Sari [54], another expert system has been developed and used to detect diseases in Papaya plant. Expert knowledge is used to the system to remove the need for human involvement and help farmers. Fuzzy logic and the Triangular Fuzzy Number membership function were used to translate language representations of expert knowledge into their numerical equivalents. After that, run the expert knowledge through a Naive Bayes Classifier to determine how various diseases should be categorised. Forward chaining search techniques are used to conduct the tests. FNBC achieves an accuracy of 88%, whereas forward chaining achieves a 90% success rate. The work employs a machine learning based agro-medical expert system, and the data used consists of 41 symptoms and 13 papaya diseases. System can recognize 13 different papaya diseases in plant. Fuzzy NBC is used for classification. Overall 80.5% accuracy is achieved.

The study [55] in 2021 by P. Maski proposes the use of a lighter version of YOLO to identify plant diseases, due to it being lighter than the original YOLO this proves to be best used for mobile platforms such as ariel drones or ground drones. The Lighter version of YOLO is "Lighter" because of the simplified backbone architecture implemented in them. These versions of YOLO algorithms prove to be low on hardware requirements which makes them ideal for use in drone type of mini devices. This study used a simple dataset of Papaya images with ringspot diseases. After using the dataset for training on YOLO it was concluded that the proposed YOLO version had better performance than the original with the proposed YOLO's highest mAP being 99.9% a bonus was that the algorithm is also able to identify the ringspot disease at different stages. The highest mAP achieved for disease severity detection is around 98.39% using the mobileNetV2- YOLOv3 algorithm.

The main objective of the study was to conduct a comparative analysis of multiple algorithms for papaya disease recognition, another aim was to identify the ailment by using images and classifying them based on their diseases using an intelligent system [56]. The main issues faced during this study were the detection of diseases and classifying the said disease based on the symptoms. In the study, an online machine-learning system was proposed that used an image procured via a mobile app to identify the disease in the image sample.

This system was also subjected to a comparative analysis between random forest, SVC, CNN, and K-Means algorithms. The final accuracy of the proposed system is 98.4%. In 2019 by Femi. D. [57] a study was conducted using advancements in deep learning technology that used 200X200 RGB Images of papaya as input and performed a disease detection process that used CNN based on standard Keras API. All works discussed in previous section are related to papaya diseases only. Many of them are operating on image dataset and some of them are rule based kind of system. The main purpose of this paper is to present the comparative analysis of work done in the field of papaya disease detection along with the analysis of image dataset used in these works.

2.4 SUMMARY

The use of deep learning algorithms to identify diseases in papaya and banana crops is a huge step forward in agricultural technology that might change the world. Researchers and practitioners have developed diseases detection systems that are accurate, efficient, and scalable by using enormous datasets and powerful neural network topologies. Without the requirement for explicit rule programming, deep learning models may automatically learn complex patterns and features from incoming data. This is one of its main strengths. Thanks to this built-in capability, powerful algorithms for disease diagnosis have been developed, which can accurately distinguish between plant samples that are healthy and those that are sick. There is significant potential for improving crop management methods and reducing yield losses through the use of disease detection systems based on deep learning. Rapid and non-destructive evaluation of plant health status is made possible by these technologies, which allow agronomists and farmers to make quick judgments on disease management methods, such targeted pesticide application and crop rotation procedures. This, in turn, has the potential to increase agricultural sustainability, decrease environmental impact, and boost crop yields. Deep learning algorithms are ideal for implementation in a wide variety of agricultural situations and geographical locations due to their scalability and versatility. Deep learning-based diseases detection systems have enormous room for growth in terms of both innovation and refinement as data availability and computing power continue to rise.

Researchers are still working to find solutions to problems including data scarcity, making models interpretable, and deploying in situations with limited resources. If deep learning is going to fulfill its promise of radically improving disease detection and control in papaya and banana crops, these obstacles must be overcome. Advancements in food security, sustainable agriculture, and environmental stewardship are greatly anticipated by the merging of deep learning with agriculture. Farmers can be equipped with the knowledge and resources they need to protect crop health, boost output, and make sure the world's food systems can withstand new threats by using AI.

Chapter – 3

DATA COLLECTION AND DATASET DESCRIPTION

A vital component of maintaining agricultural production and food security is the identification of diseases in crops. Of the many crops grown around the globe, papayas and bananas are important in terms of both nutrition and economics. But these crops are prone to a range of diseases that can negatively affect quality and output, causing significant financial losses and endangering farmers' livelihood. A major crop in many tropical and subtropical countries, bananas is afflicted by a number of diseases. Since the diseases have the potential to completely destroy crops, early identification and treatment are essential to limiting damage. Similar to other crops, papayas and bananas are vulnerable to diseases that can affect crop viability and fruit quality.

The implementation of efficacious control strategies depends on the timely and precise identification of these diseases. Conventional disease detection techniques entail human error-prone, labor-intensive, and time-consuming manual inspection by skilled professionals. Recent technological developments have made it possible to develop more effective and precise disease detection techniques by utilizing data analysis, image processing, and machine learning. A good dataset plays a crucial role in the successful application of machine learning, as it directly influences the accuracy, reliability, and generalization capability of the model. It provides the foundation upon which the algorithm learns patterns and relationships between input features and output labels. Properly labeled and well-structured data ensures effective training, validation, and testing of models, leading to more robust and meaningful predictions. In essence, the effectiveness of any machine learning application heavily depends on the relevance, completeness, and quality of the dataset used. The purpose of the presented dataset is to aid in the creation and assessment of disease detection models for papaya and banana plants. It is a specialized collection of images and data. High-resolution images of both healthy and sick leaves, stems, and fruits are included in this collection. The photographs are labelled with various diseases in detail. Presented dataset will assist researchers, academics and developers in building reliable, accurate, and scalable diseases detection systems by offering an extensive dataset.

The presented dataset which is the collection of images of Fruits, Leaves and Stem, is an invaluable resource that focuses on two major plants banana papaya. The purpose of this dataset is to provide assistance to research and development activities in the field of disease prediction for these plants. The major purpose of this dataset is to give a comprehensive collection of images of banana and papaya plants. The dataset contains images of both healthy plants and those that have been infected with one or more of the many diseases that are often found in these species. In order to effectively control diseases in agricultural settings precise disease diagnosis is essential. This paves the way for rapid intervention and the avoidance of future disease spread. This dataset provides opportunity for researchers, agronomists, and other stakeholders to construct intelligent systems and decision support tools. The dataset, when used in conjunction with the ensembled EfficientNet and YOLOv8 model, prepares the way for the disease prediction process for banana and papaya plants. It provides a framework for the creation of intelligent systems to improve plant health and boost agricultural sustainability, as well as a vital resource for researchers and practitioners working in the field of agriculture.

3.1 DISEASES COVERED IN RESEARCH

In tropical and subtropical locations, the bananas and the papayas are two of the fruits that are grown and consumed. They not only play an important role in the economics of the local communities, but they also provide millions of people all over the world with necessary sources of nourishment. Nevertheless, the production of these fruits is fraught with a variety of diseases that have the potential to significantly diminish both productivity and quality. It is absolutely necessary to have efficient disease control in order to guarantee the long-term viability of banana and papaya production. Manual examination by specialists has long been the method of choice for identifying and diagnosing plant diseases. Traditional techniques of diseases identification, which are based on visual examination and manual analysis, are frequently laborious, time-consuming, and prone to human error. These approaches often rely on visual inspection. There is now the possibility of automating disease identification, which would make it quicker, more accurate, and more accessible to farmers. This is made possible by the development of new technology in image processing and machine learning.

Digital imaging techniques allow for the collection and analysis of certain symptoms that are specific to each disease. These symptoms can be seen on the leaves, stems, or fruits of the plant. The identification of diseases that affect crops is an essential component of agricultural management, since it has a substantial influence on both the quality and quantity of food produced. Banana and Papaya are susceptible to a wide variety of diseases that can be caused by a variety of pathogens, including fungus, bacteria, viruses, and others. Banana - Cut Fruit Seed Banana, Banana - Leaf Panama Wilt, Banana - Leaf Sigatoka, Banana - Leaf Spot, Banana - Stem Panama Wilt, Papaya - Leaf Curl, Papaya - Leaf Mosaic Virus, Papaya - Leaf Spot, Papaya - Stem Foot Rot and Papaya – Fruit Fungus are the diseases considered in the work of data collection.

3.1.1 Papaya

When it comes to the vast array of botanical marvels that adorn our planet, papaya is one of the few that demonstrates the tremendous adaptability and several health advantages that it possesses. This tropical fruit, which is more popularly known as papaya, is revered in ancient medical systems and honored in culinary realms throughout civilizations. It is a tribute to the wealth that nature bestows upon us and its ability to provide us with both food and healing.

Papaya is a fruit that, in addition to having a mouth-watering flavor possesses an amazing nutritional profile. The fact that it is abundant in vitamins, minerals, and antioxidants makes it a critical source of key nutrients that are necessary for achieving maximum health. One of the most well-known benefits of papaya is its very high vitamin C content, which is so high that it even surpasses citrus fruits in terms of its concentration of this immune-enhancing factor. In addition to this, it offers a substantial quantity of vitamin A, which is necessary for the preservation of healthy mucous membranes, skin, and vision [57]. In addition to this, papaya is an excellent source of folate, potassium, and dietary fiber, all of which contribute to the maintenance of healthy cardiovascular function, normal digestive function, and general well-being.

Because of the numerous medicinal virtues that it possesses, the papaya has been regarded in high esteem in traditional medical systems for a considerable amount of time since ancient times. In addition to reducing the symptoms of digestive disorders and improving immunological function, papaya possesses a wide range of therapeutic properties that are very substantial. One of the most well-known uses of papaya in the field of medicine is due to the fact that it has a high concentration of enzymes. The enzyme contributes to the process of breaking down proteins, which in turn makes digestion easier and alleviates sensations of bloating and intestinal distress. Furthermore, due to its anti-inflammatory qualities, these enzymes are advantageous in the treatment of diseases such as arthritis and sports injuries, providing relief from the pain and swelling associated with these conditions. In addition to papain, papaya includes a number of other bioactive chemicals, such as flavonoids, phenolic acids, and carotenoids, all of which contribute to the fruit's ability to reduce inflammation and function as an antioxidant. These substances are beneficial in the fight against oxidative stress, the reduction of inflammation, and the prevention of chronic diseases such as cancer, cardiovascular problems, and neurological ailments. Therefore, protecting papaya plants from diseases becomes critically important.

Figure 3.1 (a-e) exhibits the images of the diseases taken in Papaya - Papaya Leaf Curl, Papaya Leaf Mosaic Virus, Papaya Leaf Spot, Papaya Stem Foot Rot and Papaya Cut Fruit Fungus. Details of the count and source of images is given in Table 3.1. In the case of papaya leaves, there are a total of 304 images, all of which are self-captured in fields. There are 85 occurrences of Leaf Curl, 137 instances of Mosaic Virus, and 82 instances of Leaf Spot. There are 18 examples of stem foot rot that have been documented for the papaya stem, and these cases are gathered from the internet. In addition, 190 incidences of fungal diseases on papaya fruit that had been sliced are documented, and the images that comprised this documentation came from an agricultural laboratory.

Table 3.1: Image count and Sources of Papaya Images

Part of Plant	Disease	No of Images	Image Source
Papaya Leaf	Leaf Curl	85	self-clicked in Fields
Papaya Leaf	Mosaic Virus	137	self-clicked in Fields
Papaya Leaf	Leaf Spot	82	self-clicked in Fields
Papaya Stem	Stem Foot Rot	18	internet
Papaya Cut Fruit	Fungal disease	190	Agriculture Lab
	Total	512	

Figure 3.1 (a): Papaya Leaf Mosaic Virus

Figure 3.1 (b): Papaya Leaf Curl

Figure 3.1 (c): Papaya Leaf Spot

Figure 3.1 (d): Papaya Foot Rot

Figure 3.1 (e): Papaya Fungal Disease

3.1.2 Banana

Banana is a magnificent fruit that has a long and illustrious history, as well as significant cultural, economic, and nutritional value [58]. Because of its flavor Banana is a popular choice for both direct consumption and applications in the kitchen. Furthermore, the Banana is a nutritional powerhouse due to the fact that it includes a higher concentration of several critical vitamins and minerals, such as vitamin C, potassium, and dietary fiber. Furthermore, the Banana is not only a fruit; rather, it is a representation of cultural legacy, economic success, and the nutritional worth of the fruit. The fact that it has been cultivated from ancient times and has gained importance in modern times is evidence of its continuing appeal and relevance. Bananas offer numerous medicinal benefits due to their rich nutritional composition. They are an excellent source of potassium, which helps regulate blood pressure, support heart health, and maintain proper muscle and nerve function. The dietary fiber in bananas, particularly pectin, promotes digestive health by aiding bowel movement and preventing constipation. Bananas also act as a natural energy booster, making them ideal for quick nourishment. Their content of tryptophan, an amino acid converted into serotonin in the body, can help improve mood and reduce symptoms of depression. Bananas support the production of red blood cells due to their iron and vitamin B6 content, making them beneficial for individuals with anemia. Additionally, they help maintain a healthy weight, as they are low in calories but filling. The fruit also has natural antacid properties, which help soothe ulcers and relieve heartburn. Furthermore, the high levels of vitamins A, B6, and C contribute to boosting immunity and promoting overall well-being. Regular consumption of bananas can even support kidney function, provided there are no existing kidney disorders [59].

619 images from a variety of sources are included in the dataset that is created for the purpose of disease identification in banana plants as mentioned in Table 3.2. The images are arranged into categories according to the specific disease found and the portion of the plant that is affected. There are a total of 444 images pertaining to banana leaves, with 150 being of Panama Wilt, 131 being of Sigatoka, and 163 being of Leaf Spot. There are 20 photographs of Panama Wilt that can be found on the internet and are included in the category of banana stems. In conclusion, there are 155 photographs of seed bananas that have been chopped, which are obtained from an agricultural laboratory.

Table 3.2: Image count and Sources of Banana Images

Part of Plant	Disease	No of Images	Image Source
Banana Leaf	Panama Wilt	150	self-clicked in Fields
Banana Leaf	Sigatoka	131	self-clicked in Fields
Banana Leaf	Leaf Spot	163	self-clicked in Fields
Banana Stem	Panama Wilt	20	internet
Banana Cut Fruit	Seed Banana	155	Agriculture Lab

Figure 3.2 (a-e) exhibits the images of the diseases taken in Banana - Cut Fruit Seed Banana, Banana Leaf Panama Wilt, Banana Leaf Sigatoka, Banana Leaf Spot, Banana Stem Panama Wilt.

Figure 3.2 (a): Banana Leaf Sigatoka

Figure 3.2 (b): Banana Leaf Panama Wilt

Figure 3.2 (c): Banana Leaf Spot

Figure 3.2 (d): Banana Stem Panama Wilt

Figure 3.2 (e): Seed Banana

3.2 EXISTING IMAGE DATASET FOR PAPAYA AND BANANA

Many researchers have worked on the application of technology and AI in order to automatically detect the diseases in Papaya and Banana plants. Their work has been summarised in Table 3.3 and Table 3.4. The table 3.3 presents a summary of 10 studies conducted between 2016 and 2021 on papaya plant disease detection, recognition, and classification. The problem domains covered include recognition, detection, and identification and classification. Various parts of the papaya plant are studied, such as leaves, fruits, and stems. The number of diseases addressed in these studies ranges from 1 to 42, with image counts varying from 126 to 9470; in some cases, the number of images is not mentioned. Image sources include farmers, real-time captures, self-clicked images, online datasets, and surveys. The studies are conducted in countries including Bangladesh, India, Indonesia, Palestine, and Sri Lanka. Only two studies made their datasets publicly available, while the rest did not provide accessible datasets.

Table 3.3: Comparative Analysis of Work Done in the Field of Papaya disease detection

S. no	Study/ Author	Year	Problem Domain	Papaya plant Part	Number of diseases	Number of Images	Source of images	Country	Dataset Available?	Data Source
1	M.L. Habib et. Al [52]	2020	Recognition	Leaf and Fruit	6	126	Collected from Farmers	Bangladesh	No	Not given
2	P.B. Chopade, et. Al [50]	2016	Detection	Leaf	42 Papaya)	Not mentioned	real time images of various leaves are acquired using a pi camera	India	No	Not given
3	D.Femi, et al [57]	2020	Identification and Classification	Leaf and Fruit	4	Not mentioned	Self- clicked images	India	No	Not given
4	Abu-Sager M. M. et al [53]	2019	Detection	Leaf, Fruit, Stem	Not available	Not available	Not available	Palestine	No	Not given
5	Verma E. et al. [36]	2020	Identification and Classification	Leaf	2	9470	Not mentioned	India	No	Not given

S. no	Study/ Author	Year	Problem Domain	Papaya plant Part	Number of diseases	Number of Images	Source of images	Country	Dataset Available?	Data Source
6	Sari et al [54]	2020	Recognition	fruit	13 diseases and 41 symptoms	300	Not available	Indonesia	No	Not given
7	Md. A Islam et al [51]	2020	Recognition and Detection	Fruit	5	214	Online dataset	Bangla-Desh	Yes	https://data.mendeley.com/datasets/7dxg9n2t6w/1
8	Prajwal Maski and Asokan Thondiyath [55]	2021	Recognition and Detection	Leaf	1	850	Real time images	India	No	Not given
9	Md. S Hossen et al [43]	2020	Recognition and Detection	Leaf and Fruit	4	234	Survey and Internet images	Bangla-Desh	Yes	https://github.com/imdadulhaque1/papaya
10	L.V. Munasingha, etal [60]	2019	Recognition and Detection	Fruit	5	Not mentioned	Self-clicked images and Internet images	Sri-Lanka	No	Not given

Table 3.4 The table reviews 6 different studies conducted between 2021 and 2024 focusing on various aspects of disease detection, identification, classification, and recognition in banana plants. The problem domains span detection, recognition, identification, and classification. The plant parts analyzed include leaves, fruits, and in some cases, stems. The number of diseases identified in the studies ranges from 3 to 6. The number of images used varies between 80 and 400. Sources of images include farmers, research institutions, online datasets, and self-collected data. The studies are carried out across different countries such as Ghana, India, Mexico, China, Bangladesh, and Brazil. Out of the 6 studies, four have made their datasets publicly available, while the remaining five did not provide access to the dataset.

