DETECTION OF VARIETIES AND DEFECTS OF SOYBEAN SEEDS USING DEEP LEARNING TECHNIQUES

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By

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DECLARATION

I, hereby declared that the presented work in the thesis entitled "DETECTION OF VARIETIES AND DEFECTS OF SOYBEAN SEEDS USING DEEP LEARNING TECHNIQUES" in fulfilment of degree of **Doctor of Philosophy (Ph.D.)** is the outcome of research work carried out by me under the supervision of Dr. Parminder Singh, working as Professor, in the School of Computer Science Engineering, of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgments 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 "DETECTION OF VARIETIES AND DEFECTS OF SOYBEAN SEEDS USING DEEP LEARNING TECHNIQUES" 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 Sabale Amar Vikasrao, 42000373, 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.

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ABSTRACT

Agriculture is a vital economic sector in India, which employs a large percentage of the population. India is one of the world's top agricultural producers due to its diverse climate and soil types. Rice, wheat, soybean, barley, maize, cotton sugarcane, etc. are major cultivated crops in India. Soybean known as Glycine max is a high-protein legume from the pea family (Fabaceae). Soybeans has a major commodity in international trade and contribute significantly to the economies of many countries. However, environmental factors like droughts or excessive rainfall during cultivation significantly impact the health and yield of soybean crops. Insufficient pest and disease management also compromises bean quality. Improper harvesting methods can cause physical damage to the beans which reduces their overall quality. This decline in soybean quality has economic, nutritional, and environmental consequences. A decrease in nutritional value raises concerns for both human and animal consumption also leads to nutrient deficiencies that affects overall health. Hence, it is essential to identify defects and varieties of soybean seeds from both agricultural and industrial perspectives.

This thesis proposed two neural network approaches named "soybean seed defect identification network (SSDINet)" and "Modified GoogleNet for Variety Identification (MGVI)" to differentiate the defects and variety of soybean seeds. This thesis also introduces a seed Contour detection (SCD) algorithm to enhance the quality of soybean images. Initially, we collected the soybean samples from the Vidarbha region of Maharashtra, where soybean is a major crop cultivated crop. With the assistance of local farmers and agricultural experts, the seeds were classified into 10 categories: 'cracked', 'wrinkled', 'broken', 'purple', 'damaged', 'insect-bitten', 'green seed', 'KDS726', 'JS335' and 'JS9305'. Subsequently, images

of the soybean seeds were captured using an experimental setup. The collected images were meticulously organized and processed to create a comprehensive dataset. This dataset serves as the foundation for training the neural network and allows it to learn and classify the various classes of soybean seeds effectively. By providing a diverse range of images, this research work aimed to enhance the model's ability to generalize and accurately classify new, unseen seed samples.

Initially, SSDINet was developed to differentiate between 7 classes of defective seeds, while three classes of seed varieties were grouped under the category of good seeds. The SSDINet architecture comprises a convolutional neural network, depthwise convolution blocks, and squeeze-and-excitation blocks, which collectively make the network lightweight, faster, and more accurate compared to other state-of-the-art approaches. Experimental results showed that SSDINet achieved an impressive accuracy of 98.64% with just 1.15 million parameters and a processing time of 4.70 milliseconds, that surpasses existing models. This research not only advances deep learning techniques in agricultural applications but also provides valuable insights into the practical implementation of seed classification systems for quality control in the soybean industry.

To identify the variety of soybean seeds, MGVI utilized a pre-trained Inception-V1 (GoogleNet) model. This model employs parallel convolutional paths with varying receptive field sizes. The initial part of the network consists of several convolutional layers with small filter sizes and the ReLU activation function. The core building block of GoogleNet is the inception module, which includes multiple parallel convolutional branches with different filters, max pooling, and 1x1 convolutional layers for dimensionality reduction. MGVI was tested on a dataset with an 80:20 training-to-testing ratio and achieved an average accuracy of 97.90% which outperformed state-of-the-art approaches. This proposed approach ensures precise identification and classification, promoting better crop management and quality control in the soybean industry.

All the models are implemented in GPU-enabled Intel Xeon®Gold 5222 3.8GHz processor workstation. It contains 1TB SATA hard disk and 128GB DDR4 RAM with Windows 10 Pro operating system. Spyder IDE with Python 3.11 is used for various deep-learning operations.

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Chapter 1

INTRODUCTION

1.1 Introduction

Soybean, scientifically known as Glycine max, is a leguminous plant that belongs to the Fabaceae family. It is an annual herbaceous plant, highly valued for its edible seeds which are rich in protein and oil. Originating from East Asia, soybean is now a globally important crop due to its versatile uses in food, feed, and industrial applications [1]. Soybean plays a crucial role in global agriculture and the economy because it is a source of plant-based protein and oil, which makes it essential for human nutrition and animal feed [2]. Soybean seed oil is mostly used in cooking, food processing, industrial applications such as biodiesel production and the manufacture of bioplastics [3]. Soybeans thrive in warm, temperate climates with well-distributed rainfall. The optimal temperature range for soybean growth is between 68°F to 86°F [4]. They require at least 500 mm (20 inches) of rainfall during the growing season, but well-drained soils are essential to prevent water logging, which can harm the plants. Soybeans are sensitive to frost, particularly during the flowering and pod-filling stages, making them best suited to regions with long, frost-free periods [5]. Several countries have developed substantial soybean industries and contribute significantly to global production. Some of them are listed as follows:

1. United States: The largest producer of soybeans, with major cultivation areas in states like Iowa, Illinois, and Minnesota.

2. Brazil: A close competitor to the U.S., Brazil's vast arable land in states like Mato Grosso and Paraná makes it a leading exporter.

3. Argentina: Known for its high-quality soybean production, Argentina exports a significant portion of its crop.

4. China: Although historically a major producer, China has become a significant importer of soybeans to meet its domestic demand.

5. India: Emerging as a notable producer, especially in states like Madhya Pradesh and Maharashtra.

6. Other countries: Paraguay, Canada, and Ukraine are also important contributors to the global soybean market.

India is an important player in the global soybean market, being one of the top producers of this versatile crop. The cultivation of soybeans in India primarily takes place in the central and western regions, with Madhya Pradesh, Maharashtra, and Rajasthan being the leading states. Together, these states contribute to over 90% of the soybean production [6]. As of the 2022-2023 agricultural year, India produced approximately 12.9 million metric tons of soybeans [7]. This marked a substantial increase compared to previous years, driven by favorable monsoon rains and improved farming practices. The total area under soybean cultivation in India was about 12.4 million hectares, reflecting a steady interest among farmers in this crop due to its profitability and demand. The average yield of soybeans in India hovers around 1,000-1,100 kg per hectare [8]. This yield is lower compared to major soybean-producing countries like the United States and Brazil, where advanced agricultural technologies and practices result in higher productivity. Efforts are being made to bridge this yield gap through the adoption of high-yielding varieties, better irrigation practices, and integrated pest management [9]. India is both an importer and exporter of soybeans and soybean products. The country imports soy oil primarily from Argentina and Brazil to meet domestic demand, while exporting soybean meal to countries like Vietnam, Indonesia, and Iran. The prices of soybeans in India are influenced by global market trends, domestic production levels, and policy decisions regarding tariffs and subsidies. The Indian government has implemented various policies and initiatives to support soybean farmers and enhance production. The introduction of Minimum Support Prices (MSP) for soybeans aims to ensure that farmers receive a fair price for their produce [10]. Additionally, government programs focus on providing farmers with access to quality seeds, credit facilities, and training on modern agricultural practices. Research institutions such as the Indian Institute of Soybean Research (IISR) are actively involved in developing improved soybean varieties and promoting sustainable farming techniques.

1.2 Significance of Soybean Seed

Soybean seeds are of immense significance due to their multifaceted benefits across various domains. They are a crucial source of high-quality protein and essential nutrients, making them vital for human and animal nutrition [11]. Some of major significance are listed as follows and shown in figure 1.1:-

1. **Nutritional Value:** Soybean seeds are highly nutritious, containing significant amounts of protein, essential fatty acids, vitamins, and minerals [11].

2. **Economic Importance:** Soybeans are one of the most important crops worldwide, with extensive uses in food, feed, and industrial applications. The global soybean market impacts the economy significantly, particularly in countries like the United States, Brazil, India and Argentina, which are major producers.

3. **Versatility in Food Products:** Many products like tempeh, soy milk, soy sauce, and tofu, are made from soybeans. These products are staples in many cultures and contribute to diverse culinary practices.

4. **Animal Feed:** Soybean meal, a byproduct of oil extraction, is a key ingredient in animal feed due to its high protein content. It supports the livestock

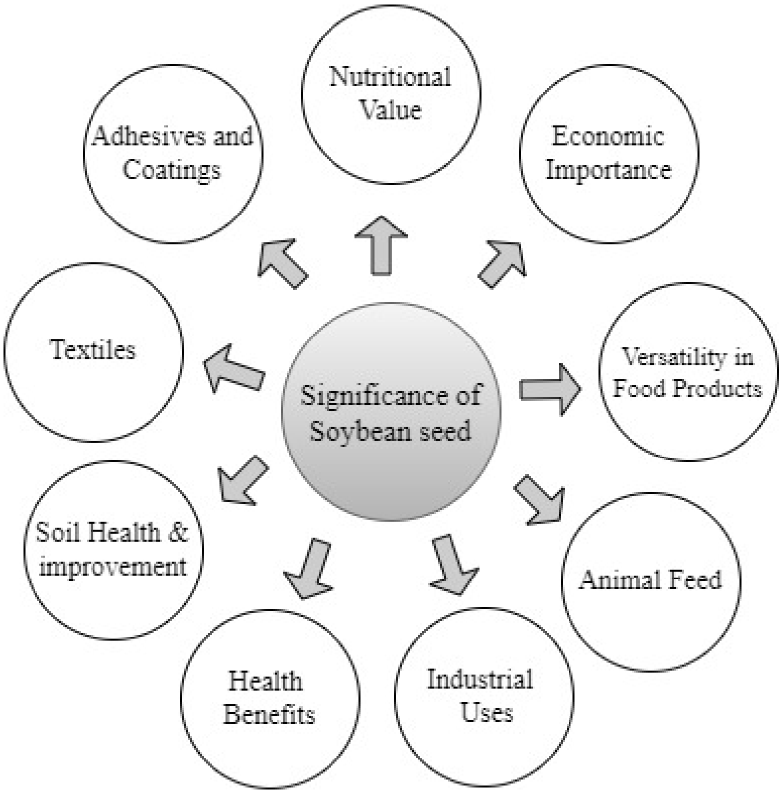

Figure 1.1: Significance of soybean seed.

industry, particularly poultry, swine, and cattle farming.

5. **Industrial Uses:** Soybeans are also used in non-food products like biodiesel, plastics, lubricants, and inks [3]. Soy-based products are considered more environmentally friendly, contributing to sustainable industrial practices.

6. **Health Benefits:** Soybean consumptions reduces the risk of heart disease that improves bone health, and manages menopausal symptoms. Isoflavones, a type of phytoestrogen found in soybeans, play a role in these health benefits.

7. **Soil Health:** Soybeans are leguminous plants that can fix nitrogen in the soil, enhancing soil fertility and reducing the need for chemical fertilizers. This makes them valuable in crop rotation systems to maintain soil health and sustainability. Lecithin Production: Soybeans are a primary source of lecithin, a byproduct of oil processing, which is a natural emulsifier. Lecithin

is widely used in pharmaceuticals, cosmetics, food products, and even as a feed additive.

8. **Soil Improvement:** The cultivation of soybeans can help improve soil fertility. As a legume, soybeans can fix atmospheric nitrogen into the soil, reducing the need for synthetic fertilizers.

9. **Textiles:** Soybean fiber, a relatively recent innovation, is used in the production of soft, absorbent, and comfortable fabrics. These textiles are used for clothing, upholstery, and other applications.

10. **Adhesives and Coatings:** Modified soy proteins are used to produce environmentally friendly adhesives and coatings. These soy-based products are used in wood adhesives, paper coatings, and other industrial applications where sustainable alternatives to synthetic products are desirable.

These applications highlight the critical role of soybeans in supporting sustainable agriculture, industry, and energy production, alongside their significant nutritional contributions.

1.3 Used of Soybean Seed

Soybean seeds have diverse uses in food products, animal feed, livestock health, and industry which highlights their versatility and economic importance [9]. Some of the major uses are mentioned below:

1. **Food Products**

   - **Soy Milk:** A popular dairy milk alternative rich in protein and suitable for lactose-intolerant individuals.
   - **Tofu:** A versatile soy product used in various dishes, known for its ability to absorb flavors and its high protein content.
   - **Soy Sauce:** A fermented product used as a condiment and flavor enhancer in many Asian cuisines.

- **Tempeh:** A traditional Indonesian product made from fermented soybeans, offering a firm texture and nutty flavor.
- **Edamame:** Young, green soybeans that are often steamed or boiled and served as a snack or appetizer.
- **Soy Flour:** Used in baking and cooking, soy flour adds protein content to various recipes [12].

2. **Animal Feed**

- **Soybean Meal:** Widely used in animal feeds due to its high protein content, supporting growth and development in livestock

3. **Industrial Products**

- **Oil Production:** Soybean seeds are primarily processed to extract oil, which is one of the most consumed vegetable oils globally. This oil is used in cooking, baking, and frying, and as an ingredient in many processed foods.
- **Biodiesel:** Soybean oil is a renewable source for biodiesel production, offering a cleaner alternative to fossil fuels.
- **Bioplastics:** Soy-based plastics are biodegradable and used in packaging and manufacturing.
- **Inks and Lubricants:** Environmentally friendly inks and lubricants are made from soybean oil [13].

4. **Health Supplements**

- **Soy Protein Isolate:** Used in dietary supplements and protein shakes, it provides a high-quality protein source for athletes and individuals seeking to increase protein intake.
- **Isoflavone Supplements:** These are used for their potential health benefits, including menopausal symptom relief and cardiovascular health.

5. **Agricultural Benefits**

    - **Soil Fertility:** Soybeans contribute to soil nitrogen fixation, improving soil health and benefiting subsequent crops in rotation systems.

1.4 Impact of Soybean Seed Degradation

Given the significance of soybeans both economically and nutritionally, any degradation in their quality can indeed have wide-reaching effects. Environmental factors such as adverse weather conditions during cultivation, including droughts or excessive rainfall, significantly affect crop health and yield. Likewise, improper pest and disease management practices can diminish bean quality. Inadequate harvesting methods may cause physical damage to the beans, reducing their overall quality. The decline in soybean quality can impact multiple sectors, leading to economic, nutritional, and environmental repercussions. A decrease in nutritional value raises concerns for both human and animal consumption, resulting in deficiencies in essential nutrients and affecting overall health. Here's a more detailed examination of how such quality degradation can impact various sectors:

1.4.1 Economic Impact

1. **Reduced Profitability for Farmers:** Poor quality beans often sell for lower prices, directly affecting farmers' income. Additionally, if the crop doesn't meet certain industry standards, it may not be sellable at all, leading to significant financial losses.

2. **Supply Chain Disruptions:** Low-quality crops can disrupt the supply chain. For instance, processors might need to slow down production lines to sort out unacceptable beans, leading to decreased efficiency and increased costs.

3. **Increased Costs for Consumers:** When supply is affected, or extra processing is needed, the costs can be passed down to consumers. Moreover,

farmers might need to invest more in future crops to mitigate past losses, potentially increasing the market prices.

1.4.2 Nutritional Impact

1. **Reduced Nutritional Quality:** Soybeans are a critical source of protein, essential fatty acids, vitamins, and minerals. A decline in their quality can mean a reduction in these nutrients, impacting the dietary quality of foods derived from soybeans, such as tofu, tempeh, and soy milk.