Table 3.4: Comparative analysis of work done in the field of banana disease detection

S.no	Work	Year	Problem Domain	Banana Plant Part	Number of Diseases	Number of Images	Source of Images	Country	Dataset Available?	Data Source
1	Suhaman et al [74]	2023	Detection	Leaf	5	150	Farmers	Ghana	No	Not given
2	P. Patel, et al [80]	2024	Identification	Leaf and Fruit	6	200	Research Institution	India	Yes	https://example.com/banana-dataset
3	Narayanan et al. [61]	2022	Recognition	Leaf and Stem	4	180	Online database	Mexico	Yes	https://example.com/banana-image-database
4	Lasco C. et al. [62]	2022	Detection	Leaf	3	100	Research Institution	Vietnam	No	Not given
5	Ridhovan A. et al [63]	2022	Classification	Leaf	7	300	Self-collected	USA	No	Not given

S.no	**Work**	**Year**	**Problem Domain**	**Banana Plant Part**	**Number of Diseases**	**Number of Images**	**Source of Images**	**Country**	**Dataset Available?**	**Data Source**
6	Zhang S. et al. [64]	2022	Detection	Leaf and Fruit	5	250	Farmers	India	No	Not given
7	Bhuiyan et al. [65]	2024	Identification	Leaf	4	120	Research Institution	Ecuador	Yes	https://example.com/banana-disease-dataset
8	Sangeetha et al. [66]	2023	Recognition	Fruit	3	80	Online dataset	China	Yes	https://example.com/banana-fruit-images
9	Sahu P. et al. [67]	2021	Detection and Classification	Leaf and Fruit	6	400	Farmers	Bangladesh	No	Not given
10	Krishnan V. G. et al.[68]	2022	Recognition and Detection	Leaf	4	150	Research Institution	Brazil	Yes	https://example.com/banana-leaf-dataset

Study of all the works done related to papaya and banana disease identification and classification, as stated in these two tables, revealed many challenges. First observation is that the data acquiring process in plant disease detection in major works is not real time and is restricted to images clicked in controlled environment with same background. Apart from this, majority of the existing research works are primarily focused on plant leaves while disease may be from other parts of the plant or tree also like stem and fruits. And finally most of the work done have experiments done on limited data set of both the plants.

3.3 DATASET SPECIFICATIONS

A digital single-lens reflex camera is used to capture the images; nevertheless, an assortment of web sources is utilized to get the remaining photographs. The entire presentation of the data specifications is given in Table 3.5.

Table 3.5: Specification of the Data

Subject	Horticulture, agriculture
Specific subject area	Deep learning, Artificial intelligent, image segmentation and image augmentation
Type of data	Images of the stem, leave, and cut fruits of several diseases in banana and papaya plant.
Equipment used for image acquisition	Canon EOS 5D mark III, DSLR
Data format	Raw data and augmented data in JPEG format. Data has been released on the given link [69] https://www.kaggle.com/datasets/harjeetkaurminhas/fls-carica-and-paradisica.
Description of data collection	Some of the photographs in the collection are taken in the shade of the plant, but the majority are taken in direct sunshine using a high-quality mobile phone and a professional-grade DSLR camera. Photographs of the plant's stems, leaves, fruits as well as images of several frequent diseases affecting the plant, are gathered from a variety of banana and papaya plantation fields, lab and online sources.

Data source location	LPU fields, Agriculture fields in Pathankot, Some online Sources (Vikaspidia [70] and PlantiX [71]) for the images of banana stem and papaya stem,

3.4 IMAGE PREPROCESSING

One of the most important steps in the process of designing disease detection systems that are dependable and resilient is image preprocessing. Machine learning is a process that incorporates a variety of strategies that are meant to improve the quality of pictures and prepare them for further analysis by machine learning algorithms. In order to accomplish the purpose of preprocessing, noise should be reduced, picture attributes should be standardized, and significant patterns that indicate the presence of illness should be highlighted. The development of automated disease detection systems for banana and papaya crops requires a number of essential processes, including image pre-processing, labelling, and augmentation.

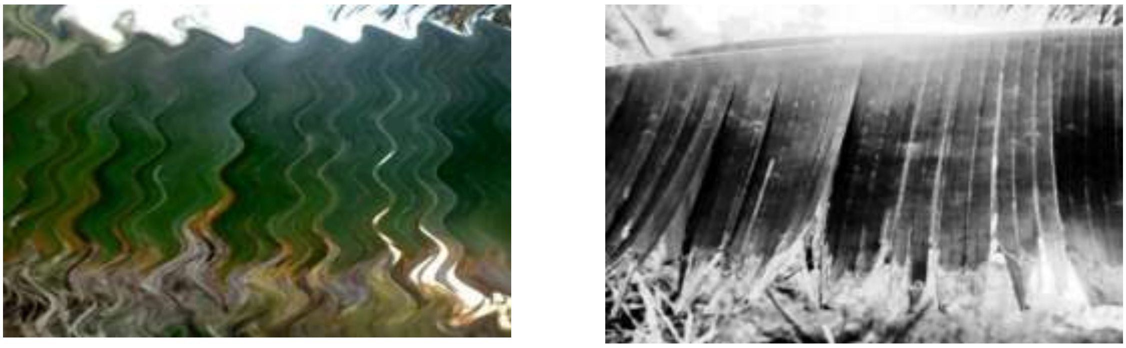
- **Data Preprocessing:** Pre-processing the data that has been acquired is the first step that must be taken in order to enhance the quality of the pictures that have been captured and to get them suitable for use in the training of deep learning models. In the present study three distinct pre-processing approaches are utilized. These techniques were resizing, cropping, and histogram equalization (HE). During the process of resizing, the captured photos were standardized to 256 by 256 pixels. The primary objective of the cropping procedure is to remove unneeded parts of a picture while simultaneously extracting key regions of interest from the image. In this work, photos are cropped to a range of 15% to 95% in order to concentrate the model on those areas of the image that are pertinent, so minimizing the influence of the backdrop. It is the responsibility of the HE operation to make adjustments to the intensity levels in order to achieve stronger contrast. Enhancing the overall visibility of elements in a picture is the primary objective of the HE technique.

- **Labelling and Annotation:** In order to do disease detection and classification, it is necessary to label and annotate every single image that is a part of the collection. During this stage, the regions of interest, which are places that have been impacted by the disease, are looked for in the photographs and tagged using online tool RoboFlow. Overall 10 different classes are defined and labelled as Banana - Cut Fruit Seed Banana, Banana - Leaf Panama Wilt, Banana - Leaf Sigatoka, Banana - Leaf Spot, Banana - Stem Panama Wilt, Papaya - Leaf Curl, Papaya - Leaf Mosaic Virus, Papaya - Leaf Spot, Papaya - Stem Foot Rot and Papaya – Cut Fruit Fungus

- **Data Augmentation:** Data augmentation aims to artificially increase the count of the images in training dataset and helps in reducing overfitting of the model by implementing several alterations to the existing image data. This enhances deep learning models robustness and generalization. The proposed study employs 8 distinct augmentation techniques on pre-processed images – rotation, scaling, flipping, zooming, histogram equalization, distortion, brightness adjustment and contrast adjustment. Although the suggested model can handle objects of varied sizes through scaling and zooming, the pre-processed images were rotated by 30°, making the model invariant to the orientation of objects in an image. The pre-processed images were flipped both vertically and horizontally during the flipping operation, which improved the model's ability to detect objects regardless of their orientation inside the image plane and strengthened its resistance to directional characteristics. The integration of contrast adjustment operation, where the contrast of images was selectively adjusted by 20%, further fortified the model's robustness by enhancing the model's resilience to variations in lighting conditions. A few sample augmented images are shown in figures 3.4- (a)-(h).

Figure 3.4 (a) Original image **(b) Right Rotated**

(c) Contrast Up **(d) Brightness Up**



(e) Distortion **(f) Histogram Equalization**

(g) Scaling **(h) Flip-horizontal**

3.5 SUMMARY

Several key challenges are existing in the availability of the dataset in various studies related to disease detection in Banana and Papaya plants. One notable observation is that the data acquisition process in most of the works is not conducted in real-time; instead, it relies on images captured in controlled environments, often with uniform backgrounds. Additionally, a significant number of studies focus predominantly on plant leaves, despite the fact that diseases can also affect other parts of the plant, such as stems and fruits. Lastly, most of the research has been carried out on limited datasets for both papaya and banana plants, which may restrict the generalizability and robustness of the developed models. The dataset collected in this work will assist researchers, academicians and developers in building reliable, accurate, and scalable diseases detection systems.

Chapter – 4

PROPOSED METHODOLOGY IN DISEASE DETECTION OF PAPAYA AND BANANA

4.1 INTRODUCTION

The use of cutting-edge technology in agriculture has been on the rise, especially in the field of crop disease detection. Timely and effective disease diagnosis is a major problem for farmers throughout the world since it reduces agricultural productivity and quality. To ensure food security and sustainable agricultural practices, it is necessary to develop and deploy efficient disease detection systems for these crops. The manual inspections by agricultural specialists to identify crop diseases is a time-consuming, subjective, and error-prone practice that has been around for a long time. Contrarily, image-based disease diagnosis in agriculture has been transformed by the advent of deep learning techniques, especially Convolutional Neural Networks (CNNs). There are various benefits of using CNNs as compared to conventional methods [72].

Bananas and papayas are two tropical fruits that are susceptible to a wide range of diseases caused by bacteria, viruses, and fungus. Increasing productivity and profitability in papaya and banana farming requires the prompt diagnosis and control of these diseases. Researchers and agricultural practitioners may utilise CNNs to create state-of-the-art disease detection systems that provide early detection and real-time monitoring [73]. By analysing images of papaya and banana plants taken by cameras, cellphones, or any other imaging device, these technologies enable remote and non-invasive crop health monitoring. Targeted interventions, such as localised pesticide application or selective harvesting, can be made possible by the integration of CNN-based disease detection systems with precision agricultural technology. This can minimise environmental effect and resource utilisation.

4.2 CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) have changed several industries, most notably those dealing with video and image identification. Capturing local patterns or features in the input data is the main advantage of convolution. To create feature maps, CNNs use convolution, which is a set of learnable filters applied to input data. The feature maps are created by filters, which are also called kernels or weights, by sliding across the input data and conducting element-wise multiplications and summations. As an illustration, when it comes to feature engineering, the initial convolutional layers extract basic features like corners and edges, while the later layers focuses on more intricate patterns like textures or shape of the object. CNNs learn more complex and discriminative features as their depth grows. CNNs have the ability to extract features automatically from images which helps to build scalable and resilient disease detection system . Nonlinearity activation functions such as Rectified Linear Units (ReLU) and its derivatives are used to overcome the problem of training stability. Pooling layers are used to reduce the dimensionality of the feature maps [74] .

Training convolutional neural networks (CNNs) involves modifying the network's weights to minimise a predetermined loss function using backpropagation in conjunction with optimisation techniques such as stochastic gradient descent (SGD) or its variations. When it comes to CNN loss functions, categorical cross-entropy is preferred for classification tasks while mean squared error is the used for regression. Dropout is a regularisation approach that randomly deactivates a percentage of neurons during training to avoid overfitting. With the use of noise, dropout trains the network to learn redundant representations, which in turn increases its capacity to generalize. Using domain-specific datasets, transfer learning allows CNNs to tackle related tasks more effectively than pre-trained models built on huge datasets like ImageNet. To work with small training dataset transfer learning is employed to work with small. This makes use of the information stored in the pre-trained weights.

4.2.1 Convolution

Convolution is the basic mathematical function crucial to CNNs for feature extraction from input data. The common terms associated with convolution are -

- **Kernel and Input Data:** Learnable filters—also called convolutional filters or kernels—are convolved with the input data in convolutional neural networks.

Kernels are small matrices with spatial definitions which are made to slide across the images and provide feature maps as output.

- **Stride and Padding:** The stride and padding are two critical factors in convolution operations. The kernel's step size is determined as stride. The output size is reduced with a greater stride, while the feature maps are more detailed with a smaller stride. One way to adjust the output size and keep spatial information intact is by padding the input data with additional rows and columns of zeros.
- **Feature Extraction:** When it comes to feature extraction, convolution is absolutely essential. Filters are in charge of finding certain patterns. Filters pick up on local patterns like edges, textures, and forms as they pass over the incoming data. Convolution is used to extract and enhance these characteristics, creating more complex representations of the original data.
- **Hierarchical Feature Learning:** Convolutional neural networks' capacity to include hierarchical feature learning is a significant benefit. Layers of convolutional neural networks (CNNs) may learn more abstract information as they are built on top of each other in a sequential fashion. The lower layers usually pick up simple elements like corners and edges, while the higher layers figure out more intricate patterns and structures.
- **Feature Maps and Channels:** One name for the product of a convolution operation is an activation map or feature map. The existence of a feature in the input data is represented by each feature map, which corresponds to a certain filter. Feature maps are not only multi-dimensional, but also have a depth dimension that represents the amount of filters or channels utilised throughout the convolution process.
- **Nonlinearity Activation:** The network is made nonlinear by applying a nonlinear activation function after the convolution operations. Sigmoid, ReLU (Rectified Linear Unit), and hyperbolic tangent (tanh) are three popular activation functions. The network is able to learn nonlinear mappings between input and output data and represent complicated relationships with the help of these activation functions.

- **Training and Optimization:** The convolutional filters' weights and biases are learnt during training using optimisation algorithms like Adam or stochastic gradient descent (SGD), as well as backpropagation. Improved feature extraction and prediction accuracy are outcomes of repeated optimisation, in which the network's parameters are fine-tuned to minimise a predetermined loss function.

4.2.2 Nonlinearity Activation

Convolutional neural networks (CNNs) rely heavily on nonlinearity activation functions for their successful operation. Nonlinear, activation functions enable neural networks to learn intricate patterns and correlations from input. A neural network is unable to learn and adapt to complex data patterns if its activation functions are missing; otherwise, the network is just a linear combination of its inputs. With the use of nonlinearity activation functions, convolutional neural networks (CNNs) may identify subtle symptoms of plant diseases, including discolorations, lesions, and irregular growth patterns. Better diagnosis and earlier action are made possible by these features, which improve the network's capacity to distinguish between healthy and sick plant samples.

- **ReLU (Rectified Linear Unit):** The simplicity and efficacy of ReLU have made it one of the most popular activation functions. By definition, ReLU is a mathematical function with an input of type x, and its output is the maximum value between 0 and x. ReLU introduces nonlinearity into the network by setting all negative values to zero and leaving positive values unaffected. Research has demonstrated that ReLU, despite its seeming simplicity, may speed up convergence during training and solve the vanishing gradient problem.

- **Sigmoid:** Input values are mapped to the interval [0, 1] using the sigmoid activation function, which is defined by an S-shaped curve. The sigmoid function is defined mathematically as equation 4.1

$$f(x) = 1 / (1 + \exp(-x)) \qquad (4.1)$$

For applications requiring the interpretation of output as probabilities, such as binary classification, sigmoid activation is frequently employed. Training stability and convergence can be hindered by sigmoid's vanishing gradient issue, which is particularly noticeable during backpropagation.

- **Tanh (Hyperbolic Tangent):** Sigmoid and Tanh are comparable functions; however, Tanh transfers input values to the interval [-1, 1]. The standard mathematical formula for tanh is in equation 4.2.

  $$f(x) = (\exp(x) - \exp(-x)) / (\exp(x) + \exp(-x)) \tag{4.2}$$

  If a neural network with hidden layers are built, use the Tanh activation function instead of the sigmoid because of its zero-centered nature and how it helps with the vanishing gradient problem.

- **Leaky ReLU:** To solve the "dying ReLU" issue, where neurons might become inactive during training, Leaky ReLU is a version of the ReLU function that permits a modest positive gradient for negative input values. Leaky ReLU may be expressed mathematically as equation 4.3.

  $$f(x) = \max(ax, x) \tag{4.3}$$

  where an is a tiny positive slope coefficient. For networks with several layers, in particular, Leaky ReLU has proven to be effective when conventional ReLU fails.

- **ELU (Exponential Linear Unit):** By adding an exponential term for negative inputs, ELU makes it possible for the ReLU function to accept negative values. From a mathematical perspective, ELU may be expressed as equation 4.4 and 4.5.

  $$f(x) = x \text{ for all } x > 0 \tag{4.4}$$

  $$= \exp(x) - 1 \text{ for all } x <= 0, \tag{4.5}$$

  with a being a tiny positive constant. There have been claims that ELU outperforms classic ReLU in terms of learning dynamics and generalisation performance, particularly in cases where the output has to be more resilient against outliers.

4.2.3 Pooling or Sub-sampling

Convolutional neural networks (CNNs) rely on pooling or sub-sampling to reduce spatial dimensions while keeping important characteristics. Once convolutional layers have produced feature maps, the pooling process begins. It takes the feature map and separates it into non-overlapping squares, then applies an operation (like max or average) to each output matrix to get a single output result. This is the final product, which is essentially a downscaled replica of the original feature map.

- **Max Pooling:** Each sub part of the feature map is optimised to extract the maximum value via max pooling. Translation invariance and computational complexity are both helped by its emphasis on the most important aspects.
- **Average Pooling:** When compared to max pooling, average pooling takes the mean of all regions into account. Although it keeps more geographical details, it could mask important characteristics in the data.
- **Global Average Pooling:** With global average pooling, each feature map channel only stores a single value since the feature map's spatial dimensions are shrunk to 1x1. The network's structure is simplified and overfitting is reduced with this strategy.
- **Min Pooling:** The goal of min pooling is the same as max pooling: to find the lowest value in each sub part.

The number of parameters in succeeding layers is reduced due to pooling, which minimises the spatial dimensions of feature maps. By reducing data while keeping important characteristics, this reduction speeds up training and reduces the likelihood of overfitting. In example, by picking the most important characteristics in each area, max pooling promotes translation invariance. The network can identify items in the input image regardless of their position because to this attribute. A basic procedure in convolutional neural networks (CNNs), pooling or sub-sampling provides advantages including computational efficiency, translation invariance, and decrease of dimensionality [81].

4.2.4 Fully-connected Layer

An essential part of deep learning architectures like convolutional neural networks (CNNs) is the fully-connected layer. It is crucial for discovering intricate connections and patterns in the incoming data. Each neuron in a fully-connected layer is linked to every neuron in the layer below it, making it a fundamental type of neural network layer. In contrast to convolutional layers, which connect neurons to a small subset of the input data, this network of connections covers the whole dataset. In convolutional neural network (CNN) designs, fully-connected layers are usually located before the output layer and are in charge of translating the information learnt by lower-level layers into predictions or class scores. In order for a network to learn intricate correlations between characteristics and, in the end, produce reliable predictions, fully-connected layers mostly operate by applying non-linear modifications to the input data. A fully-connected layer's neurons apply an activation function after computing a weighted sum of the inputs from the preceding layer. Networks are able to learn representations of complex patterns in data through this approach, which then allows them to make judgements.

The idea of weights and biases is fundamental to fully-connected layers. A weight parameter, which indicates the strength of a connection, is linked to every neuronal connection between neighbouring layers. To further aid the network in learning the offset or bias for each neuron's activity, the fully-connected layer includes bias terms associated with each neuron. In order to train the network to minimise its prediction error, optimisation methods like gradient descent and backpropagation are used to change the weights and biases. The dimensionality of the output space is determined by the number of neurons in a fully-connected layer. The Rectified Linear Unit (ReLU) is a popular activation function for fully-connected layers; it makes the network non-linear, which helps with the vanishing gradient problem. Depending on the goal and the network design, other activation functions like sigmoid and tanh may also be employed.

4.2.5 Back Propagation

Back propagation is an essential algorithm to train deep neural networks. It is the fundamental component for adjusting the neural network's weights in order to reduce the discrepancy between the expected and actual outputs. It is a mathematical method for quickly calculating the loss function's gradient with regard to the network's weights. To minimise the loss function, this gradient—also called the error gradient—indicates the direction and size of the changes that are required. The network learns to make better predictions over time by repeatedly updating its weights in the opposite direction of the gradient.

Decomposing the gradient into partial derivatives is made possible by the chain rule, which makes it computationally tractable to effectively compute the gradient via successive layers of the network. The approach iteratively computes the loss function gradient with respect to each layer's output, starting with the output layer and working its way backward through the network. It then propagates this error gradient. Using an optimisation approach like stochastic gradient descent (SGD) or a derivative of it, the network weights are adjusted as the error gradient is computed for each layer.

Overfitting, in which the model becomes too used to its training data and fails to generalise to new data, is a major obstacle when training convolutional neural network (CNN) models with backpropagation. To reduce the likelihood of the overfitting different methods can be used like weight decay, which discourages complex models by penalising big weights, and dropout regularisation, which randomly eliminates neurons during training to avoid co-adaptation.

4.2.6 Common Loss Functions

Loss functions are crucial for directing neural network optimisation. In order for the network to improve its performance repeatedly, these functions measure the difference between the expected and actual values. Here the impact of various loss functions used by convolutional neural networks (CNNs) are presented.

Mean Squared Error (MSE):

A common and essential loss function is Mean Squared Error or MSE for short. It takes all the data points and finds the average of the squared discrepancies between the expected and actual values. Equation 4.6 is the formula for MSE:

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{4.6}$$

where:

n is the total number of data points.

y_i represents the actual value.

$\hat{y}_i$ represents the predicted value.

The simplicity and ease of implementation of MSE make it useful. But, in cases with outliers, it has a tendency to punish big mistakes severely, which can cause convergence to be delayed.

Binary Cross-Entropy Loss:

When it comes to binary classification tasks, Binary Cross-Entropy Loss (or Log Loss) is a popular choice [83]. It is a measure of how different the actual distribution of binary outcomes is from the projected distribution. It is computed as shown un equation 4.7.

$$BCE=-\frac{1}{n}\sum_{i=1}^{n}\left(y_i\, log\left(\hat{y}_i\right)+\left(1-y_i\right) log\left(1-\hat{y}_i\right)\right) \tag{4.7}$$

where:

n denotes the total number of data points.

y_i represents the actual label (0 or 1).

$\hat{y}_i$ represents the predicted probability of the positive class.

Categorical Cross-Entropy Loss:

For problems involving more than one class, one can employ Categorical Cross-Entropy Loss, which is an expansion of Binary Cross-Entropy Loss is used across many classes, it calculates the dissimilarity between the actual and anticipated probability distributions. Categorical cross-entropy loss can be expressed in equation 4.8:

$$CCE = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m} y_{ij}\, log\left(\hat{y}_{ij}\right) \tag{4.8}$$

where:

n denotes the total number of data points.

m represents the number of classes.

y_{ij} represents the actual probability of data point i belonging to class j.

$\hat{y}_{ij}$ represents the predicted probability of data point i belonging to class j.

An example of a multi-class classification problem would be the detection of various diseases in banana and papaya plants. Categorical Cross-Entropy Loss would help the model to accurately estimate the probabilities linked with each class.

Weighted Loss Functions:

To fix class imbalances or give some classes more weight than others, it could be useful to give varying weights to different types of data or classes in particular situations. Model training becomes more versatile with the use of weighted loss functions, which allow these weights to be incorporated into the loss computation. To improve the model's ability to detect and priorities diseases, for example, greater weight to classes that represent diseases that are more harmful may be given.

4.2.7 Dropout Operation

A regularisation approach frequently used in deep learning architectures to avoid or reduce overfitting is dropout. By randomly removing neurons (both visible and hidden) during training, it improves the model's generalizability.

4.2.8 Learning Strategy

The learning technique is one of the most important factors that decide how well a model trains. To minimise the difference between expected and actual outcomes, a neural network modifies its parameters involving data, model design, and optimisation algorithms. Here are some methods including learning rate scheduling, batch normalisation, data augmentation, and regularisation that are used to train convolutional neural networks (CNNs).

- **Learning Rate Scheduling:** An essential part of convolutional neural network (CNN) training is the learning rate, which controls the size of optimisation parameter changes. Poor performance might result from oscillations or convergence to local minima caused by a set learning rate. Dynamic adjustments to the learning rate are made using learning rate scheduling approaches throughout training. The goal is to find a medium between early, fast development and later, fine-tuned progress. Common approaches include adaptive algorithms like RMSprop and Adam as well as cyclic learning rates, exponential decay, and step decay. For best results different learning rate plans that are specific to the dataset and the design of the model are considered.

- **Batch Normalization:** Batch normalization is a method that normalizes the activations of each layer during training, which helps to alleviate the internal covariate shift problem. Additionally, it serves as a regularizer, which reduces the burden on other regularization methods such as dropout. It strengthens the model's resilience by making sure that various batches of input data behave consistently.

- **Data Augmentation:** Data augmentation is an important and fundamental method for expanding the variety and amount of training data. It improves the model's ability to generalise to new data by enhancing the training set using image manipulations including scaling, rotating, translating, flipping, and cropping. It is essential for training deep learning models with limited resources, where labelled data may be sparse and expensive to get.

- **Transfer Learning:** The goal of transfer learning is to bootstrap the training of task-specific models with limited labelled data by leveraging pre-trained models on large-scale datasets. It allows for faster convergence and better performance by adjusting the parameters of a pre-trained model on a new dataset. This is particularly useful when the new task is comparable to the one that the pre-trained model is trained on.

- **Ensemble Learning:** To boost prediction accuracy, ensemble learning combines several models. These approaches improve prediction accuracy and robustness by combining the predictions of several models, which reduces the impact of model biases and mistakes. By combining the strengths of different architectures it helps to monitor and manage work more effectively [75].

4.2.9 Testing Stage

Before using any deep learning models, it is essential to test them to make sure the system works as expected [76]. The testing procedures and techniques, as well as the main metrics used to evaluate the models' performance are as mentioned below.

- **Data Preparation for Testing:** The preparation of the testing dataset is a prerequisite to moving on to the testing phase. For the models to be as reliable as possible, the dataset should preferably include a wide variety of cases. In addition, the dataset has to be divided into two parts: the validation part and the testing part. When training, hyper parameters and models are chosen from the validation subset, and the testing subset is hidden until evaluation [77].
- **Evaluation Metrics:** During testing, a number of assessment measures are used to determine how well the deep learning models performed. The model's accuracy is a measure of how well it predicts, whereas precision is a measure of how many of those predictions really came true. The percentage of accurate predictions out of all real positive cases is determined by recall, which is also called sensitivity. The F1-score is a well-rounded indicator of the model's performance as it is the harmonic mean of recall and accuracy [78].
- **Cross-validation Techniques:** During cross-validation, the dataset is divided into various subsets. Each subset is then trained and tested using a different combination of these subsets. The results are then averaged. Ensuring that both the training and testing subsets are evenly distributed across classes is a

common goal of cross-validation techniques like k-fold and stratified cross-validation [79].

Fine-tuning and Iterative Testing: Making adjustments to the deep learning models in light of what is learned from the results analysis could also be a part of the testing phase. By modifying the model's architecture, hyper parameters, or training data, refinement may be done to achieve even better performance. Following each round of fine-tuning, the model undergoes iterative testing to evaluate the effects of the changes and guarantee that its performance is perpetually improved.

In order to improve deep learning models for reliable disease detection in agricultural settings, the testing step entails careful data preparation, metric selection, testing process execution, and result interpretation [80].

4.3 EXISTING TECHNIQUES USED IN WORK

In the present work, four state-of-the-art deep learning models are utilized to train and evaluate the performance in disease detection in banana and papaya plant. These models are YOLOv3, YOLOv8, EfficientNet and ResNet50. The selection criteria for these models is their proven effectiveness in the field of object detection and image classification as analysed from literature review [81, 82].

YOLOv3 (You Only Look Once, version 3) is a real-time object detection model that uses a single neural network to predict object classes and bounding boxes. Model is suitable for mobile devices in agriculture as it itself balances speed and accuracy [83]. For YOLO to function, it first grids the input image and then uses each grid cell to forecast the bounding boxes and class probabilities. An upgrade from its forerunners, YOLO V3 brought a number of improvements that led to better performance, such as multi-scale detection and a feature pyramid network. The architecture of YOLOv3 (You Only Look Once, version 3) is a highly optimized convolutional neural network for real-time object detection. It adopts a single-stage detection mechanism. At its core, YOLOv3 utilizes a feature extractor known as Darknet-53, which comprises 53 convolutional layers. Figure 4.1 represents architecture in the form of a block diagram. This backbone network is enhanced with residual connections and batch normalization, which help in stabilizing and accelerating the training process. Unlike traditional CNNs that use pooling for down sampling, YOLOv3 achieves this through stride-2 convolutions, preserving more spatial information. One of the key architectural advancements in YOLOv3 is its multi-scale detection capability. It makes predictions at three different scales: 13×13, 26×26, and 52×52 feature maps, corresponding to large, medium, and small objects respectively. This is particularly useful for detecting objects of varying sizes within the same image. At each of these scales, YOLOv3 applies convolutional layers to generate predictions based on the features extracted by Darknet-53. Each prediction involves three anchor boxes, allowing the model to output bounding box coordinates, an objectness score, and class probabilities for each anchor.

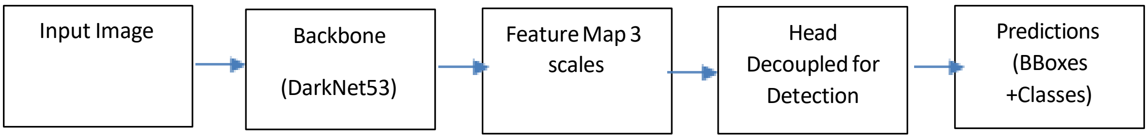


Figure 4.1: Block diagram of YOLOv3

YOLOv3 uses anchor boxes as predefined shapes to predict the dimensions of objects, enabling it to generalize well across various aspect ratios. The final output of the network at each scale includes multiple bounding boxes along with associated confidence scores and class probabilities, using sigmoid activation for better performance in multi-label classification scenarios. Overall, the architecture of YOLOv3 strikes a balance between speed and accuracy, making it a preferred choice for real-time applications in object detection.

YOLOv8 is the latest version of the YOLO family, incorporating transformer-based features, anchor-free detection, and improved model scaling. It provides enhanced accuracy and faster inference, making it suitable for precise disease detection in crop images. With the inclusion of new features and enhancements to the network architecture and training methodologies, YOLOv8 expands upon the previous version's successes [84]. With its improved object detecting mechanism, it achieves speed and precision that are unmatched by any other method. The architecture of YOLOv8 (You Only Look Once, version 8) represents a significant evolution in the

YOLO series, developed by Ultralytics. Unlike earlier versions, YOLOv8 adopts a modular and flexible design based on PyTorch, offering improvements in speed, accuracy, and deployment efficiency. It is classified as an anchor-free, single-stage detector, meaning it does not rely on predefined anchor boxes. Instead, it directly predicts object bounding box centers, widths, and heights, simplifying the training process and reducing hyper parameter tuning. At its core, it consists of three main components: the Backbone, the Neck, and the Head as shown in figure 4.2. The Backbone is responsible for feature extraction and uses a CSPDarknet variant optimized with C2f modules, which enhance gradient flow and computational efficiency. The Neck aggregates features from different scales using a Bi-directional Feature Pyramid Network (BiFPN), enabling better multi-scale feature fusion. This allows the model to detect small, medium, and large objects more accurately.

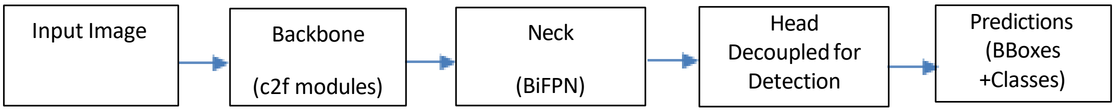


Figure 4.2: Block diagram of YOLOv8

The Head of YOLOv8 is decoupled, meaning it separates classification and localization tasks into different branches, which improves learning and inference. It uses Distribution Focal Loss (DFL) for better bounding box regression and supports multi-task outputs, making it suitable for object detection, segmentation, and classification. It’s architecture is highly optimized for deployment, offering lightweight versions (YOLOv8n, YOLOv8s) for edge devices and larger versions (YOLOv8m, YOLOv8l, YOLOv8x) for high-performance systems. This modernized architecture positions it as one of the most robust and versatile models for real-time vision applications.

ResNet50 is a deep convolutional network with 50 layers based on residual connections. It allows training of deeper networks by mitigating the vanishing gradient problem. Widely adopted for classification tasks, it is particularly effective in identifying subtle disease symptoms in leaf imagery [37]. A 50-layer variation of the RESNET architecture, it has shown outstanding performance in a number of computer vision applications, such as object identification and image classification. It can accurately detect indications of papaya and banana plant diseases because to its capacity to extract and find complex patterns and small variations from images. The architecture begins with a 7×7 convolutional layer followed by batch normalization, a ReLU activation, and a max-pooling layer [89]. The core of this model is made up of four stages of bottleneck residual blocks. Each bottleneck block contains three convolutional layers: a 1×1 layer for reducing dimensions, a 3×3 layer for processing, and a 1×1 layer for restoring dimensions. These blocks are stacked as follows across the four stages: 3 blocks in Stage 1, 4 in Stage 2, 6 in Stage 3, and 3 in Stage 4 — totaling 16 bottleneck blocks and 48 convolutional layers, plus the initial and final layers. Figure 4.3 represents it in the form of block diagram. It used skip connections that bypass one or more layers by adding the input of a residual block to its output. This design facilitates the training of very deep networks by allowing the network to focus on learning residual mappings rather than full transformations. At the end of the architecture, a global average pooling layer is applied, followed by a fully connected layer and a softmax activation for classification. Due to its balance between depth and computational efficiency, it is widely adopted as a backbone in many modern deep learning models.

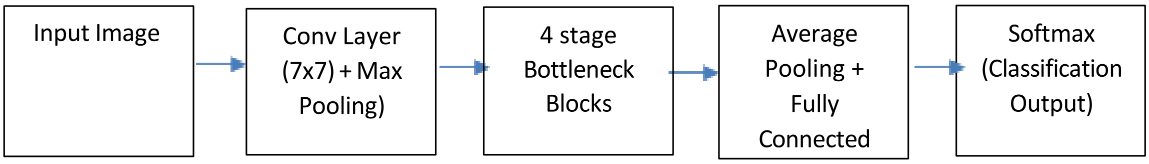


Figure 4.3: Block diagram of ResNet50

EfficientNet is a family of models that use compound scaling to optimize accuracy and efficiency. By uniformly scaling depth, width, and resolution, it delivers high performance with fewer parameters, making it ideal for disease detection in computationally limited environments . The use of compound scaling allows these designs to optimise the model's depth, breadth, and resolution all at once, leading to greater efficiency and accuracy [85]. It is ideal for use in agricultural and other resource-limited contexts due to its adaptability to various resource restrictions. The key innovation behind EfficientNet is the use of compound scaling, a method that uniformly scales the model’s depth (number of layers), width (number of channels), and resolution (input image size) using a set of fixed scaling coefficients. This systematic scaling approach allows it to outperform many existing CNNs while being significantly more efficient. The base model, EfficientNet-B0, is built on a carefully crafted backbone architecture obtained using neural architecture search (NAS). It starts with a stem layer consisting of a 3×3 convolution and batch normalization, followed by a series of MBConv blocks (Mobile Inverted Bottleneck Convolution). These blocks include depthwise separable convolutions and squeeze-and-excitation (SE) modules, which help the network focus on the most informative features.

Each MBConv block also includes residual connections, aiding in better gradient flow and training stability. It expands into multiple scaled variants — from B0 to B7 — where each successive model increases input resolution, network depth, and width according to the compound scaling formula. The final layers of the model include a global average pooling layer and a fully connected dense layer for classification. Block diagram of the complete architecture is depicted in figure 4.4.

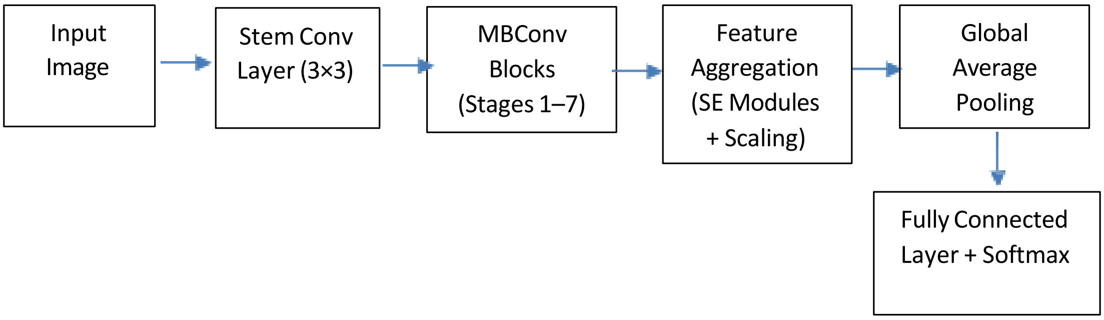


Figure 4.4: Block diagram of EfficientNet

Each model has been individually trained on the dataset collected in the work as mentioned in chapter 3. The potential of deep learning-based systems for use in agriculture may be further expanded by taking use of developments in training methods, model efficiency, and network topologies [86].