2. **Health Implications for Livestock:** Soybeans are also a major component of animal feed, particularly for poultry and swine. Lower nutritional quality can affect the growth, health, and productivity of these animals, further influencing the food industry and food security.

3. **Impact on Food Security:** Soybeans are a staple in many diets around the world. Any reduction in their availability or affordability can compromise food security, particularly in less developed regions where alternative protein sources are not as readily available.

1.4.3 Environmental Impact

1. **Resource Inefficiency:** Growing crops that end up being of low quality wastes resources like water, land, and energy. This inefficiency is particularly significant in areas where these resources are scarce.

2. **Increased Use of Chemicals:** If pests and diseases are mismanaged, there might be an increased reliance on pesticides and fungicides, which can have deleterious environmental effects, such as harming non-target species and contaminating water sources.

1.5 Motivation

The classification of soybean seeds is a significant task for several reasons, primarily within the agricultural and agribusiness sectors. Here are the main reasons why this process is crucial:

1. **Quality Control:** Classifying soybean seeds helps in distinguishing high-quality seeds from those of lower quality. High-quality seeds generally ensure better germination rates, healthier plant growth, and more robust yields, which are critical for profitable farming.

2. **Disease Management:** Some classifications are based on the resistance of seeds to diseases. Identifying and categorizing seeds based on their disease resistance allows farmers to select varieties that are best suited to their local environmental conditions and disease prevalence, reducing losses due to seed and crop diseases.

3. **Genetic Diversity:** Classification helps in maintaining and exploiting genetic diversity within soybean cultivars. Different classes might have specific desirable traits such as drought tolerance, pest resistance, or improved nutritional content. By effectively classifying seeds, breeders and farmers can select specific traits to meet environmental challenges and market demands.

4. **Research and Development:** In the field of agricultural research, classifying soybean seeds is essential for conducting experiments and studies related to crop improvement. Accurate classification allows researchers to ensure that the results are attributable to the genetic makeup of the seed rather than external factors.

5. **Customization for Specific Markets:** Different markets may demand different types of soybean seeds based on local cuisine, climate, or soil conditions. Classification allows producers to target specific markets more effectively with seeds that are more likely to thrive and meet local consumer preferences.

6. **Regulatory Compliance:** In many regions, agricultural products, including seeds, must meet certain standards before they are sold. Classification can be part of the compliance process, ensuring that only seeds that meet specific standards are distributed and planted.

7. **Optimization of Planting and Cultivation Strategies:** By classifying seeds, farmers can optimize their planting strategies according to the specific characteristics of seeds. This leads to more effective use of resources like water, fertilizers, and pesticides.

8. **Enhanced Traceability and Accountability:** When seeds are classified and labeled properly, it enhances traceability throughout the supply chain, from breeders to farmers to consumers. This can help in case of a recall or when determining the source of any issues related to crop failures or food safety.

Farmers, distributors, and processors face significant economic losses due to the reduced market value of soybeans, increased production costs, and the potential rejection of substandard batches. These economic impacts can disrupt livelihoods and exacerbate food insecurity, particularly in regions where soybeans are a key staple or primary protein source. Therefore, it is vital to separate low-quality soybean seeds from high-quality ones. Traditionally, visual inspections are conducted to identify visible signs of damage, discoloration, or mold. Beans are also sorted by size and shape using screening or sieving mechanisms, as damaged beans often display distinct physical characteristics. However, this traditional approach relies heavily on subjective human judgment, leading to inconsistencies and misidentification of degraded beans. Manual inspection is also labor-intensive and time-consuming, increasing production costs and slowing processing speeds. Given that damage to soybean seeds is mainly visible on the surface, computer vision methods are crucial for effectively classifying affected seeds.

1.6 Review of Deep Learning

"Deep learning is not just a tool, but a revolution in how we understand and model complex patterns in data, offering unprecedented capabilities in transforming raw information into actionable insights [14]".

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Deep Learning (DL) and Machine Learning (ML) are branches of Artificial Intelligence (AI). DL is distinguished by its use of Artificial Neural Networks (ANN) with multiple layers, referred to as Deep Neural Networks (DNN), to capture and model intricate data patterns. DL has revolutionized various fields by enabling significant advances in tasks such as image classification, speech recognition e.t.c. The detailed exploration traces the history and development of DL, from its early conceptual stages to its existing applications are explained in further subsections:

1.6.1 Evolution of Deep Learning

The evolution of DL has been marked by significant milestones and rapid advancements, transforming it from a theoretical concept to a cornerstone of modern AI. From the early foundations laid by McCulloch and Pitts, through the challenges of the AI winter, to the breakthroughs in the 2010s and the diverse applications in the 2020s, DL has consistently pushed the boundaries of AI which is mentioned below.

1. **Primary Foundations (1940s-1970s)**

   The origins of deep learning date back to the 1940s when Warren McCulloch and Walter Pitts proposed a model of artificial neurons that could carry out simple logical functions. Their work laid the groundwork for the development of ANN. In the 1950s, Frank Rosenblatt developed the Perceptron, the first algorithm modeled after the neural network concept. The Perceptron was a simple linear classifier, capable of learning weights from input data to make predictions. Although it was limited to solving linearly separable problems, the Perceptron represented a significant step forward in neural network research. The 1960s and 1970s saw the emergence of the first multi-layer networks, known as Multi-Layer Perceptrons (MLPs). These networks consist of many layers of neurons that allow them to learn more complex patterns. However, training these networks proved challenging due to the lack of effective learning algorithms.

2. **The Winter of AI (1980s)**

   The development of backpropagation in the 1980s marked a turning point in neural network research. Backpropagation, developed by Rumelhart, Hinton, and Williams, is a supervised learning technique for training multi-layer networks. It works by adjusting the network's weights to reduce the difference between the predicted and actual outputs. This breakthrough made it feasible to train deeper networks, although computational limitations and the scarcity of large datasets hindered progress. Despite the promise of backpropagation, neural network research faced significant challenges in the late 1980s and early 1990s.

3. **Renaissance of Neural Networks (1990s-2000s)**

   The resurgence of interest in neural networks in the 1990s and 2000s can be attributed to several factors. First, the advent of more powerful computing hardware, particularly Graphics Processing Units (GPUs), enabled researchers to train larger and more complex models more efficiently. Second, the availability of vast amounts of data, driven by the rise of the internet and digital data storage, provided the necessary resources for training deep networks.

   During this period, important advances were made in network architectures and training techniques. The introduction of Convolutional Neural Networks (CNN) by Yann LeCun and his colleagues revolutionized image-processing tasks. Convolutional layers in CNN capture spatial feature hierarchies from input images and used these features for tasks like image classification and Object Detection (OD). Another significant development was the introduction of Recurrent Neural Networks (RNN), which can handle sequential data.

4. **The Deep Learning Revolution (2010s)**

   The 2010s witnessed an explosion of interest and progress in DL, driven by several landmark achievements and technological advancements. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) played a crucial role in showcasing the power of DL models. In 2012, Alex Krizhevsky and his team developed a DNN named AlexNet that achieved groundbreaking performance on the ImageNet dataset and significantly outperformed traditional computer vision methods [15]. AlexNet's success sparked widespread interest in DL, leading to the development of more sophisticated architectures. VGGNet, developed by the Visual Geometry Group at the University of Oxford, further improved image classification accuracy by using very deep networks with small convolutional filters [16]. Another notable model, GoogLeNet (Inception), introduced by Szegedy et al., employed a novel architecture with inception modules to improve computational efficiency and performance [17].

   In 2016, the progress of Residual Networks (ResNet) addressed the problem of training DNN by introducing residual connections, which allowed gradients to flow more easily through the network during training. ResNet achieved state-of-the-art performance on several benchmarks and became a foundation for many subsequent DL models [18]. In natural language processing, the introduction of sequence-to-sequence models and the attention mechanism revolutionized tasks like machine translation. The Transformer model, introduced by Vaswani et al., replaced recurrent layers with self-attention mechanisms, enabling parallel processing and improving performance on various Natural Language Processing (NLP) tasks [19]. This led to the development of large-scale pre-trained language models, such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer(GPT) which achieved remarkable results on a wide range of NLP benchmarks [20].