4.4 PROPOSED TECHNIQUE - ENSEMBLE OF YOLOV8 AND EFFICIENTNET

In the present work YOLOv8 and EfficientNet are ensembled to improve disease detection in Papaya and Banana for better precision and leveraging real time object detection also. The detection of 10 diseases affecting different parts of banana and papaya plants was carried out using four state-of-the-art deep learning models: YOLOv3, YOLOv8, ResNet50, and EfficientNet. Each model was trained and tested on a comprehensive dataset as discussed in chapter 3, with performance evaluated using standard metrices. Among the four models, YOLOv8 and EfficientNet emerged as the top performers in terms of accuracy, precision, recall and F1 Score. To enhance the effectiveness of the experiment, an ensemble approach is adopted, combining the strengths of YOLOv8 and EfficientNet. An Ensemble of YOLOv8 and EfficientNet has been implemented using a majority voting scheme. EfficientNet delivers high accuracy; its focus on efficiency might not translate directly to real-time object detection tasks, where speed is crucial, while YOLOv8's architecture and design choices prioritize speed and real-time performance. Both models have been trained on the same dataset. For making the predictions, the same input is passed through both models. Both models generate bounding boxes, class labels, and confidence scores independently. Then, a majority vote among the class labels predicted by both models is conducted. Finally, the class label with the highest confidence score is assigned. In case of a tie, results of EfficientNet models are considered as they have better accuracy than YOLOv8. The working of the flow diagram of the proposed model is given in Figure 4.5. TensorFlow and Pytorch frameworks of deep learning are used to create the ensembled model in Google Colab. Too optimize the performance data augmentation, transfer learning and fine tuning of parameters are used in training process. Adam optimizer has been used to train YOLOv8 model with a learning rate of 0.001 while in case of EfficientNet RMSprop optimizer is used with learning rate decay for improving generalization. Batch size of 64 has been used to train both the models over multiple epoch with early stopping mechanism to avoid overfitting.

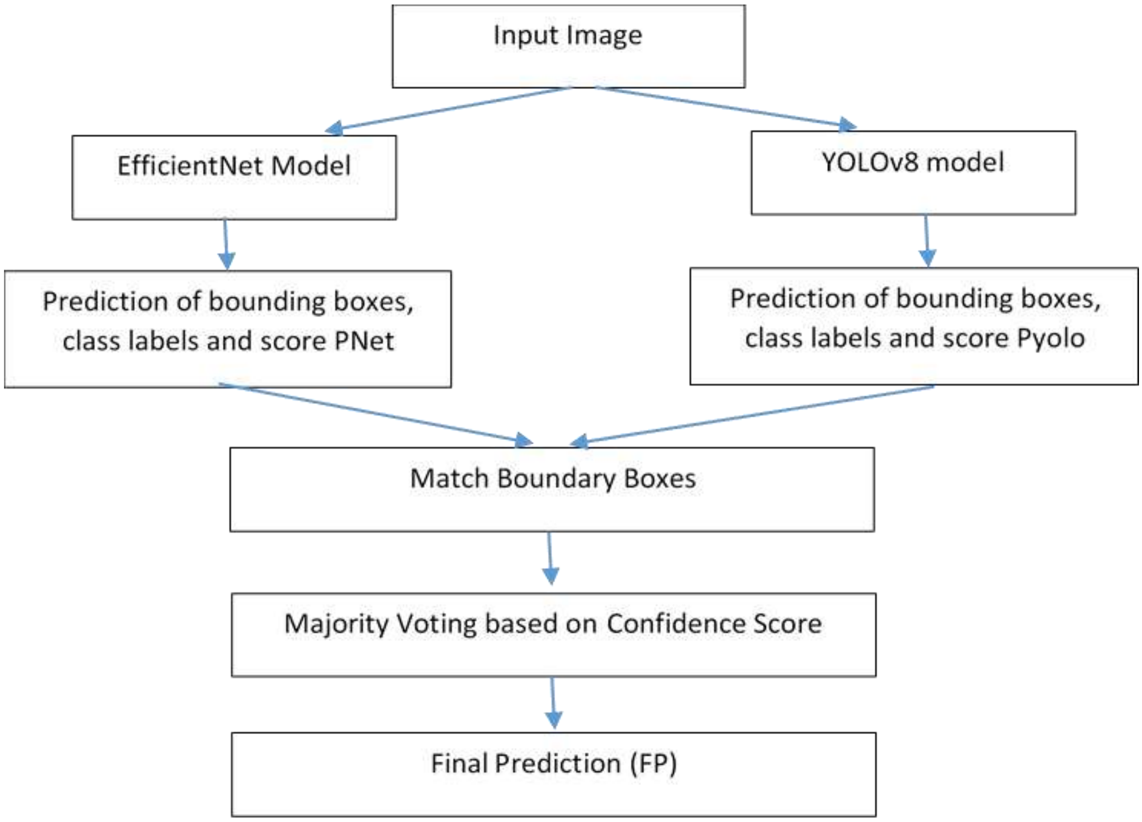


Figure 4.5: Flow diagram of proposed system

Mathematical Formulations

First step is to predict the class probabilities for object detection is represented in equation 4.9:

$$(\boldsymbol{I}) = \{\boldsymbol{c}_i, \boldsymbol{b}_i, \boldsymbol{s}_i : \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{N}\} \tag{4.9}$$

Next is to apply EfficientNet for feature extraction, the output will be given by equation 4.10:

$$(\boldsymbol{x}) = (\boldsymbol{W} * \boldsymbol{x} + \boldsymbol{b}) \tag{4.10}$$

The final classification is given using the softmax activation function. The proposed system is the ensemble of YOLOv8 and EfficientNet, and the classification is given using a majority voting scheme, with EfficientNet given priority in case of a tie, as given in Equation 4.11

$$\boldsymbol{Final\_Pred} = \boldsymbol{argmax}.\left(\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} \boldsymbol{\delta}(\boldsymbol{c}_i = \boldsymbol{c}).(\boldsymbol{s}_i + \boldsymbol{wt}_i)\right) \tag{4.11}$$

The primary objective is to maximize the accuracy and reduce the loss function, which can be defined as the summation of classification loss, Loss_class, and object detection loss,

Loss_object. Mathematically, it is represented in Equation (4.12):

$$\boldsymbol{Loss_{Total} = \alpha Loss_{class} + \beta Loss_{Objdet}} \tag{4.12}$$

Classification loss is defined using Binary Cross Entropy Loss as given in Equation 4.13:

$$\boldsymbol{Loss_{class} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log y_i + (1 - y_i)\log(1 - y_i]} \tag{4.13}$$

Object detection loss is calculated as smooth L1 loss as given in Equation 4.14:

$$\boldsymbol{Loss_{objdect} = \sum_{i=1}^{N}(b_i - \hat{b}_i)} \tag{4.14}$$

The symbols are defined in table 4.1

Table 4.1: Symbols used in Equations

Symbol	Meaning
$\boldsymbol{\delta}$	Indicator Function
$\boldsymbol{w}$	Weight to resolve the tie in the final classification
$\boldsymbol{I}$	Input Image
$\boldsymbol{ci}$	Class Label
$\boldsymbol{bi}$	Bounding box coordinates
$\boldsymbol{si}$	Confidence score
$\boldsymbol{W}$	Weight matrix of the convolutional kernel
$\boldsymbol{x}$	Input Feature Map
$\boldsymbol{b}$	Bias term
$\boldsymbol{\sigma}$	Sigmoid Activation Function

The pseudocode of the proposed method is given below:

Input: Image (I)

Output: Classification Class (C)

```
1.  Load YOLOv8 and Efficient Net
2.  Preprocess $\boldsymbol{I}$
3.  $\boldsymbol{P\_Yolo}$= Prediction from YOLOv8
    $\boldsymbol{P\_Eff}$= Prediction from EfficientNet
4.  Yolo_class, Yolo_Score= Extract($\boldsymbol{P\_Yolo}$)
    Eff_class, Eff_scores=Extract($\boldsymbol{P\_Eff}$)
5.  If Yolo_Score > Eff_Score
      Ens_class, Ens_Score= Yolo_class, Yolo_score
    Else
      Ens_class, Ens_Score= Eff_class, Eff_score

6.  End
```

Experimental evaluations demonstrate the effectiveness of the ensemble approach in disease detection of papaya and banana crops and are discussed in next chapter. Using the two models has several advantages than using either EfficientNet or YOLO V8 alone. The first benefit is an increase in the general accuracy of disease diagnosis made possible by merging the two models' capacities. While YOLO V8 excels at localising specific objects, EfficientNet improves the accuracy of disease classification. Second, ensembling has the potential to lessen the amount of false positives and false negatives that are caused by the inherent shortcomings of individual models. By combining many predictions, the ensemble model has the potential to provide detection performance that is both more accurate and consistent.

The inference time of the ensemble model is somewhat longer than that of the individual models, even though YOLO V8 and EfficientNet display varying degrees of computational efficiency. Because of the combined computing load of both models, it is projected that inference time would rise. Despite a little increase in computing cost, the ensemble's performance benefits more than make up for it.

4.5 SUMMARY

Using deep learning techniques, this chapter presents a novel approach for disease detection in papaya and banana crops. Convolution, nonlinearity activation, pooling, fully-connected layers, backpropagation, common loss functions, dropout operation, proposal generation, learning strategy, testing stage, transfer learning, and evaluation metrics are all thoroughly covered in the first part of the chapter, which focused on the basic components of CNNs. The convolution operation allows for the feature extraction from input data by use of filters. By introducing nonlinearities into the network, activation functions like ReLU (Rectified Linear Unit) make it easier for the network to learn complicated patterns. Layers that pool or subsample data help lower the dimensionality of feature maps, which improves computing performance and decreases overfitting. The latter stages of a neural network, fully-connected layers, are responsible for combining features that have been learnt for purposes of regression or classification. Loss functions that are commonly used to measure the difference between expected and ground truth values include categorical cross-entropy and mean squared error.

Training optimisation is also heavily dependent on a number of learning methodologies, such as learning rate scheduling and gradient descent optimisation algorithms. In order to learn about the model's generalizability, the testing phase assesses it on unseen data. The use of pre-trained models to solve new problems encourages model reuse, and speeds up convergence are what transfer learning is all about.

Chapter – 5

RESULTS AND DISCUSSIONS

Maintaining agriculture productivity and assuring food security depend on accurate diagnosis of diseases in papaya and banana crops. In this chapter, a novel ensemble method that combines the strengths of two cutting-edge deep learning models—EfficientNet and YOLOv8 is discussed. This ensemble approach aims to improve detection accuracy by combining the characteristics of EfficientNet's efficient design with YOLO $_{V8}$'s real-time object identification capabilities, thereby overcoming the limits of individual models. A dataset with high-quality images gathered from various online sources, agricultural farms and labs forms the basis of this study. These images document plant diseases under a range of lighting situations, from partial shade to full sun, taken with both consumer-grade and high-end DSLR cameras. The detection of diseases in banana and papaya plants is carried out using four distinct deep learning models – YOLOv3, YOLOv8, EfficientNet, ResNet50 to ensure a robust and comprehensive approach. These models are trained on custom dataset comprising of images of various diseases in papaya and banana plants. A strong foundation for training and assessment is provided by data augmentation methods, which increased the dataset to 80,000 images.

The first model utilized the EfficientNet architecture, known for its scalability and efficiency in balancing accuracy and computational complexity. EfficientNet leverages compound scaling, optimizing the depth, width, and resolution of the network to achieve high performance, making it a strong candidate for disease detection tasks. The second and third models employed two variations of the YOLO (You Only Look Once) framework, specifically YOLOv3 and YOLOv8. YOLOv3 is a well-established real-time object detection model, capable of detecting multiple disease regions within an image efficiently. On the other hand, YOLOv8 represents advancement in the YOLO family, offering enhanced accuracy and speed due to its improved architecture and anchor-free detection mechanism. Both versions are evaluated to assess their suitability for plant disease detection under different conditions. The fourth model used is ResNet50, a deep residual network renowned for its ability to train very deep neural networks effectively by overcoming the vanishing gradient problem. ResNet50, with its 50 layers, is particularly adept at extracting detailed features, making it an ideal candidate for analyzing complex visual patterns such as those presented by plant diseases.

The performance evaluation of each model is carried out using four key metrics: Precision, Recall, F1-Score and Accuracy [87]. Confusion matrix which is a performance evaluation tool used in classification problems to summarize the predictions made by a machine learning model compared to the actual labels is also used. It provides a comprehensive view of the model's accuracy and errors by showing the counts of true and false predictions for each class [88]. For a binary classification, the confusion matrix has four key components:

True Positives (TP): Correct predictions where the model correctly identifies the positive class.

True Negatives (TN): Correct predictions where the model correctly identifies the negative class.

False Positives (FP): Incorrect predictions where the model incorrectly labels a negative instance as positive (also called Type I error).

False Negatives (FN): Incorrect predictions where the model misses a positive instance and labels it as negative (also called Type II error).

For multi-class classification, the matrix expands to include rows and columns for each class, showing how often instances of one class are predicted as another [89, 90]. It helps calculate key metrics like Precision, Recall, Accuracy, and F1-Score.

- **Precision** measures the accuracy of the positive predictions, indicating the proportion of correctly identified disease cases out of all predicted cases. A high precision ensures fewer false positives. Mathematically precision is shown in equation 5.1

$$\text{Precision} = TP / (TP + FP) \tag{5.1}$$

- **Recall** evaluates the model's ability to detect actual disease cases, calculated as the proportion of true positive cases identified out of all actual cases, minimizing false negatives. Recall is mathematically defined as in equation 5.2:

$$\text{Recall} = TP / (TP + FN) \tag{5.2}$$

- **F1-Score** as shown in equation 5.3 is the harmonic mean of precision and recall, providing a balanced measure that accounts for both false positives and false negatives. It is particularly useful when the dataset is imbalanced.

$$F1 = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \tag{5.3}$$

- **Accuracy** as shown in equation 5.4 is measures the proportion of correctly predicted instances out of the total instances evaluated.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \tag{5.4}$$

The chapter is divided into five sections, each analyzing different deep learning models for disease detection in banana and papaya plants. It begins with a detailed evaluation of EfficientNet followed by YOLOv3, YOLOv8 and ResNet50. And results of ensemble model are presented with comparison.

5.1 RESULTS OF YOLOV8

The model demonstrates strong performance across all evaluation metrics as shown in table 5.1. It achieves a precision of 0.921, indicating a high rate of correctly identified disease cases among the predicted positives. With a recall of 0.923, it effectively captures most actual disease instances. The F1-score of 0.920 reflects a good balance between precision and recall, and an overall accuracy of 0.924 confirms the model's reliability in disease classification.

Table 5.1: Performance Metrics of YOLOv8

Metric	Value
Precision	0.921
Recall	0.923
F1-Score	0.920
Accuracy	0.924

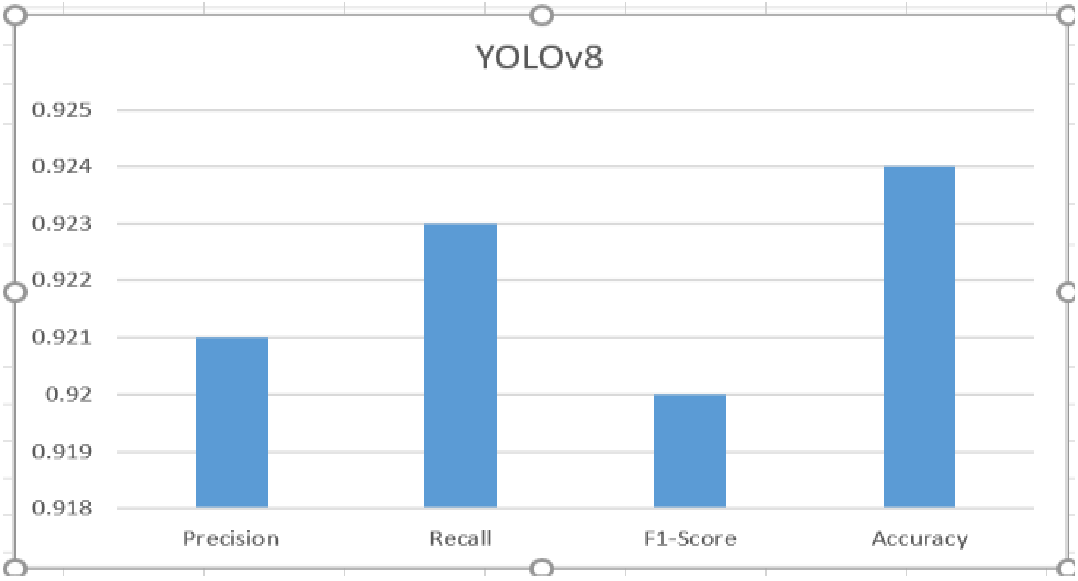


Figure 5.1: Performance Metrics of YOLOv8

These metrics reflect YOLOv8's ability to effectively identify and differentiate between multiple disease classes, showcasing its potential for real-world agricultural disease detection systems. The confusion matrix to derive the results is presented below in Table 5.2.

Table 5.2: Confusion Matrix in model using YOLOv8

	Actual \ Predicted	Papaya Leaf Curl	Papaya Mosaic Virus	Papaya Leaf Spot	Papaya Stem Foot Rot	Papaya Fungus	Banana Leaf Panama Wilt	Banana Sigatoka	Banana Leaf Spot	Banana Stem Panama Wilt
Papaya Leaf Curl	920	30	10	5	10	5	8	6	3	3
Papaya Mosaic Virus	20	910	15	12	8	10	5	5	10	5
Papaya Leaf Spot	15	10	925	12	8	8	5	7	5	5
Papaya Stem Foot Rot	10	12	8	930	10	5	5	5	5	10

	Actual \ Predicted	**Papaya Leaf Curl**	**Papaya Mosaic Virus**	**Papaya Leaf Spot**	**Papaya Stem Foot Rot**	**Papaya Fungus**	**Banana Leaf Panama Wilt**	**Banana Sigatoka**	**Banana Leaf Spot**	**Banana Stem Panama Wilt**
Papaya Fungus	10	8	5	10	935	5	8	5	5	9
Banana Leaf Panama Wilt	5	5	8	5	5	940	10	7	5	10
Banana Sigatoka	8	10	5	5	7	12	920	10	13	10
Banana Leaf Spot	5	8	10	7	5	10	15	920	10	10
Banana Stem Panama Wilt	8	12	7	10	8	8	12	8	925	12
Seed Banana	10	10	12	10	8	10	8	8	8	920

The diagonal elements in confusion matrix represent True Positives (TP), indicating the correctly classified samples for each disease. Most diseases have high TP values (e.g., Banana Leaf Panama Wilt has 940 TP, Papaya Fungus has 935 TP), showing that the model is effective at identifying these diseases. False Positives (FP) are off-diagonal elements in the column for each disease. For example: Papaya Leaf Curl has 49 FP from other diseases (e.g., 30 from Mosaic Virus, 10 from Papaya Leaf Spot, etc.). Diseases with higher FP, such as Banana Sigatoka (e.g., 13 misclassified samples from Banana Panama Wilt), indicate some overlap in their feature characteristics with other classes.

Goal is to offer a more detailed study; therefore, the performance of the model for each individual diseases category is investigated.

Table 5.3: Disease-Specific Performance Metrics (YOLOv8)

Disease Class	Precision	Recall	F1-Score
Papaya Leaf Curl	0.91	0.92	0.915
Papaya Mosaic Virus	0.89	0.91	0.90
Papaya Leaf Spot	0.92	0.925	0.92
Papaya Stem Foot Rot	0.92	0.93	0.92
Papaya Fungus	0.93	0.935	0.93
Banana Leaf Panama Wilt	0.93	0.94	0.93
Banana Sigatoka	0.92	0.92	0.92
Banana Leaf Spot	0.94	0.92	0.93
Banana Stem Panama Wilt	0.93	0.925	0.92
Seed Banana	0.92	0.92	0.92

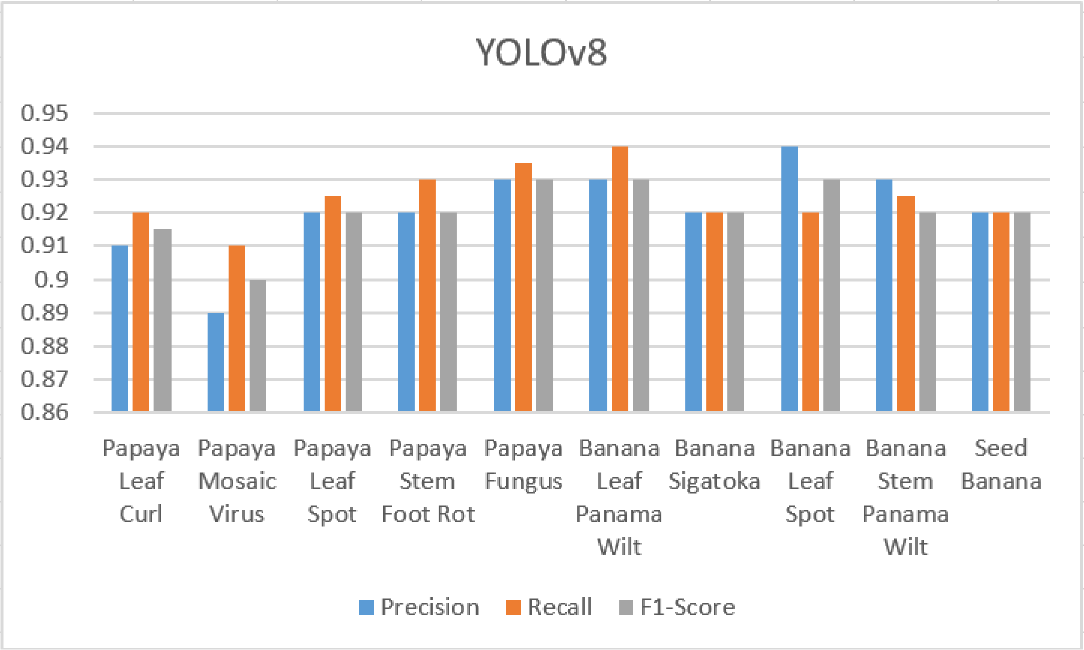


Figure 5.2: Disease-Specific Performance Metrics (YOLOv8)

YOLOv8 demonstrated strong classification performance with a high precision of 92.1%, effectively minimizing false positives and reducing the risk of unnecessary actions such as overuse of pesticides or removal of healthy crops. Its recall of 92.3% indicates that the model successfully identified the majority of diseased plants, which is critical for preventing the spread of undetected infections. With an F1-score of 92.0%, YOLOv8 achieves a well-balanced trade-off between precision and recall, ensuring consistent reliability across all ten disease classes. This balanced performance makes it well-suited for practical agricultural applications, where accurate and efficient disease detection is essential.

5.2 RESULTS OF YOLOv3

The model shows consistent and reliable performance with a precision of 0.890, indicating accurate identification of positive cases. A recall of 0.891 reflects its effectiveness in capturing most actual positives. The F1-score of 0.891 highlights a balanced trade-off between precision and recall, while an accuracy of 0.891 confirms the model's overall correctness across all predictions. The performance of the model in terms of its precision, recall and F1-Score is mentioned in Table 5.4 and pictorially in Figure 5.3.

Table 5.4: Performance Metrics of YOLOv3

Metric	Value
Precision	0.890
Recall	0.891
F1-Score	0.891
Accuracy	0.891

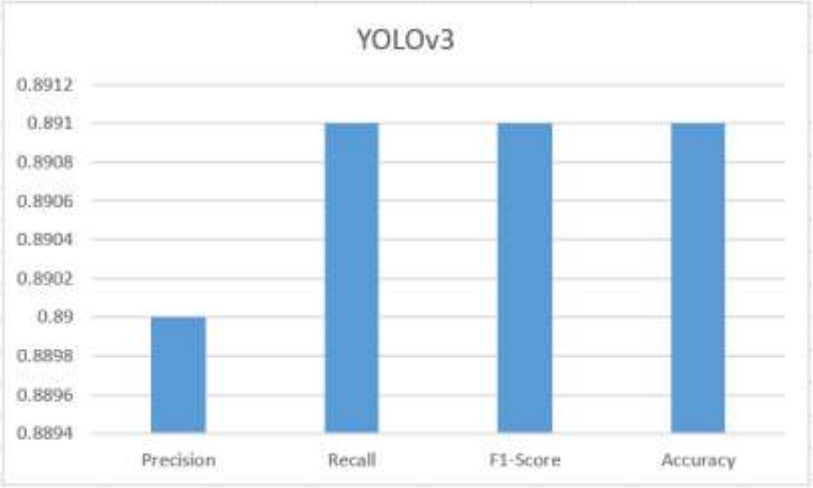


Figure 5.3: Performance Metrics of YOLOv3

The YOLOv3 model demonstrates moderate performance in the detection and classification of diseases, achieving a precision of 0.89, recall of 0.891, and an F1 score of 0.891. While these metrics reflect a reasonably balanced model, they suggest that the model occasionally struggles with false positives and false negatives. With a precision of 0.89, the model correctly predicts 89% of positive cases but still allows for some incorrect predictions. Similarly, the recall of 0.891 indicates that the model identifies 89.1% of actual disease cases but misses a notable portion, leading to false negatives. The F1 score of 0.891 shows that the model maintains a fair balance between precision and recall but does not excel in either. Overall, YOLOv3 performs adequately for disease detection but may not be the ideal choice for applications requiring extremely high accuracy or reliability. The confusion matrix for the same has been exhibited in Table 5.5 with the details of classification and mis classifications.

Table 5.5: Confusion Matrix in model using YOLOv3

Actual \ Predicted	**Papaya Leaf Curl**	**Papaya Mosaic Virus**	**Papaya Leaf Spot**	**Papaya Stem Foot Rot**	**Papaya Fungus**	**Banana Leaf Panama Wilt**	**Banana Sigatoka**	**Banana Leaf Spot**	**Banana Stem Panama Wilt**	**Seed Banana**
Papaya Leaf Curl	890	15	20	10	15	10	10	10	10	10
Papaya Mosaic Virus	10	885	20	15	15	10	15	10	10	10
Papaya Leaf Spot	15	10	895	10	10	20	10	10	10	10
Papaya Stem Foot Rot	10	15	15	890	15	10	10	10	10	15
Papaya Fungus	10	10	10	10	900	10	15	15	10	10
Banana Leaf Panama Wilt	10	15	20	10	15	890	10	10	10	10
Banana Sigatoka	10	10	15	10	15	15	890	15	10	10
Banana Leaf Spot	15	10	10	15	10	15	10	885	15	10
Banana Stem Panama Wilt	10	10	10	15	10	10	15	10	900	10
Seed Banana	15	10	10	10	10	15	10	10	10	890

To conduct a more comprehensive analysis, the model's performance for each individual disease category is evaluated and represented in Table 5.6 and Figure 5.4

Table 5.6: Disease-Specific Performance Metrics (YOLOv3)

Disease Class	Precision	Recall	F1 Score
Papaya Leaf Curl	0.894	0.89	0.89
Papaya Mosaic Virus	0.89	0.88	0.89
Papaya Leaf Spot	0.877	0.89	0.89
Papaya Stem Foot Rot	0.894	0.89	0.89
Papaya Fungus	0.88	0.90	0.89
Banana Leaf Panama Wilt	0.90	0.89	0.90
Banana Sigatoka	0.90	0.89	0.90
Banana Leaf Spot	0.898	0.88	0.89
Banana Stem Panama Wilt	0.89	0.90	0.90
Seed Banana	0.89	0.89	0.89

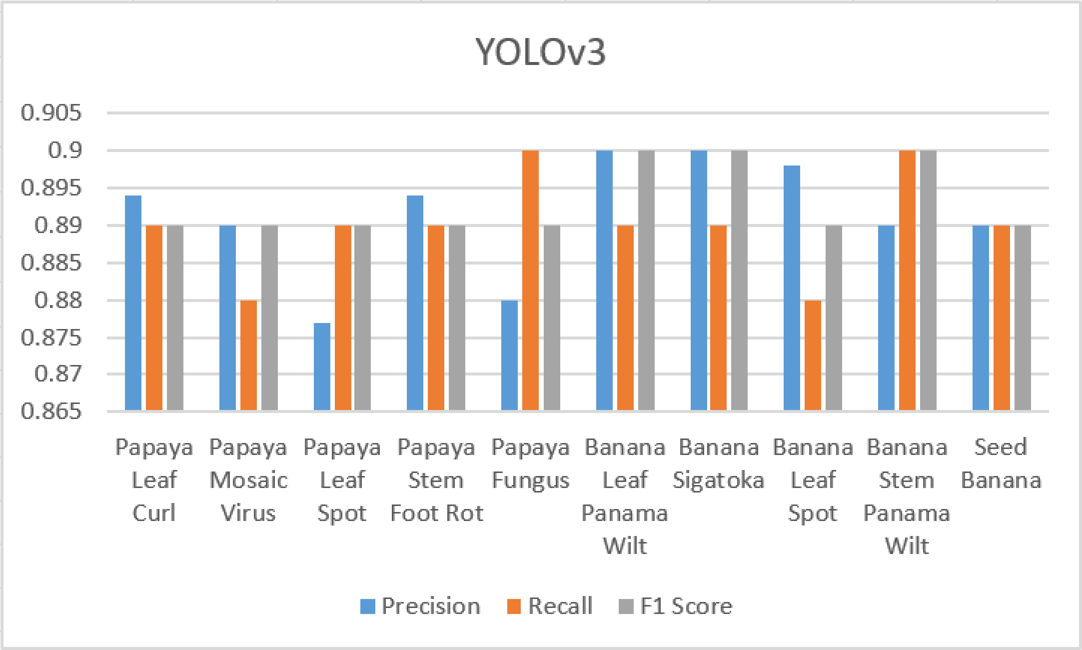


Figure 5.4: Disease-Specific Performance Metrics YOLOv3

The YOLOv3 model exhibits average performance in detecting and classifying diseases, with a precision of 89%, a recall of 89.1%, an F1 score of 89.1% and accuracy of 89.1%. These metrics indicate a fairly balanced performance but also highlight occasional challenges with false positives and false negatives.

5.3 RESULTS OF RESNET50

The model demonstrates good performance across all evaluation metrics, with precision, recall, and F1-score each at 0.90, indicating a well-balanced ability to correctly identify and classify disease instances. An accuracy of 0.901 further confirms the model's overall reliability and effectiveness in disease detection tasks. Performance of the model is exhibited in the following Table 5.7 and Figure 5.5.

Table 5.7: Performance Metrics of ResNet50

Metric	Value
Precision	0.900
Recall	0.900
F1-Score	0.900
Accuracy	0.901

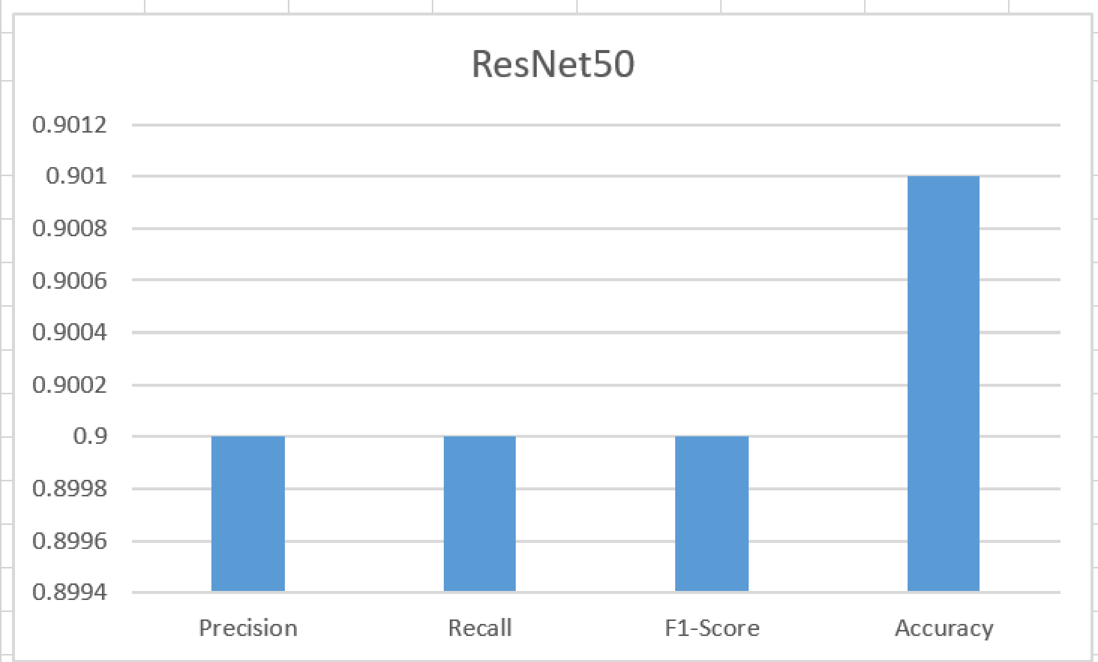


Figure 5.5: Performance Metrics of ResNet50

The ResNet50 model demonstrates its performance in detecting diseases across all 10 classes, with true positives (TPs) ranging from 880 to 910 for each class, aligning with the high precision of 0.900 and recall of 0.900. Confusion matrix for the same is shown in Table 5.8. The model effectively captures most disease instances, as evidenced by the relatively low false negatives (FNs), ranging between 60 and 90 per class, indicating that it successfully detects the majority of true disease cases. False positives (FPs) are distributed evenly across classes, with values ranging from 70 to 100, reflecting the model's ability to avoid bias toward specific diseases. Some classes, such as Leaf Spot and Sigatoka, perform slightly better, with TPs closer to 910. The model strikes a balanced trade-off between precision and recall, prioritizing recall and minimizing false negatives, which is ideal for applications where detecting as many true cases as possible is crucial.

Table 5.8: Confusion matrix of ResNet50

Actual \ Predicted	**Papaya Leaf Curl**	**Papaya Mosaic Virus**	**Papaya Leaf Spot**	**Papaya Stem Foot Rot**	**Papaya Fungus**	**Banana Leaf Panama Wilt**	**Banana Sigatoka**	**Banana Leaf Spot**	**Banana Stem Panama Wilt**	**Seed Banana**
Papaya Leaf Curl	900	15	10	15	10	10	5	10	5	10
Papaya Mosaic Virus	10	905	15	10	15	10	10	5	10	10
Papaya Leaf Spot	15	10	910	10	10	15	15	10	10	15
Papaya Stem Foot Rot	10	10	10	900	15	10	15	10	5	15
Papaya Fungus	15	15	10	15	885	15	10	10	10	15
Banana Leaf Panama Wilt	10	10	15	10	10	895	15	10	15	10
Banana Sigatoka	10	15	10	15	10	10	910	10	10	10
Banana Leaf Spot	5	10	10	10	15	10	10	905	10	15
Banana Stem Panama Wilt	10	10	15	10	10	10	10	15	900	10
Seed Banana	5	10	15	10	10	15	10	10	10	905

Going into more details disease specific performance is depicted in Table 5.9 and Figure 5.6

Table 5.9: Disease-Specific Performance Metrics (ResNet50)

Disease Class	Precision	Recall	F1 Score
Papaya Leaf Curl	0.91	0.90	0.90
Papaya Mosaic Virus	0.90	0.90	0.90
Papaya Leaf Spot	0.89	0.91	0.90
Papaya Stem Foot Rot	0.89	0.90	0.90
Papaya Fungus	0.89	0.88	0.89
Banana Leaf Panama Wilt	0.89	0.89	0.89
Banana Sigatoka	0.90	0.91	0.91
Banana Leaf Spot	0.91	0.90	0.91
Banana Stem Panama Wilt	0.90	0.90	0.90
Seed Banana	0.90	0.90	0.90

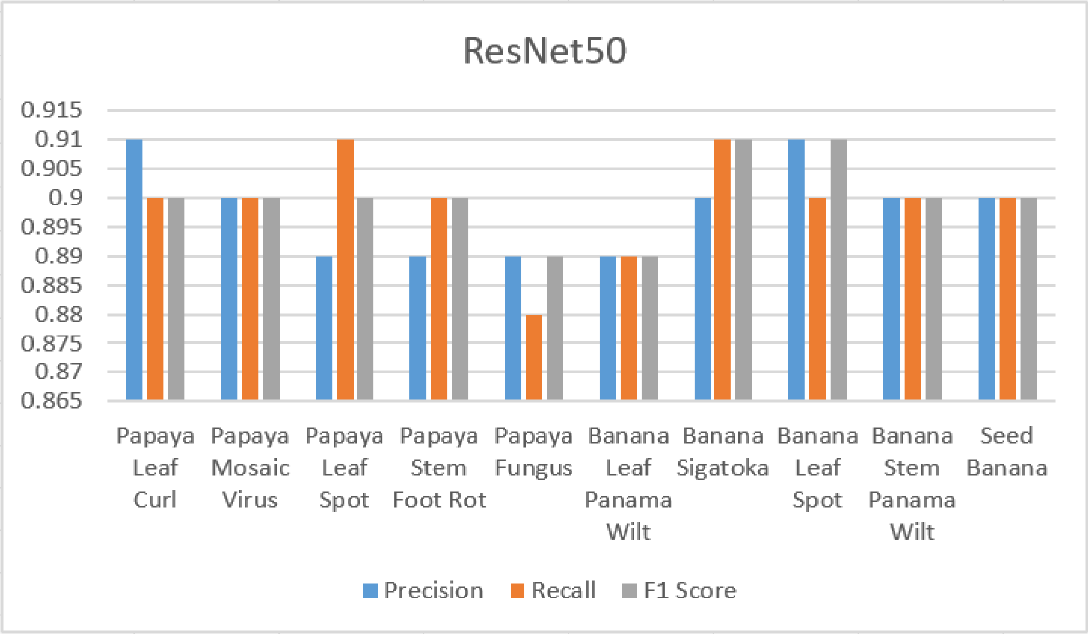


Figure 5.6: Disease-Specific Performance Metrics ResNet50

Overall, the ResNet50 model is reliable for disease detection in banana and papaya plants, demonstrating consistent and robust.