5. **Current State and Applications (2020s)**

DL has become a cornerstone of modern AI, with applications spanning numerous domains. In computer vision, models like You Only Look Once (YOLO) and Mask R-CNN enable real-time OD and instance segmentation [21]-[22]. In healthcare, DL models assist in medical imaging, disease diagnosis, and drug discovery, providing tools for early detection and personalized treatment plans [23]. In speech recognition and synthesis, models like WaveNet and Tacotron have significantly improved the naturalness and accuracy of generated speech [24]- [25]. Autonomous vehicles leverage DL for perception, decision-making, and control, enabling advances in self-driving technology [26]. DL also plays a critical role in recommendation systems, enhancing user experiences on platforms like Netflix, YouTube, and Amazon by predicting user preferences and suggesting relevant content [27]. In finance, DL models are used for algorithmic trading, fraud detection, and risk management, helping institutions make data-driven decisions and mitigate risks [28]. Table 1.1 provides the overview of DL milestone.

Table 1.1: Overview of the Evolution of Deep Learning

Period	**Milestone**	**Advances & Key Figures**	**Significant Models & Techniques**	**Applications**
1940s-1970s	Foundations of ANN	- McCulloch and Pitts propose artificial neurons (1940s) - Multi-layer perceptrons developed	- Perceptron	Basic pattern recognition

Period	Milestone	Advances & Key Figures	Significant Models & Techniques	Applications
1980s	Backpropagation and Neural Network Training	- Backpropagation algorithm - Computational and data limitations lead to AI Winter	- Enhanced training for multi-layer networks	Neural network training gains feasibility despite limited datasets
1990s-2000s	Neural Network Resurgence	- GPUs enable efficient training - Internet and digital storage drive large datasets	- CNN - RNN	Image classification, speech recognition
2010s	DL Revolution	- AlexNet wins ImageNet Challenge, revitalizing DL - Development of VGGNet, GoogLeNet, ResNet - Attention mechanism in NLP	- AlexNet, VGGNet, GoogLeNet, ResNet, Transformer	Image classification, NLP, medical imaging

Period	Milestone	Advances & Key Figures	Significant Models & Techniques	Applications
2020s (Current)	DL becomes a cornerstone of modern AI	- Models for real-time OD, segmentation, and NLP	- YOLO, Mask R-CNN, BERT, GPT	Real-time OD, healthcare, autonomous vehicles, speech recognition, fraud detection and agriculture sector

1.6.2 Deep Learning Use Cases in Agriculture Sector

Agriculture, the backbone of food production, faces numerous challenges, from optimizing crop yields to managing pests and diseases. By leveraging vast amounts of data and advanced algorithms, DL models can provide valuable insights and predictions. It also revolutionized various aspects of agricultural practices which are summarized as follows. Figure 1.2 shows the use of DL in agriculture sector.

1. **Crop Monitoring and Yield Prediction:** Crop monitoring and yield prediction are essential tasks in modern agriculture. Accurate assessments of crop health and yield forecasts enable farmers to make informed decisions regarding irrigation, fertilization, and harvesting schedules. DL models, particularly CNN, have shown remarkable capabilities in analyzing satellite imagery and sensor data to monitor crop growth and predict yields. These models can identify subtle differences in plant color, texture, and structure, enabling early detection of issues that may affect crop yields [29].

2. **Pest and Disease Detection:** Pests and diseases are significant affects to

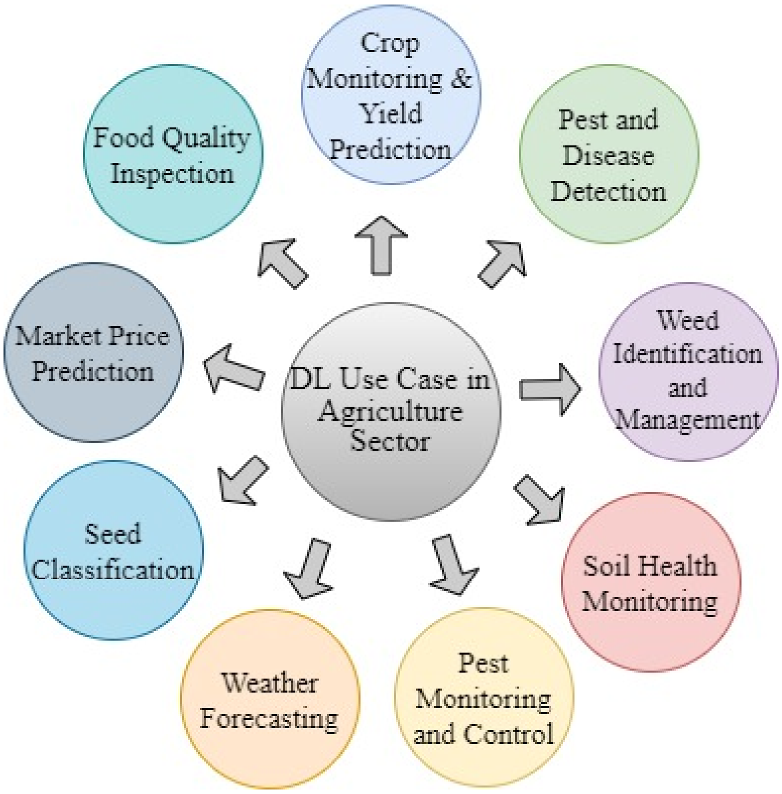

Figure 1.2: DL use case in the agriculture sector.

crop production, often causing substantial losses if not detected and managed promptly. DL models offer a promising solution by automating the detection and diagnosis of plant diseases and pest infestations. By analyzing images of crops, these models can identify symptoms and patterns indicative of specific diseases or pest damage [30].

3. **Weed Identification and Management:** Weed control is essential for maintaining crop yields and minimizing competition for resources. DL models prove beneficial in weed identification and management by differentiating crops and weeds in field images. By enabling targeted herbicide application or mechanical weed removal, these models contribute to sustainable farming practices and reduced chemical usage [31].

4. **Soil Health Monitoring:** Soil health is critical for crop productivity and sustainability. DL models can analyze soil sensor data, such as moisture levels and nutrient content, to assess soil health and recommend appropri-

ate interventions. By optimizing irrigation and fertilization practices, these models help conserve resources and enhance crop yields [32].

5. **Pest Monitoring and Control:** DL algorithms can detect and track pest populations using data from trap cameras, sensors, and monitoring devices. By predicting pest outbreaks and movement patterns, farmers can implement targeted control measures. It also reduces the used of pesticides and minimizes environmental impact [33].

6. **Weather Forecasting:** Plays a crucial role in agriculture, helping farmers make informed decisions about planting, irrigation, harvesting, and pest management. DL has emerged as a powerful tool for improving the accuracy and reliability of weather forecasts, enabling more precise predictions of short-term and long-term weather patterns. DL-based weather forecasting systems can provide valuable insights into short-term weather phenomena, such as thunderstorms, hurricanes, and heatwaves, as well as long-term climate trends. By integrating DL models into existing forecasting systems, meteorologists can improve the accuracy and reliability of weather forecasts, helping farmers mitigate risks and optimize their agricultural practices in an ever-changing climate [34].

7. **Seed Classification:** Seed classification is the process of categorizing seeds into distinct groups depending on various parameters such as shape, species, color, variety, size, and genetic traits. This classification is essential for seed producers, farmers, researchers, and regulatory bodies to ensure quality control, breeding programs, seed certification, and efficient management of seed resources. CNN is well-suited for seed classification tasks due to their ability to learn hierarchical features from raw input data [35].

8. **Market Price Prediction:** Through the analysis of historical market information, DL models predict future commodity prices, guiding farmers to decide when to plant, harvest, and market their products. [36].

9. **Food Quality Inspection:** DL systems inspect food products for quality attributes such as size, shape, color, and defects, ensuring food safety and meeting quality standards.