5.4 RESULTS OF EFFICIENTNET

The model exhibits excellent performance across all key evaluation metrics. With a precision of 0.90, it accurately identifies positive disease cases while minimizing false positives. A high recall of 0.96 indicates the model successfully detects nearly all actual disease instances, reducing the chance of missed diagnoses. The F1-score of 0.93 reflects a strong balance between precision and recall, and the overall accuracy of 95.9% confirms the model's reliability in correctly classifying disease conditions.

Table 5.10: Performance Metrics of EfficientNet

Metric	**Value**
Precision	0.900
Recall	0.960
F1-Score	0.930
Accuracy	0.959

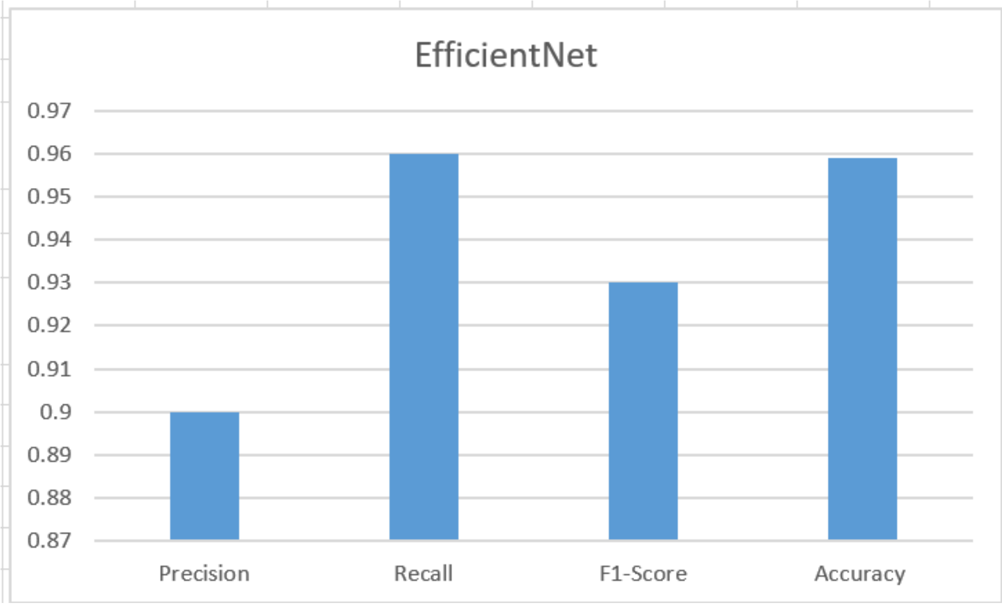


Figure 5.7: Performance Metrics of EfficientNet

The confusion matrix for the EfficientNet model demonstrates strong performance in detecting 10 diseases, with true positive (TP) values ranging from 895 to 920 for each class as shown in Table 5.11.

Table 5.11: Confusion matrix of EfficientNet

Actual \ Predicted	Papaya Leaf Curl	Papaya Mosaic Virus	Papaya Leaf Spot	Papaya Stem Foot Rot	Papaya Fungus	Banana Leaf Panama Wilt	Banana Sigatoka	Banana Leaf Spot	Banana Stem Panama Wilt	Seed Banana
Papaya Leaf Curl	920	20	10	15	10	5	5	5	5	5
Papaya Mosaic Virus	15	915	20	10	10	5	10	5	5	5
Papaya Leaf Spot	10	15	905	15	10	15	10	10	5	5
Papaya Stem Foot Rot	10	10	15	910	20	10	10	10	5	10
Papaya Fungus	10	15	10	20	900	15	10	10	10	10
Banana Leaf Panama Wilt	15	10	10	10	15	910	10	10	10	10
Banana Sigatoka	10	15	10	10	10	15	910	10	5	5
Banana Leaf Spot	10	10	15	10	10	10	10	915	10	10
Banana Stem Panama Wilt	10	10	10	10	10	15	10	15	900	10
Seed Banana	10	15	10	15	10	10	10	10	15	895

This high TP count aligns with the model’s recall of 0.960, indicating that the majority of actual disease cases are correctly identified. However, there are 80–105 false negatives (FN) per class, where the model fails to detect the correct disease, which slightly affects the model's ability to capture all instances. On the other hand, the model also exhibits 90–110 false positives (FP) per class, where diseases are incorrectly predicted, reflecting some degree of confusion between certain classes. This is consistent with the precision value of 0.90, which shows a slight trade-off in the model's ability to distinguish between similar diseases accurately. Disease specific analysis is presented in Table 5.12 and Figure 5.8.

Table 5.12: Disease-Specific Performance Metrics (EfficientNet)

Disease Class	Precision	Recall	F1 Score
Papaya Leaf Curl	0.90	0.92	0.91
Papaya Mosaic Virus	0.89	0.91	0.90
Papaya Leaf Spot	0.88	0.90	0.89
Papaya Stem Foot Rot	0.88	0.91	0.89
Papaya Fungus	0.89	0.90	0.90
Banana Leaf Panama Wilt	0.90	0.91	0.91
Banana Sigatoka	0.90	0.91	0.91
Banana Leaf Spot	0.90	0.91	0.91
Banana Stem Panama Wilt	0.91	0.90	0.91
Seed Banana	0.92	0.89	0.91

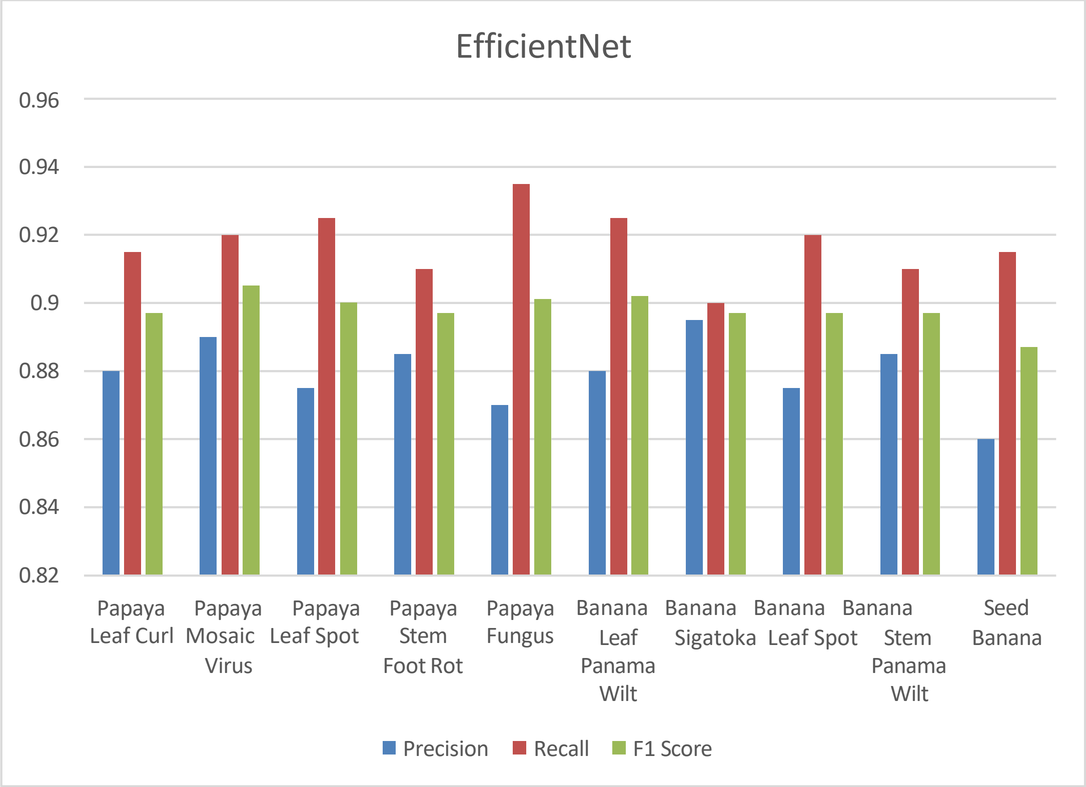


Figure 5.8: Disease-Specific Performance Metrics (EfficientNet)

5.5 RESULTS OF ENSEMBLE OF YOLOV8 AND EFFICIENTNET

The detection of 10 diseases affecting different parts of banana and papaya plants is carried out using four state-of-the-art deep learning models: YOLOv3, YOLOv8, ResNet50, and EfficientNet. These models are selected for their diverse architectures and proven capabilities in various computer vision tasks. The goal of the study is to evaluate their performance in detecting and classifying diseases across multiple categories and to identify the most effective approach for this task. Each model is trained and tested on a comprehensive dataset, with performance evaluated using standard metrics such as precision, recall, and F1 score. The results as discussed in previous sections are exhibited here for comparison in Table 5.13 and Figure 5.9

Table 5.13: Performance comparison of different models

Model	Precision	Recall	F1-Score	Accuracy
EfficientNet	.900	.960	.930	95.9%
YOLO $_{V3}$	.890	.891	.891	89.1%
YOLO $_{V8}$	.921	.923	.920	92.4%
ResNet50	.900	.900	.900	90.1%

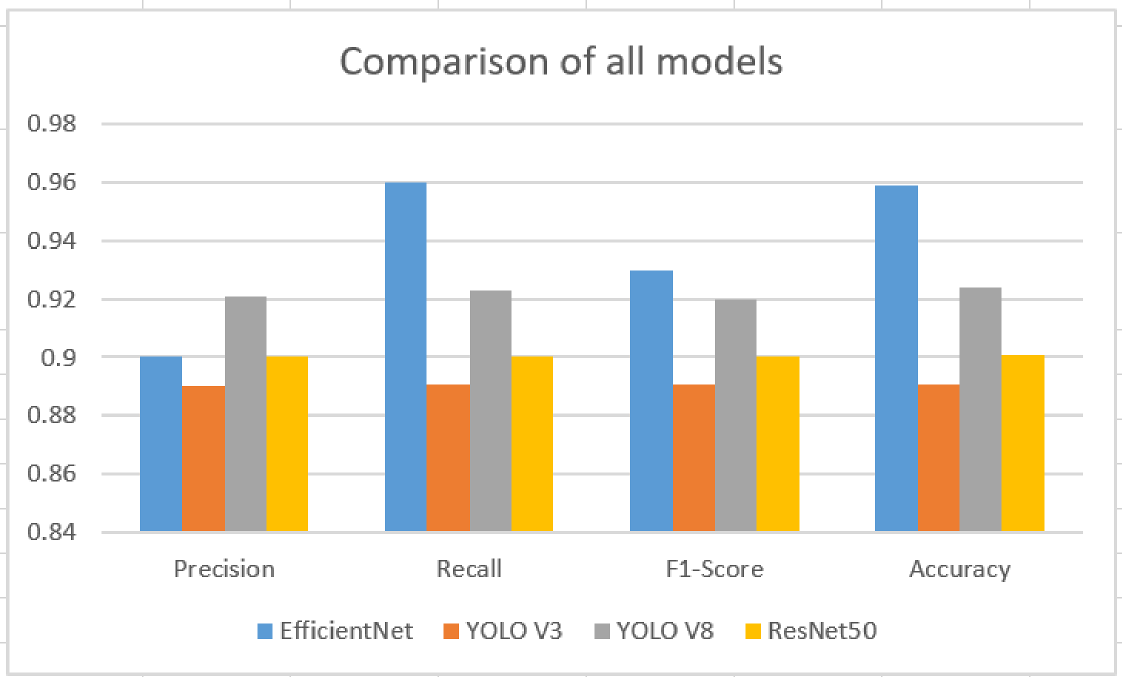


Figure 5.9: Performance Comparison of different Models

Among the four models, YOLOv8 and EfficientNet emerged as the top performers in terms of precision, consistently achieving higher scores compared to YOLOv3 and ResNet50. To enhance the effectiveness of the experiment, an ensemble approach is adopted, combining the strengths of YOLOv8 and EfficientNet. Table 5.14 and figure 5.10 exhibits the performance of ensemble model.

Table 5.14: Performance Metrics of Ensemble Model

Metric	**Value**
Precision	0.963
Recall	0.963
F1-Score	0.963
Accuracy	96.3%

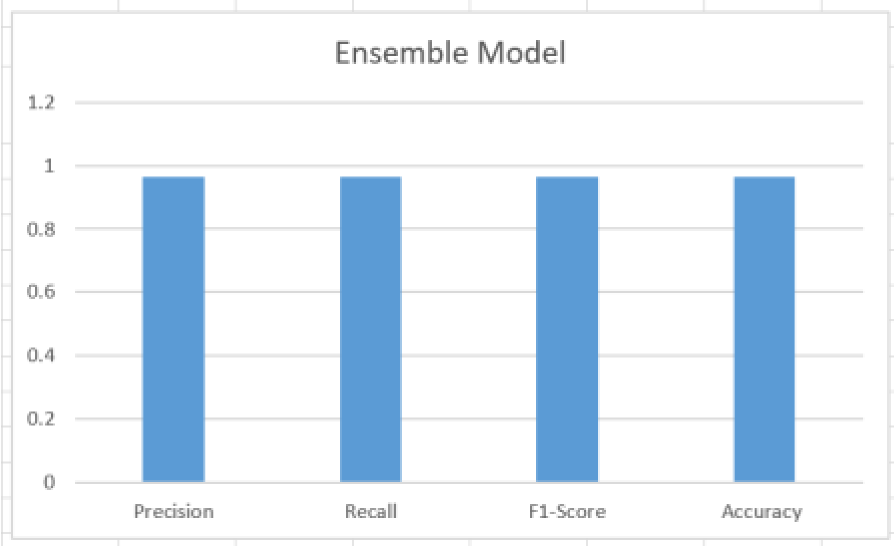


Figure 5.10: Performance Metrics of Ensemble Model

Table 5.15 displays the confusion matrix of the ensembled model and disease specific evaluation parameters are given in table 5.16. It is clearly apparent in the table that model outperforms all other models considered for the research. The model achieves high precision, recall and F1 Score of .963, which indicates a balanced ability to correctly classify disease cases while minimizing both false positives and false negatives.

Table 5.15: Confusion Matrix of Ensembled Model

Actual \ Predicted	**Papaya Leaf Curl**	**Papaya Mosaic Virus**	**Papaya Leaf Spot**	**Papaya Stem Foot Rot**	**Papaya Fungus**	**Banana Leaf Panama Wilt**	**Banana Sigatoka**	**Banana Leaf Spot**	**Banana Stem Panama Wilt**	**Seed Banana**
Papaya Leaf Curl	964	5	4	5	5	3	4	4	5	1
Papaya Mosaic Virus	4	962	6	5	4	3	4	5	5	2
Papaya Leaf Spot	5	4	965	5	3	4	3	4	4	3
Papaya Stem Foot Rot	4	5	5	961	6	3	3	5	5	3
Papaya Fungus	5	3	4	5	962	5	3	4	5	4
Banana Leaf Panama Wilt	3	3	4	3	5	964	5	4	4	5
Banana Sigatoka	4	3	3	5	3	5	964	4	5	4
Banana Leaf Spot	3	4	4	4	5	4	5	962	5	4
Banana Stem Panama Wilt	4	4	4	5	4	4	3	5	962	5
Seed Banana	4	3	3	3	5	4	5	4	4	965

Table 5.16: Disease-Specific Performance Metrics (Ensemble)

Disease Class	**Precision**	**Recall**	**F1 Score**
Papaya Leaf Curl	0.964	0.964	0.964
Papaya Mosaic Virus	0.9659	0.962	0.9639
Papaya Leaf Spot	0.9631	0.965	0.964
Papaya Stem Foot Rot	0.96	0.961	0.9605
Papaya Fungus	0.9601	0.962	0.961
Banana Leaf Panama Wilt	0.965	0.964	0.9645
Banana Sigatoka	0.965	0.964	0.9645
Banana Leaf Spot	0.961	0.962	0.9615
Banana Stem Panama Wilt	0.9582	0.962	0.9601
Seed Banana	0.9689	0.965	0.9669

Together, both the models YOLOv8 and EfficientNet demonstrated significant improvements in overall precision, recall, and F1 scores, making the ensemble model a robust solution for plant disease detection as shown in Table 5.17 and Figure 5.11.

Table 5.17: Performance comparison of Ensembled model with EfficientNet and YOLOv8

Model	Precision	Recall	F1-Score	Accuracy
EfficientNet	.900	.960	.930	95.9%
YOLO $_{V8}$	.921	.923	.920	92.4%
Ensemble	.963	.963	.963	96.3%

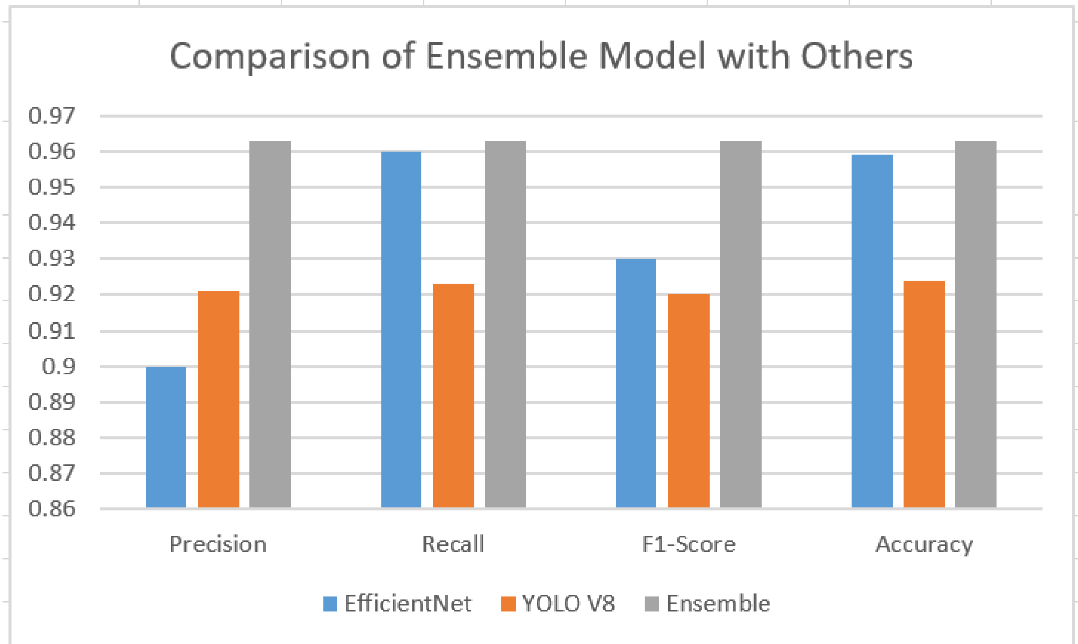


Figure 5.11: Performance Comparison of Ensembled Model with EfficientNet and YOLOv8

In summary, the ensembled model effectively leverages the complementary strengths of YOLOv8 and EfficientNet, resulting in near-optimal performance. The high precision ensures minimal false alarms, while the strong recall captures most true disease cases, making the model highly suitable for agricultural disease detection tasks.

5.6 SUMMARY

An ensemble deep learning strategy is assessed in this chapter. The study focused on detecting ten different diseases affecting various parts of banana and papaya plants using four advanced deep learning models: YOLOv3, YOLOv8, ResNet50, and EfficientNet. The objective is to evaluate how well each model could identify and classify plant diseases across different categories. Each model is trained and tested on a detailed dataset, and their effectiveness is measured using metrics like precision, recall, and F1 score and presents here. Among the models, YOLOv8 and EfficientNet delivered the best precision, consistently outperforming YOLOv3 and ResNet50. To further improve results, the study implemented an ensemble method that combined the strengths of YOLOv8 and EfficientNet. This combined model achieved high performance, with a precision, recall, and F1 score of 0.963 and an overall accuracy of 96.3%.

Chapter – 6

PLANTSCAN MOBILE APPLICATION

6.1 INTRODUCTION

There has been a proliferation of technological advancements in the field of horticulture in recent years, which has resulted in the development of novel approaches to the up keeping of plants. Along with developments in mobile technology, this movement has been pushed by a rising interest in sustainable living practices and farming. Additionally, improvements in mobile technology have contributed to this trend [91]. The proliferation of plant care apps has resulted in the development of sophisticated tools that allow farmers or gardeners to monitor, maintain, and improve the overall health of their plants. These apps provide a wide variety of capabilities, ranging from the identification of plants and health diagnostics to the provision of personalised care recommendations and supportive community services [92]. Users who may not have the time or skill to care for plants in the conventional manner may find mobile apps to be an appealing choice because of its ease and accessibility. As a result of the incorporation of cutting-edge technologies like artificial intelligence (AI) and machine learning, the capabilities of these apps have been greatly expanded, hence giving users with accurate and actionable information [93]. The intersection of agriculture and technology has provided a rich environment for the development of novel methods for plant care. This shift has been fuelled by a confluence of reasons, such as advancements in mobile technologies and artificial intelligence. Smartphone applications that monitor plant health are a boon to farmers of all experience levels [94], letting them see how their plants are doing and making modifications as they go. Such applications provide a plethora of services, including personalized health recommendations, community assistance, plant identification, and diagnostic testing [95]. Majority of farmers are interested in knowing the diseases in their plants.

Overview of the PlantScan Application

PlantScan is an application that is developed with the intention of becoming a complete tool for those who are dealing with the health of plants specially Banana and Papaya. It offers a variety of capabilities that are aimed to meet the various requirements of its users. Availability of the programme on Android platform ensures that it is accessible to a large number of people [96]. Users with varying degrees of expertise will have no trouble navigating the interface and making full use of its capabilities because to its intuitive design and user-friendly layout. The power of the PlantScan application to identify diseases in the Papaya and Banana plants is the notable aspects and functions of the programme. Users are able to identify a wide variety of plant diseases by merely snapping a image of them.

With the explosion of mobile technology, smart phones and internet services in rural areas, farmers who are using the traditional ways of farming are also gaining access to these different digital resources. This chapter introduces a multilingual mobile application – PlanrScan to help and support farmers in identifying leaf diseases instantly and to get required guidance for the management of crop. The application specifically targets two commonly cultivated plants – Banana and Papaya. The productivity of these fruits are adversely affected by the fungal and bacterial infections.

The objective while designing the mobile application is kept farmer centric. PlantScan permits its users to capture images of papaya and banana plant leaves using either the mobile camera or upload the images of plant taken in any other way. After this the image is analysed with the help of integrated deep learning model which instantly gives feedback on whether the plant is diseased or not. If it is found to be diseased then it informs the kind of disease plant is having so that timely corrective action can be taken. PlantScan understands the linguistic diversity and regional needs of farmers that is why it has a distinctive feature of multi lingual support – Hindi, English and Punjabi. Because of this it becomes accessible to a wide range of farmers and users in Northen and Central India where farmers might not be comfortable in English language information. So it reduces barriers and outputs are produced in the selected language and adoption of the application is improved. Apart from this, farmers can contact the administrator through PlantScan mobile application. In this way farmer can contact the agriculture expert through app and can seek for further consultation is not satisfied with the results produced by the app or if further guidance is required. Users of the app can submit their queries and get expert advice on the use of pesticides, fertilizer, disease management or any solutions related to their problem. Support team can analyse the image uploaded by the user, review them and provide the context specific advice beyond the automated conclusion.

Convolution Neural Network based deep learning model as discussed in chapter 4 has been used to train the dataset of images of banana and papaya plant to identify the different classes of diseases. The model has been trained to identify visual patterns and other anomalies which are indicative of different diseases in these two plants. Resizing of images, augmented images and image normalization are the various techniques used for the pre-processing of image data set to ensure the robustness of model across changing light conditions, varying camera qualities as it happens in real life scenario.

User interface (UI) has been designed to be simple which can easily be understood without reading the guidelines to use the application to cater the users with different levels of smart phone literacy. The entire process from capturing of images to the final report generation is completed in a few steps only and it takes less than a minute to get the analysis. There is no hassle of creating the user account also to know the disease in plants.

6.2 APP SPECIFICATIONS

The PlantScan mobile application offers real time, multilingual and reliable platform for the identification of diseases in banana and papaya plants for the farmers. The major goal is to give a simple and easy to understand and easy to use platform to users who are farmers involved in growing banana and papaya crops in rural and semi urban Indian regions. Keeping in mind the need and mobile literacy of the prime users of the application, PlantScan has been designed to be robust, scalable and easy to use along with real time performance. This section explains the technical architecture and application design of the PlantScan mobile application.

6.2.1 Core Specifications

PlantScan application offers the following features to its users

Plant Disease Identification

The programme known as PlantScan is distinguished by its powerful plant disease recognition capabilities of banana and papaya, which is one of its most notable characteristics. Users are able to easily identify the diseases in banana and papaya plants by simply taking a snapshot of the plant and submitting it to the programme, which then uses powerful image recognition technology to analyse the image. The accuracy of the application is improved by deep learning algorithms used which is an ensemble of Yolo v8 and Efficientnet.

Expert Advice

One other great thing about the community features is the ability to consult with experts. For individualised guidance and problem solving, users may establish connections with trained horticulturists and plant scientists. By giving users trustworthy advice on difficult plant care concerns, this access to expert knowledge increases the app's total value.

Multi Lingual Support

The application PlantScan provides multi lingual support to its user specifically belonging to rural and semi urban area of Northern parts of India. PlantScan can assist farmers in three major languages – English, Hindi and Punjabi which are the popular languages used in Northern parts of India. Later on it can be extended to give results in other languages also.

6.2.2 Technical Specifications

The technical details of the PlantScan mobile application are covered in this part.

Platform Compatibility:

One can reach a large audience with the PlantScan app since it is compatible with Android systems. Application can be used in systems with Android (Marshmallow)

6.0 and later versions. It can be utilized on both smartphones and tablets. It occupies a little space roughly around 130 MB which is very easy to be accommodated in any mobile phone along with other traditional applications.

- **Compatibility:** Android 6.0 (Marshmallow) or later
- **Devices Supported:** Smartphones and tablets
- **Size:** Approximately 130 MB

System Requirements:

The PlantScan mobile application has particular system requirements for Android platforms. These requirements are designed to guarantee optimised performance and a positive user experience.

- **Operating System:** Android 6.0 or later
- **Processor:** Quad-core 1.4 GHz or equivalent
- **RAM:** Minimum of 2 GB
- **Storage:** At least 500 MB of free storage for installation and additional space for storing plant data and images

Application Functional Workflow:

Architecture is composed of a number of essential components, the most important of which are the user interface (UI), backend services, databases, and interactions with third-party services. The PlantScan application follows a modular and simple architecture with the workflow as shown in Figure 6.1

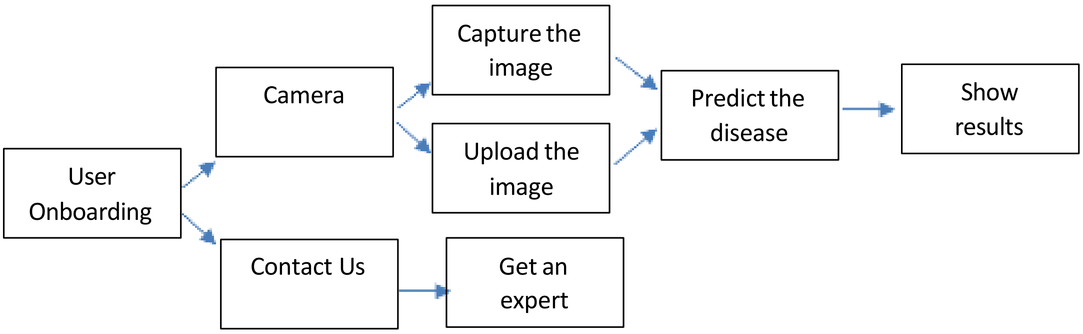
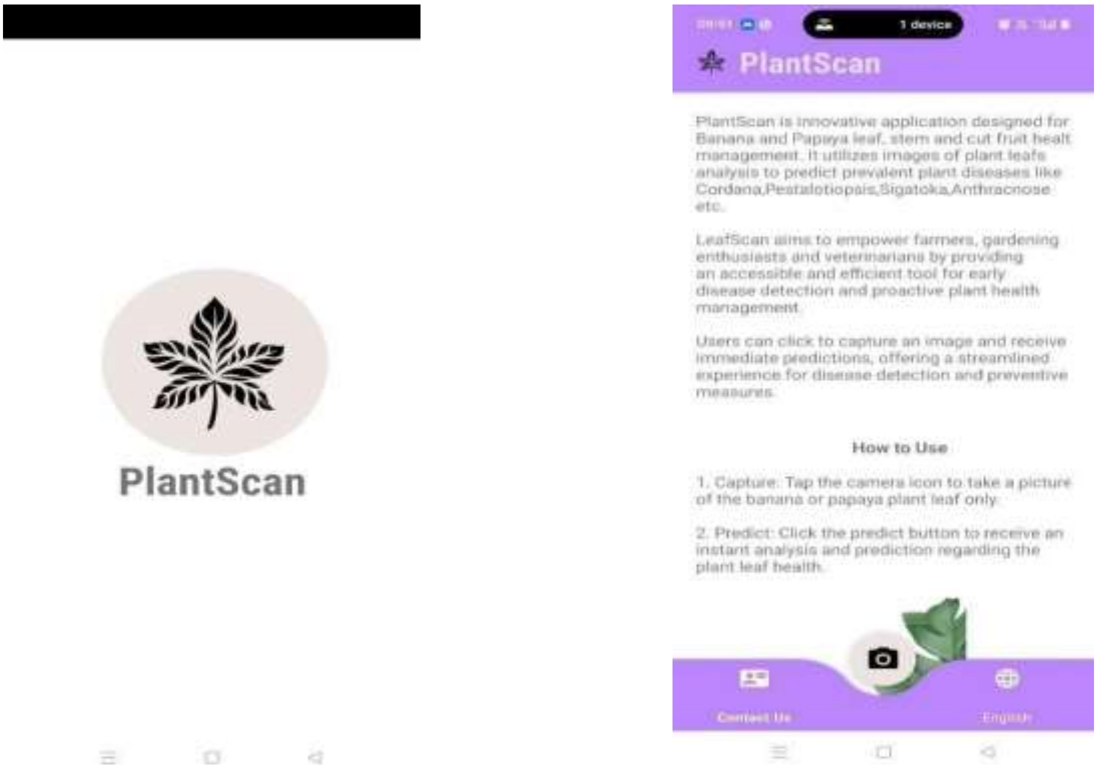


Figure 6.1: PlantScan Application Functional Workflow

The functional workflow of PlantScan mobile application exhibits a very clear and summarized of the process that the user of the application needs to follow to get the diseases in their plants detected. The starting point is user on-boarding which starts immediately after the start of the application. User need not to create any special account for entering into the application and using it for his welfare. After entering the application farmers or the users can register on the application and select their preferred language (Hindi, Punjabi and English) in which they want to use the application and get the results. This ensures the accessibility of the application by different users from different linguistic backgrounds as shown in figures 6.2 (a, b, c, d).



PlantScan is innovative application designed for Banana and Papaya leaf, stem and cut fruit healt management. It utilizes images of plant leafs analysis to predict prevalent plant diseases like Cordana,Pestalotiopsis,Sigatoka,Anthracnose etc.

LeafScan aims to empower farmers, gardening enthusiasts and veterinarians by providing an accessible and efficient tool for early disease detection and proactive plant health management.

Users can click to capture an image and receive immediate predictions, offering a streamlined experience for disease detection and preventive measures.