These use cases demonstrate the versatility of DL in addressing various challenges across the agricultural value chain, from production and management to distribution and market analysis. Implementing DL offers a more efficient and automated method for processing large volumes of soybeans with speed and accuracy. DL algorithms are particularly effective in image recognition and classification, making them well-suited for detecting soybean defects and varieties. The main goal of these techniques is to improve accuracy and reliability, reducing the chances of false positives or overlooked defects compared to traditional methods. From a financial standpoint, automated DL-based defect detection systems can result in substantial savings by decreasing the need for manual labor and reducing losses due to undetected defects. With the rising global demand for soybeans, the necessity for efficient and precise quality control measures is growing. Developing advanced computational approaches for soybean defect quantification addresses this need and aligns with industry objectives to enhance efficiency and quality.

1.7 Thesis Objectives

The major contribution of thesis and objectives of research work are listed as follows: -

i. To collect good and defective soybean seeds image dataset.

ii. To pre-process soybean seeds image dataset.

iii. To develop a recognition model for soybean seeds defects.

iv. To develop an identification model for soybean seeds varieties.

v. To compare and validate the proposed models with existing models based on various performance metrics.

1.8 Research Methodology

To achieve the proposed objectives, Intel Xeon®Gold 5222 3.9GHz processor workstation with 1TB 7200 RPM SATA HDD, 8*16 GB DDR4 2933 RAM is used. Python 3.10 was installed on the Windows 11 Pro operating system for implementation purposes. The process of achieving the proposed research methodology is explained in Figure 1.3.

1. To achieve the first objective, samples of soybean seed are collected from the Vidarbha region of Maharashtra, India. As the research work began in 2020, at that time soybean seed dataset was not publicly available. Hence, initially soybean samples of different defects and varieties are collected and with the help of agriculture expert and farmers samples are splits into 10 different classes. Using the experimental setup mentioned in Figure 3.1 images are captured and the dataset is developed. Simultaneously various research works related to the classification of seeds are studied and identified the exact problem associated with existing methods. Details steps of soybean dataset preparation is mentioned in Chapter 3.

2. In the second objective of the research work, soybean seed images are pre-processed using the seed contour detection (SCD) algorithm. As the DL model required pre-processed data, using SCD algorithm dataset is filtered, and images quality are enhanced. The complete process is explained in Chapter 4.

3. To classify the defective seeds of soybeans in third objective, initially ML algorithms and CNN architecture are used. Later, soybean seed defect identification network (SSDINet) is developed which outperforms all existing methodologies and identify seven defects and one good quality of soybean seed. In addition, using the transfer learning technique, EfficientNetv2 with customized head detects the seven defects and one good quality of soybean seed and also outperforms existing methodology.

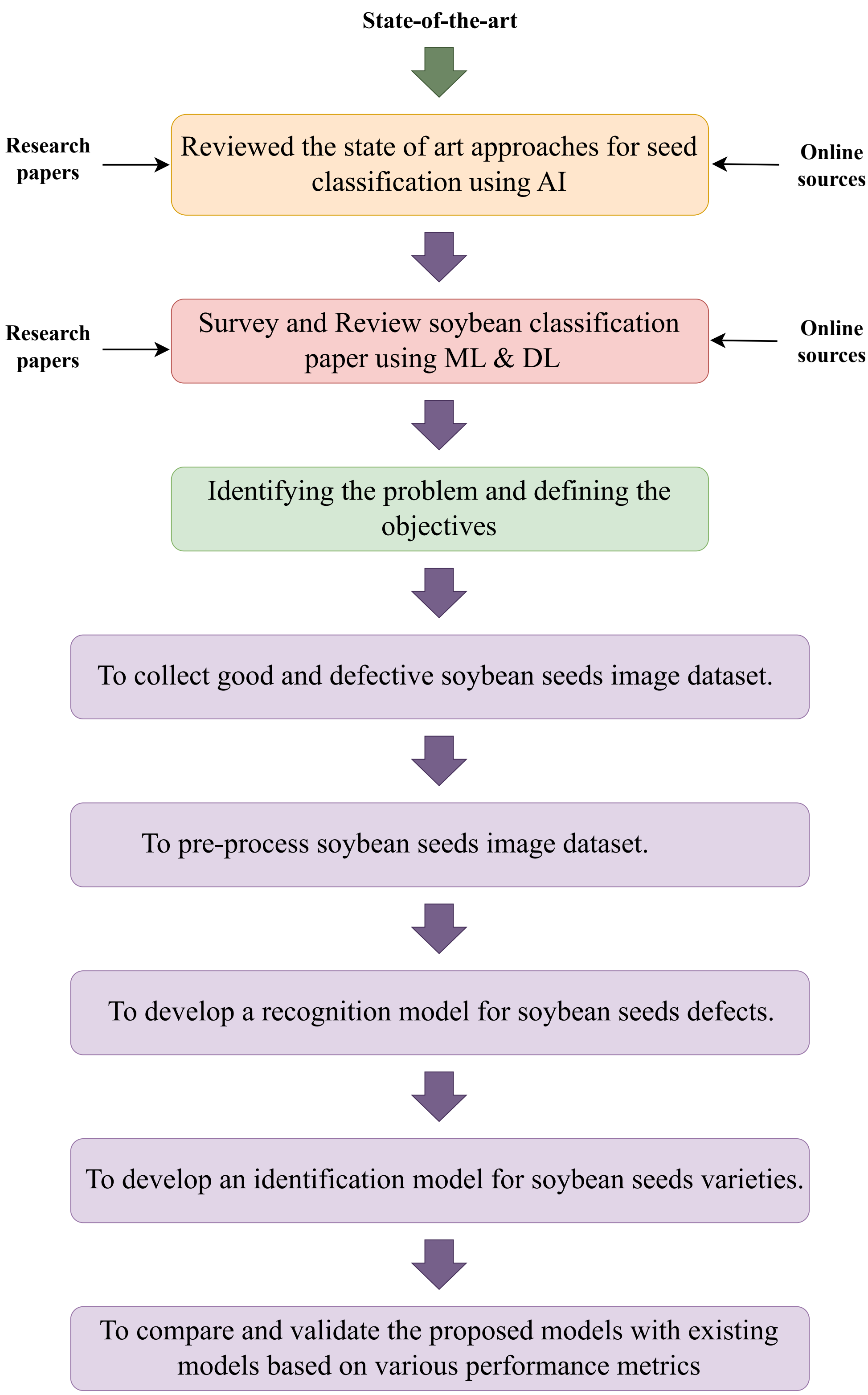

Figure 1.3: Flowchart of the research methodology.

4. To achieve the fourth objective, GoogleNet with the modified head is used to classify three soybean seed varieties which is elaborated in brief in Chapter 6.

5. In the fifth objective proposed SSDINet and DVINet is compared with existing methodology and outperform existing approaches in all evaluation metrics. Details are mentioned in Chapter 7.

1.9 Summary

This chapter introduces the significance and use of soybean seed in all sectors from agriculture to India's growth perspective. It also explains the effect of soybean seed degradation from an economic, nutritional, and environmental point of view. The motivation behind the development of this research work is also explained in this chapter. Later, as the classification of seed is carried out using DL approaches this chapter explains the evolution and use case of DL from an agriculture perspective. At the end, it highlights the objectives of thesis and the research methodology adopted to achieve the classification of soybean seed into 10 different classes.

1.10 Thesis Organization

The subsequent sections of this thesis are arranged into eight chapters. Chapter 2 deals with the background of ML and DL techniques. It also explains the various existing approaches used to classify various seeds (including defects and varieties) using DL and ML approaches. Chapter 3 presents the process of soybean seed collection and preparation of the dataset (objective 1). Using farmers and agriculture experts knowledge, the dataset is split into 10 different classes is also mentioned in this chapter. Chapter 4 details the proposed SCD algorithm. This chapter mainly highlights the image enhancement process (objective 2) of soybean seed. The process of soybean seed defect identification using SSDINet and DVINet (objective 3) is explained in Chapter 5. Chapter 6 explained variety identification of soybean seed using a DL approach (Objective 4). Chapter 7 compares SSDINet and DVINet with existing methodology and explains how the proposed research work surpasses other approaches (Objective 5). At the end, chapter 8 provides a comprehensive summary of the thesis key findings and contributions. Figure 1.4 shows the organization of the thesis in the pictorial format.

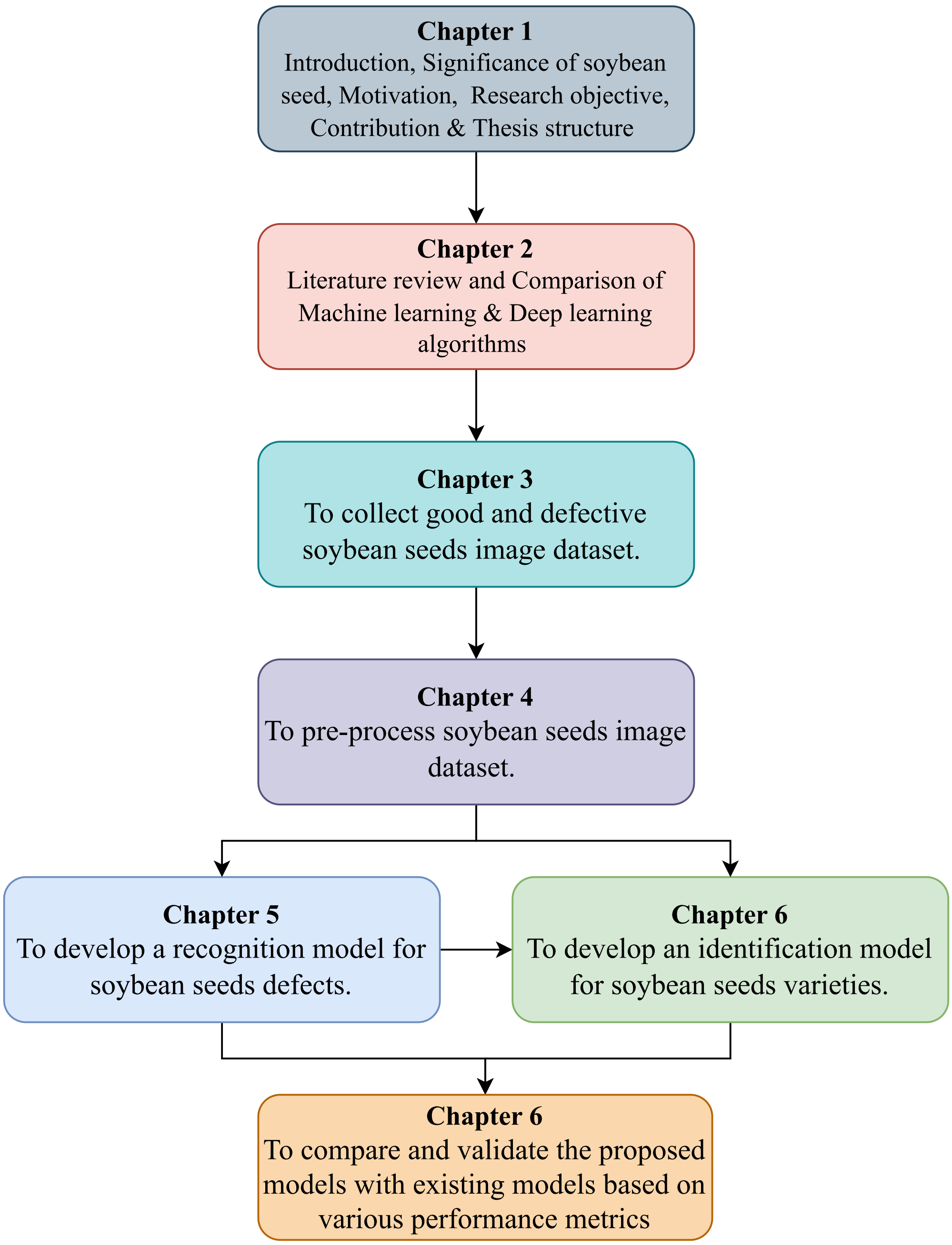

Figure 1.4: Organization of the thesis.

Chapter 2

RELATED WORK

2.1 Introduction

Agriculture plays a pivotal role in India's economy, particularly in regions like northern India where rice farming is predominant. However, traditional methods for ensuring grain quality prevail despite technological advancements. The main objective of this chapter is to illustrate AI's potential in the agriculture sector. Utilizing DL algorithms, the study focuses on detecting and classifying various seeds. It also deals with the basics of image classification and explains various algorithms of ML and DL models used to detect the class of seed. Image classification is a process in computer vision where an algorithm assigns a label or category to an input image [37]. It involves several key steps to accurately recognize and identify the objects, patterns, or features present in the image. The process begins with an input image that can be in various formats such as JPEG or PNG. Before feeding the image into a classification model, it often undergoes preprocessing steps such as resizing, normalization, and data augmentation to improve the accuracy and robustness of the model. Feature extraction is a crucial step where distinctive characteristics of the image such as edges, textures, colors, and shapes, are identified and quantified. Traditional methods use techniques like edge detection and histograms, while modern approaches rely on DL models to automatically learn relevant features. A classification model, typically a machine learning or deep learning algorithm, is then used to assign a label to the image.

CNN are widely used for classification due to their ability to capture spatial hierarchies in images. Models like Visual Geometry Group (VGG) [16], Residual Network (ResNet) [18], and Inception [17], which are pre-trained on large datasets such as ImageNet, are often fine-tuned for specific tasks [38].

During training, the model learns to map the input images to their respective labels by minimizing the prediction error. Once trained, the model can predict the label of new, unseen images. This involves feeding the new image into the model, which then outputs a probability distribution over the possible categories, with the category having the highest probability being chosen as the predicted label. The performance of the classification model is evaluated using various metrics to assess how well the model is performing and to identify areas for improvement. Image classification has numerous applications, including object recognition, scene classification, medical imaging, and autonomous vehicles. It forms the basis for more complex tasks such as object detection, segmentation, and image generation, making it a fundamental task in computer vision. To achieve the task image classification various approaches of ML and DL are listed in section 2.2. This chapter is derived from the article [1].

[1] Sable A, Singh P, Singh J, Hedabou M. A Survey on Soybean Seed Varieties and Defects Identification Using Image Processing. in International Semantic Intelligence Conference (IHIC-2021). Proceedings are published in Advances in Computational Intelligence, its Concepts & Applications (ACI 2022).

2.2 Technology Background

This sub-section explain the working model of ML and DL techniques used to classify the seed of soybean.

2.2.1 Machine Learning (ML)

"We are moving towards a world where data is the new oil and machine learning is the engine that extracts insights from it [39]".

Amit Ray, Compassionate Artificial Intelligence (2018)

The goal of ML is to create statistical models and algorithms that let computers carry out tasks without having explicit instructions. ML develops systems that enhance their performance on specific tasks over time through accumulated experience. Many leading companies use ML for prediction or operational tasks. Based on the nature of the learning process and the type of feedback received by the algorithm there are four types of ML algorithms shown in Figure 2.1.