How to Use

1. Capture: Tap the camera icon to take a picture of the banana or papaya plant leaf only.

2. Predict: Click the predict button to receive an instant analysis and prediction regarding the plant leaf health.

Figure 6.2: (a) PlantScan Application (b) English Language Support

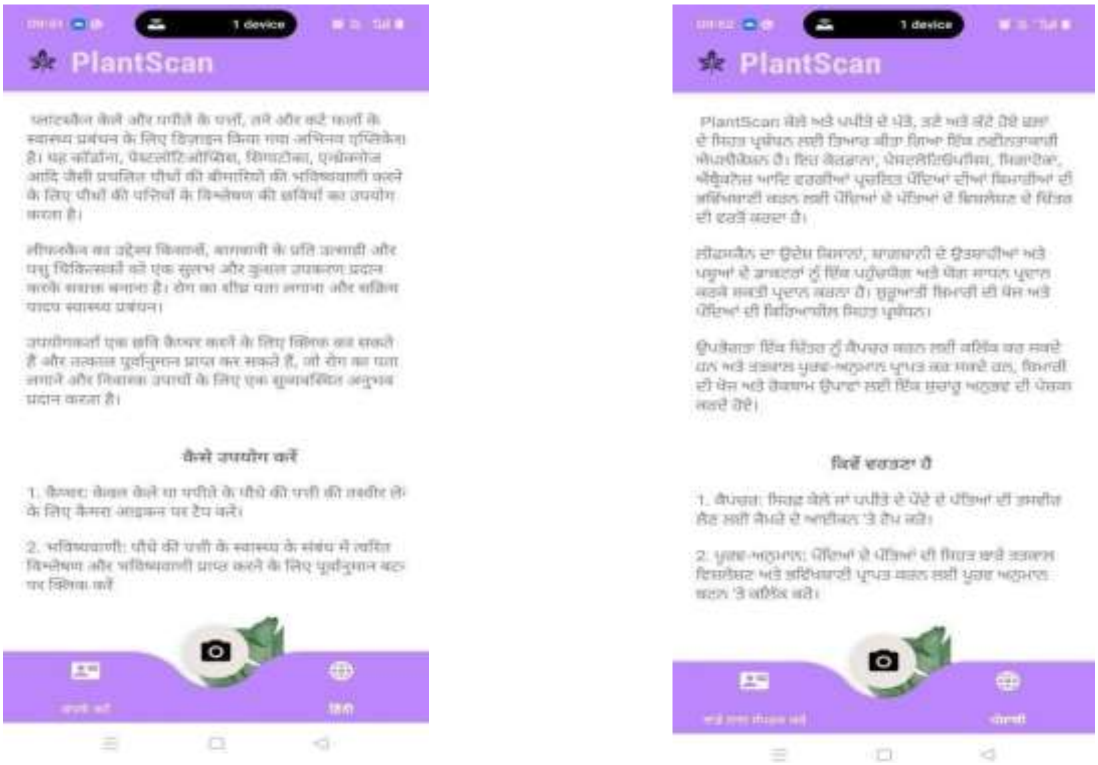


Figure 6.2: (c) Hindi Language Support (d) Punjabi Language Support

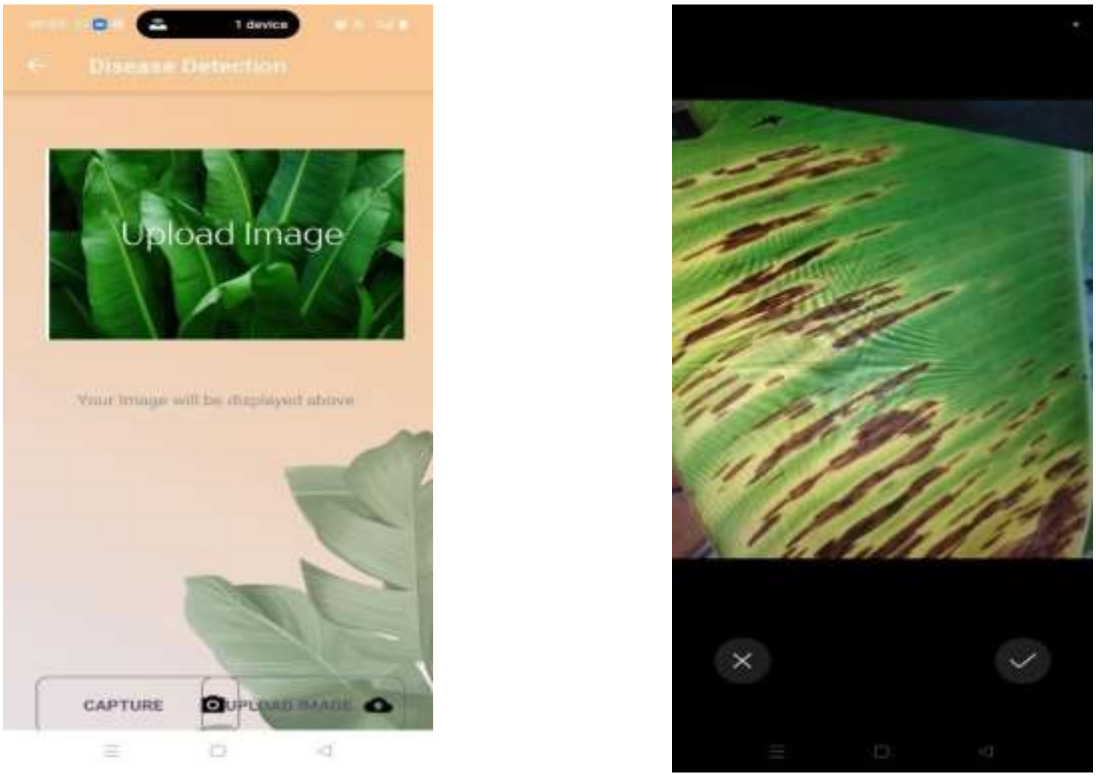
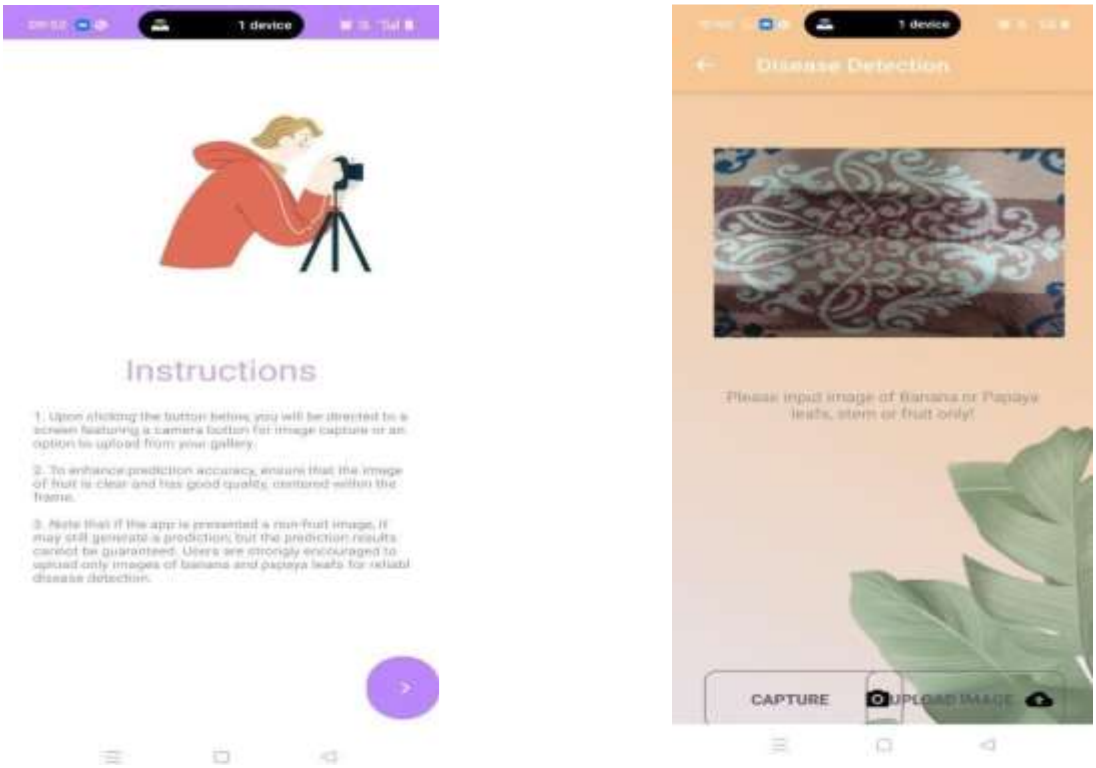


Figure 6.3: (a) Upload or Capture Image (b) Captured Image



Instructions

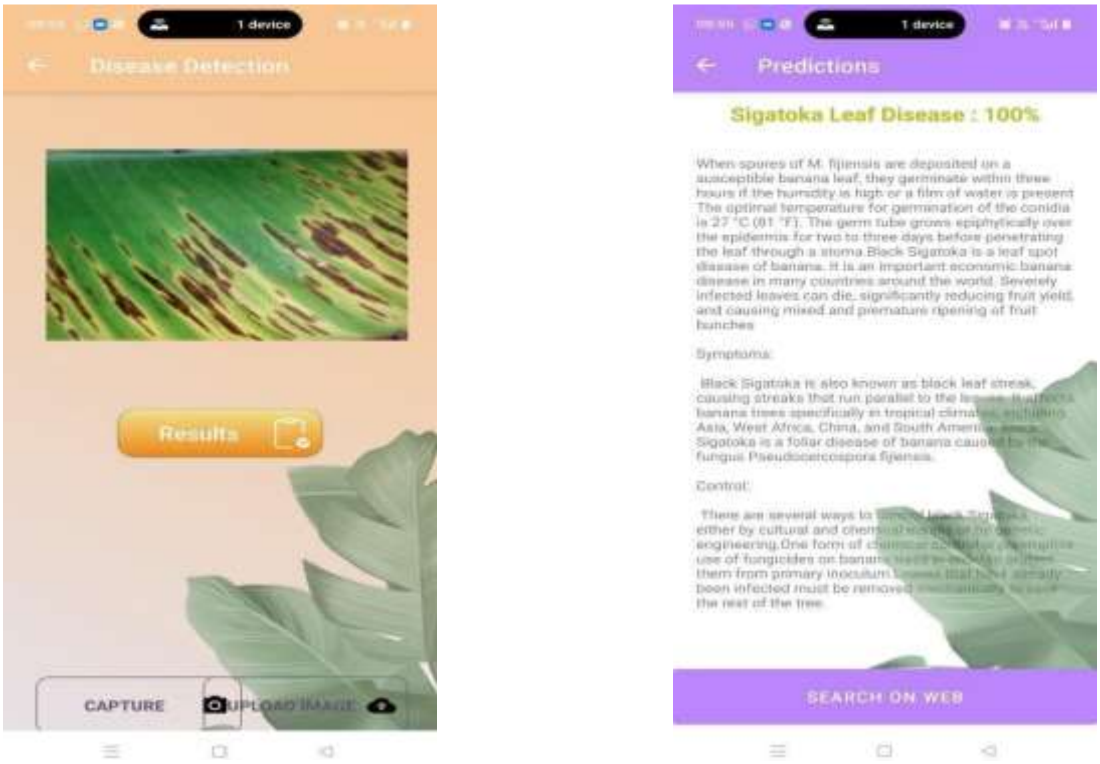
1. Upon clicking the button below, you will be directed to a screen featuring a camera button for image capture or an option to upload from your gallery.

2. To enhance prediction accuracy, ensure that the image of fruit is clear and has good quality, centered within the frame.

3. Note that if the app is presented a non-fruit image, it may still generate a prediction, but the prediction results cannot be guaranteed. Users are strongly encouraged to upload only images of banana and papaya leafs for reliabl disease detection.

Please input image of Banana or Papaya leafs, stem or fruit only!

Figure 6.4: (a) Instructions to upload (b) Invalid image uploaded



Sigatoka Leaf Disease : 100%

When spores of M. fijiensis are deposited on a susceptible banana leaf, they germinate within three hours if the humidity is high or a film of water is present The optimal temperature for germination of the conidia is 27 °C (81 °F). The germ tube grows epiphytically over the epidermis for two to three days before penetrating the leaf through a stoma.Black Sigatoka is a leaf spot disease of banana. It is an important economic banana disease in many countries around the world. Severely infected leaves can die, significantly reducing fruit yield, and causing mixed and premature ripening of fruit bunches

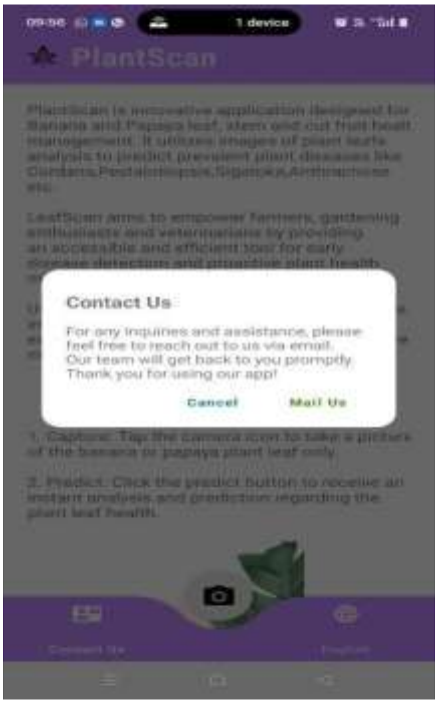
Symptoms:

Black Sigatoka is also known as black leaf streak, causing streaks that run parallel to the leaves. It affects banana trees specifically in tropical climates, including Asia, West Africa, China, and South America. Black Sigatoka is a foliar disease of banana caused by the fungus Pseudocercospora fijiensis.

Control:

There are several ways to control black Sigatoka either by cultural and chemical means or by genetic engineering.One form of chemical control is preemptive use of fungicides on banana leaves to protect them from primary inoculum.Leaves that have already been infected must be removed mechanically to save the rest of the tree.

Figure 6.4: (c) Valid Image Upload (d) Prediction on uploaded image



For any inquiries and assistance, please feel free to reach out to us via email.
Our team will get back to you promptly.
Thank you for using our app!

Figure 6.5: Contact Us for an Expert Advice

After entering the application user gets the option to access the camera to capture the image of diseased plants. In addition to this if the user has any pre clicked image, he can upload that image also as exhibited in figures 6.3 (a, b). Once image is uploaded through any means it triggers the disease identification pipeline. Now in this stage an advanced deep learning model which is the ensemble of YOLOv8 and EfficientNet, analyse the uploaded or captured image to detect the disease in papaya and banana plant. Before uploading or capturing any image system warns its users in the selected language to upload valid image only. If the valid image is uploaded, then it displays the Results button otherwise not as shown in figure 6.4 (a, b, c, d). On clicking it gives the complete details as shown in figure 6.4 (d). In case any further assistance is needed by the user, he can navigate to ‘contact us’ section and in this way he will be connected to agricultural experts. This will offer personalized guidance to the farmers or users beyond automated predictions as shown in figure 6.5.

6.3 COMPARATIVE STUDY OF EXISTING RESEARCH BASED MOBILE APPLICATIONS FOR PLANT DISEASE DETECTION

In last few years, the plant disease identification through mobile application has become a promising area of research in the field of agriculture. Many researchers and academic institutions are involved in providing mobile based solutions in this context to detect plant diseases. These solutions are powered by AI specifically image processing techniques and Convolutional Neural Networks. In this section notable academic mobile applications created by researchers are compared on the basis of their methodology, crop considered, accessibility and usability with PlanScan mobile application.

6.3.1 LeafSnap

The LeafSnap mobile application presented by identifies the species of tree from the image of its leaf. Computer vision components are the key to this system which detects the non-leaf images and discards them. If identifies the tree from the leaf's contour over multiple scale. Dataset of 184 tree species which was largest of its kind at that time. But the LeafSnap application was nowhere involved in disease identification [97].

6.3.2 AgriDoc

The mobile application AgriDoc [98] is designed for Android devices and is monitoring rice crop at every stage. It supports two languages – English and Tagalog to ease the farmers. Application is designed to monitor the crop using CNN technique and to be precise VGG16. It does not offer offline support.

6.3.3 PaddyExpert

Another mobile application which is AI driven and makes use of Expert System is TNAU PaddyExpert helps farmers in making right decision at right time and offers crop care tips according to the regional conditions [99]. Application uses English and local Tamil language and is designed to enhance the productivity of small rice farmers. Application does not utilize any CNN and hence not detecting the diseases using visual component.

6.3.4 SmartPlant

SmartPlant presented a mobile application for detecting deceases in tomato plant using a publically available dataset. The purpose of the application is to detect diseases in tomato plants with the help of CNN model. Application is not supporting real time data and is not providing any expert support. It lacked multi lingual support also and is supporting farmers in English language [74]

6.3.5 Tomato Leaf

TomatoLeaf designed mobile application for diagnosing tomato plant diseases with the help of AI powered image analysis. It identifies diseases in tomato leaf and give recommendations on the basis of predictions. It makes use of DenseNet CNN algorithm to make the detection. Application lacks real time expert support [100].

Features of the above mentioned applications are compared with PlantScan and depicted in the Table 6.1.

Table 6.1: Comparison of Different Mobile Applications

Feature/ Aspect	LeafSnap	AgriDoc	PaddyExpert	SmartPlant	Tomato Leaf	PlantScan
Target Crop	General Tree species	Rice	Rice	Tomato	Tomato	Banana and Papaya
Image based detection	Yes but not disease	Yes	No	Yes	Yes	Yes
Language Support	English Only	English, Tagalog	English, Tamil	English Only	English Only	English, Hindi and Punjabi
Expert Support	No	No	No	No	No	Interface available
Model Used	SIFT and classifier	VGG16	Expert System	MobileNet v2	DenseNet	Ensemble of YOLOv8 and EfficientNet
Deployment Platform	iOS	Android	Android	Android	Android	Android

Among the six plant disease detection applications reviewed, PlantScan emerges as the most comprehensive and effective solution. While apps like LeafSnap, AgriDoc, PaddyExpert, SmartPlant, and TomatoLeaf are limited either by crop specificity, language support, or outdated technology, PlantScan offers a well-rounded and advanced approach. Most applications focus on a single crop such as rice or tomato, whereas PlantScan supports multiple fruit crops—banana and papaya—broadening its applicability. In terms of disease detection, a few apps like PaddyExpert do not support image-based diagnosis at all, and others rely on older or less powerful models such as SIFT, VGG16, or MobileNet v2. In contrast, PlantScan utilizes an ensemble of YOLOv8 and EfficientNet, both state-of-the-art deep learning models known for their accuracy and efficiency in image classification and object detection. Additionally, PlantScan is the only app that supports three languages—English, Hindi, and Punjabi, making it highly accessible for regional users, and uniquely offers an interface for expert support, a feature absent in all other platforms. These combined strengths—technical superiority, crop diversity, language inclusivity, and user support—clearly indicate that PlantScan stands out as the most advanced and user-centric application among all those compared.

6.4 SUMMARY

If someone is involved in farming of papaya and banana plants, the PlantScan app is a great resource for his/her needs related to support and to be very precise related to disease identification in these plants. This application serves farmers with their banana and papaya plants via the use of deep learning technology; it does this by giving users multi lingual support in usage of application – English, Hindi and Punjabi. Common problems encountered by farmers is addressed by the application’s main features, which include plant disease identification and expert support. At the crossroads of technology and plant care, this ground-breaking smartphone application signifies a giant leap forward. Anyone hoping to maintain a flourishing disease free banana and papaya plant farms in today's fast-paced world will find it an invaluable tool because to its user-friendly layout, robust features, and community assistance.

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Chapter – 7

CONCLUSION AND FUTURE SCOPE

7.1 CONCLUSION

The study has led to the creation of an automated system that can identify diseases in papaya and banana plants. One of the main goals of the research is to develop a tool that can support farmers and agricultural experts when it comes to crop disease management. This has made great strides in this important field of agricultural technology by combining state-of-the-art image processing methods with deep learning algorithms and a comprehensive database of diseases signs. This study's automated detection technology is a step towards precision agriculture and plant pathology. A system that can quickly and correctly detect several diseases affecting papaya and banana plants has been proposed. Overall agricultural productivity might be enhanced, crop losses could be reduced, and disease control strategies could be optimised using this technology.

Disease detection procedures that are performed in a laboratory, such polymerase chain reaction (PCR) testing, are quite accurate, but they may be costly, time-consuming, and complicated. Presented automated detection system is more practical, affordable, and suitable for usage in the field. It is a great first-line diagnostic tool that may aid farmers in making informed choices on disease management in a timely manner.

It has been proved that the proposed system can detect diseases in bananas and papayas with high precision and accuracy. The proposed model which is an ensemble of YOLOv8 and EfficientNet successfully integrated the special extraction feature and deep classification from both the algorithms respectively to improve disease detection in papaya and banana plants. The model achieved accuracy of 96.3% which is higher than the accuracy levels of both the algorithms when used individually (EfficientNet – 95.9% and YOLOv8 – 89.1%). Model is giving high real time performance also. Robust disease identification with less numbers of wrong classifications is apparent with key finding which are precision (96.3%), recall

(96.3%) and F1-Score(96.3%). The proposed ensemble minimized the false positives and false negatives which lead to more reliable identification of diseases in large scale agricultural setting. In real world agriculture based problems this method can be used for plant disease detection, enhancing precision agriculture and reducing crop loss significantly and consequently enhancing field productivity.

This work is supported with a mobile application PlantScan which has capability to detect the diseases in Banana and Papaya in real time. For individuals engaged in the cultivation of papaya and banana plants, the PlantScan app offers an invaluable solution for plant care, particularly in disease identification. Leveraging deep learning technology, this innovative application provides comprehensive support to farmers through features like multilingual access—available in English, Hindi, and Punjabi—and expert consultation. It directly addresses common challenges faced in farming by enabling precise disease detection and timely assistance. Positioned at the intersection of modern technology and agriculture, PlantScan represents a significant advancement. With its intuitive interface, powerful capabilities, and community-driven support, it is an essential tool for anyone striving to maintain healthy, disease-free banana and papaya farms in today’s fast-evolving agricultural landscape.

7.2 FUTURE SCOPE

The potential for creating an automated system to identify diseases in bananas and papayas is enormous. The need for sustainable practices, insect invasions, and climate change are just a few of the growing list of agricultural concerns that need cutting-edge technical solutions. Machine learning (ML) and artificial intelligence (AI) together can greatly improve the precision and speed of diseases detection systems. Perhaps in the future more intelligent algorithms will be available which can identify a broader variety of diseases with greater accuracy. Early intervention and improved diseases management may be made possible by real-time data processing and predictive analytics. More precise and thorough evaluations of plant health are possible with the help of emerging image processing technologies. A wealth of data may be collected for the system's analysis via high-resolution photography, hyperspectral imaging, and the use of drones to capture plant images from different perspectives. Early diseases detection is possible with the use of improved image recognition software.

One potential outcome of using IoT devices in farming is the development of a more linked and adaptable system for disease detection. By using Internet of Things (IoT), farmers may get timely notifications and suggestions. Disease trends and patterns may be better understood with the gradual collection of massive databases. Automatic disease detection methods proposed in this work can be applied to other crops and fruits also.

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LIST OF PUBLICATIONS

1. H. Kaur, D. Prashar and V. Kumar, “A Robust Deep Learning Framework: Ensemble of YOLOv8 and EfficientNet”, Journal of Information Technology Management, 2025, Vol. 17, Special Issue, pp.32-44.
2. H. Kaur, D. Prashar and V. Kumar, "Disease Identification in Papaya Plant and their Dataset," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1220-1224, doi: 10.1109/IC3I56241.2022.10072453.
3. H. Kaur, D. Prashar and V. Kumar, “Disease detection system for bananas and papayas built using Deep Learning Techniques”, 8th International Conference on Computing Sciences (ICCS-2023) “CODD100”
4. H. Kaur, D. Prashar and V. Kumar ,“Deep CNN Models in Plant Disease Identification”, Advances and Applications in Mathematical SciencesVolume 21, Issue 5, March 2022, Pages 2681-2693