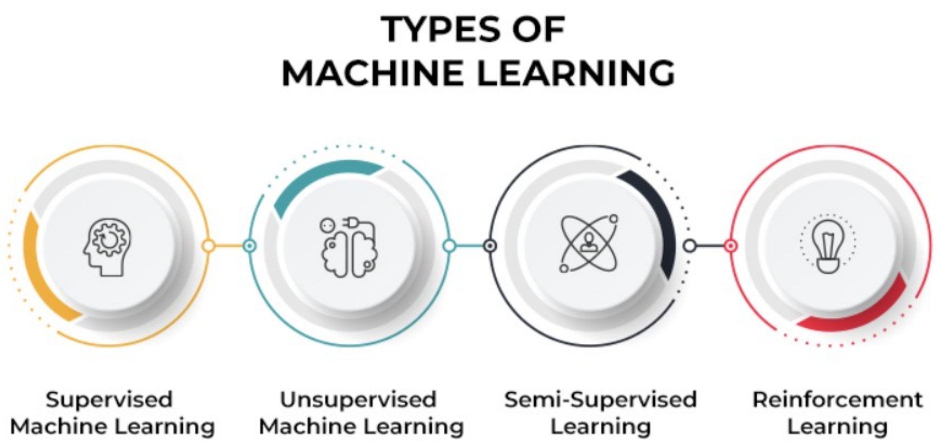

Figure 2.1: Types of ML.

i. **Supervised Learning:** In this approach, the training process involves a labeled dataset, where each data point is paired with an output. The model learns to predict the target output based on the given inputs [40].

ii. **Unsupervised Learning:** This approach handles data without labels, where the model attempts to find patterns, structures, or relationships on its own, without being directed toward a specific output [41].

iii. **Semi-Supervised Learning:** This approach used the training process between supervised and unsupervised learning. It uses a small amount of labeled data and a large amount of unlabeled data for training. This approach can significantly improve learning accuracy when labeled data is scarce [42].

iv. **Reinforcement Learning:** Reinforcement learning allows an agent to make decisions by interacting with an environment, aiming to optimize cumulative rewards. Feedback in the form of rewards or punishments helps the agent refine its actions as it learns over time [43].

In this thesis, four algorithms of ML are used which are explained as follows:-

i. **K-Nearest Neighbors (KNN) Algorithm:** KNN is a basic yet highly effective algorithm in ML, used for classification and regression. KNN specifically belongs to the supervised learning category because it requires labeled training data to make predictions. This algorithm falls under instance-based learning, where no prior assumptions are made regarding the data distribution. Instead, it makes predictions based on the instances in the training dataset. In the prediction stage, the algorithm calculates the distance between the new data point and all points in the training set, identifies the K nearest neighbors, and predicts based on their class labels or values. The Figure 2.2 shows the basic classification performed by KNN. KNN does not involve any explicit training phase since it is a lazy learning algorithm. It simply stores the training data. To classify or predict a new query point, the algorithm computes its distance to all training data points, using metrics like Euclidean, Manhattan, or Minkowski distances. In classification tasks, the most common class among the K nearest neighbors is chosen, whereas in regression, the algorithm predicts by averaging the values of these neighbors [44].

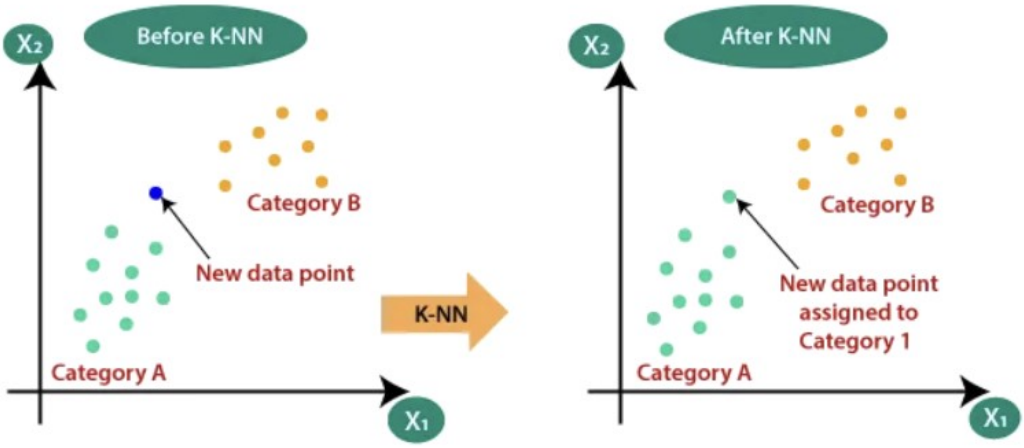

Figure 2.2: KNN classifier.

Pros of KNN

(a) **Simplicity:** It does not require any complex parameters or training algorithms.

(b) **Adaptability:** Used for both classification and regression tasks.

(c) **Versatility:** Effective in multi-class classification problems.

Cons of KNN

(a) **Computationally Expensive:** KNN involves calculating the distance between the query point and all training points, which can be time-consuming and resource-demanding, particularly with large datasets.

(b) **Memory Intensive:** KNN needs to store all the training data, which can be problematic for large datasets.

(c) **Sensitivity to Irrelevant Features:** KNN's performance can degrade if the dataset has many irrelevant or redundant features.

(d) **Choice of Distance Metric:** The performance of KNN depends on the choice of distance metric, which might need domain-specific knowledge to select appropriately.

ii. **Logistic Regression (LR) Algorithm:** LR is a widely used ML algorithm, mainly applied to binary classification tasks, but it can also be adapted for multiclass classification. It predicts the probability of a class, which is often mapped with classes using a threshold (commonly 0.5). Logistic Regression models the probability that a given input x belongs to a particular class. This probability is modeled using the logistic sigmoid function mentioned in Equation 2.1. The cost function for LR is the log-loss or binary cross-entropy function. The model parameters w and b are optimized to minimize the cost function using methods such as Gradient Descent, which iteratively updates the parameters to reduce the error [45].

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2.1}$$

where

$$z = \mathbf{w}^T \mathbf{x} + b. \tag{2.2}$$

Here, $\mathbf{w}$ represents the weights, $\mathbf{x}$ is the feature vector, and b is the bias term.

Pros of LR

(a) **Simplicity and Interpretability:** LR is easy to understand and implement. The model parameters (coefficients) can be interpreted as the impact of the corresponding features on the probability of the target class.

(b) **Efficiency:** It is computationally efficient and works well on relatively small datasets.

(c) **Less Prone to Overfitting:** With proper regularization (such as L1 or L2 regularization), LR is less prone to overfitting.

Cons of LR

(a) **Not Suitable for Complex Relationships:** For complex and non-linear decision boundaries, LR may not perform well compared to more advanced techniques like Decision Trees or Neural Networks.

(b) **Feature Scaling:** LR requires careful feature scaling (standardization or normalization) to ensure that the model converges properly and performs well.

iii. **Random Forest (RF) Algorithm:** RF classifier is versatile as it addresses classification and regression tasks. It employs ensemble learning and amalgamates multiple classifiers to tackle intricate problems [46]. Significantly, its accuracy exceeds that of the Decision Tree (DT) algorithm, as it combines multiple DTs, resulting in a more robust prediction. Utilizing the bagging method combines diverse learning models and augments overall performance. The RF algorithm begins by creating random samples from the dataset. Each sample constructs a DT to contribute to the final prediction. Subsequently, the RF classifier assesses the output from all DTs and predicts the final result based on majority voting. By increasing the number of trees, accuracy improves while minimizing overfitting concerns.

Pros of RF

(a) **High Accuracy:** RF yields higher accuracy compared to single decision trees, especially for complex datasets with non-linear relationships.

(b) **Handles Missing Values:** RF can handle missing values in the dataset without requiring imputation.

(c) **Parallelization:** Training of individual decision trees in a Random Forest can be parallelized, leading to faster training times.

Cons of RF

(a) **Less Effective on Noisy Data:** RF may struggle with noisy datasets, as individual decision trees can be sensitive to noise.

(b) **Memory Consumption:** Storing multiple decision trees in memory can consume a significant amount of memory, particularly for large forests with deep trees.

iv. **Support Vector Machine (SVM):** SVM is a robust supervised ML algorithm utilized for classification as well as regression tasks [47]. SVM falls under the domain of supervised learning, where it gains knowledge from training data that has been labeled and then uses that knowledge to create predictions. A linear hyperplane can effectively divide the data points in this space shown in Figure 2.3. Depending on the type of data, different kernel functions, including polynomials, Radial Basis Functions (RBF), and sigmoid, can be used. Here are some common types of SVM:

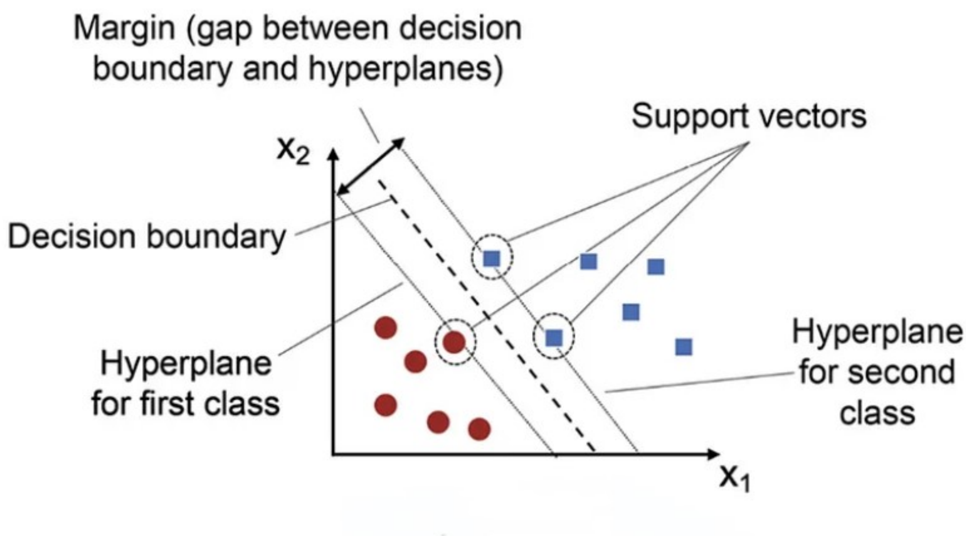

Figure 2.3: SVM classifier

(1) **Linear SVM:** Linear SVM is the most straightforward variant, suitable for problems where the data is linearly separable. It finds the optimal hyperplane that linearly separates the data points into different classes. This hyperplane is a line in 2D or in 3D. Linear SVM is effective when the classes can be separated by a straight line or a hyperplane, such as in binary classification tasks with linearly separable data.

(2) **Polynomial Kernel SVM:** Polynomial Kernel SVM is used when the data is not linearly separable and requires a higher-dimensional space to be separated. It employs a polynomial kernel function to convert input features

into a higher-dimensional space, which allows SVM to locate a nonlinear decision boundary that effectively differentiates the classes. Polynomial Kernel SVM is suitable for problems with complex decision boundaries, such as image classification tasks where the relationship between features may not be linear.

(3) **Radial Basis Function (RBF) Kernel SVM:** RBF Kernel SVM is a popular choice for nonlinear classification problems. It transforms the input features into an infinite-dimensional space using a radial basis function kernel. This kernel function measures the similarity between data points in the original feature space and assigns higher weights to nearby points. RBF Kernel SVM can capture complex relationships in the data and is effective for tasks where the decision boundary is highly irregular or nonlinear.

(4) **Custom Kernel SVM:** In addition to the predefined kernel functions mentioned above, SVM also allows the use of custom kernel functions tailored to specific problem domains. Custom Kernel SVM enables flexibility in modeling complex relationships in the data by defining a kernel function that captures the domain knowledge or characteristics of the data.

Pros of SVM

(a) **Effective in High-Dimensional Spaces:** VM performs well in high-dimensional spaces, making it suitable for tasks with a large number of features, such as text classification and image recognition.

(b) **Robust to Overfitting:**SVM maximizes the margin between classes, which helps reduce overfitting and improves generalization performance.

(c) **Effective for Nonlinear Data:** SVMs can model complex decision boundaries by using kernel functions, allowing them to handle nonlinear data effectively.

Cons of SVM

(a) **Sensitive to Noise:** SVMs can be sensitive to noisy data, which can affect the placement of the decision boundary and lead to suboptimal performance.

(b) **Parameter Sensitivity:** SVM performance can be sensitive to the choice of hyperparameters, such as the kernel type and regularization parameter. Tuning these parameters effectively can require significant computational resources and expertise.

2.2.2 Deep Learning (DL)

DL is a subset of ML that involves the use of ANN to learn complex patterns and data. These deep neural networks are capable of learning hierarchical representations of data through the composition of multiple nonlinear transformations. Figure 2.4 shows the components commonly found in deep learning architectures:

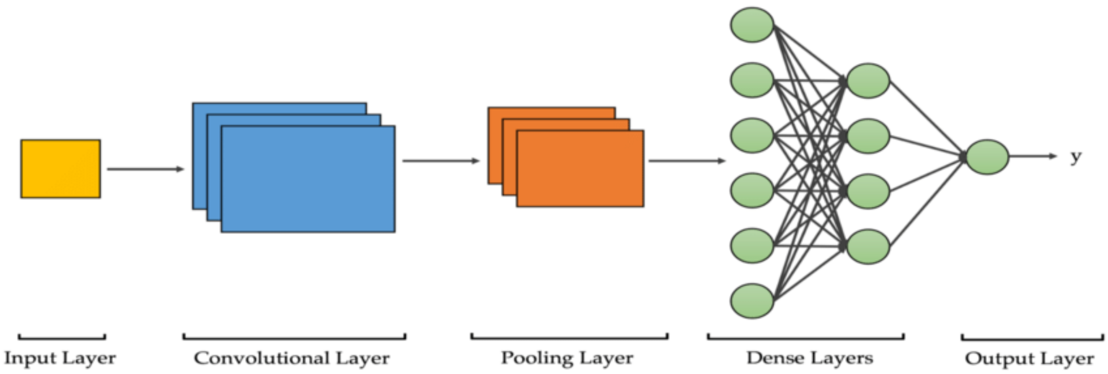

Figure 2.4: Architecture of CNN.

Input Layer: The input layer serves as the first layer of the neural network, hence it receives raw input data. Each neuron in this layer corresponds to a feature or input variable, and the number of neurons is based on the dimensionality of the input data.

Convolutional Layer: Convolutional layers are the primary building blocks of CNN, extensively used in computer vision applications. This layer performs convolution operations on the input data using learnable filters or kernels and effectively captures spatial patterns by detecting features like edges, textures, and shapes. They are defined by parameters such as the number of filters, filter size, and stride.

Pooling Layer: Pooling layers are often integrated after convolutional layers in CNN architectures to lower the spatial dimensions of feature maps while retaining key information. Utilizing techniques like max pooling or average pooling, these layers downsample the feature maps, which helps decrease the network's computational complexity and enhances its robustness to variations in the input data.

Dense Layer: Dense layers, often referred to as fully connected layers, are fundamental components of neural networks, where every neuron connects to all neurons in the preceding layer. They are essential for capturing intricate nonlinear relationships within the data. Typically positioned in the later stages of the network, dense layers aggregate the features extracted by earlier layers to facilitate predictions.

Output Layer: The output layer serves as the final component of a neural network to generate the network's predictions or outputs. The configuration of neurons in this layer varies based on the specific task. In binary classification tasks, a single neuron with a sigmoid activation function is often employed to yield a probability score. For multi-class classification, the output layer generally features multiple neurons (one for each class) and uses a softmax activation function to provide class probabilities. In regression tasks, the output layer may consist of a single neuron with a linear activation function, producing continuous output values.

2.3 State-Of-The-Art (SOTA)

This section explores existing research, methodologies, and advancements in DL-based seed identification. Researchers investigate various techniques, including image processing, machine learning, and hyperspectral imaging, to improve classification accuracy and efficiency in agricultural applications [48]. Subsection 2.3.1 presents the various approaches for seed defects identification while subsection 2.3.2 introduces state-of-the-art methods for variety identification using neural network approaches.

2.3.1 Defect Identification

This sub-section delves into the applications of DL techniques in agriculture, to detect defects of seed and perform seed classification. Table 2.1 highlights a few articles to identify defects of various seeds. Zhao et al. [49] emphasize the potential of computer vision for classifying seeds and seedlings, which is vital for purity analysis and germination assessments. The study discusses various challenges, including a lack of expertise, the lengthy training process, and the requirement for large reference specimens. It recommends optimizing processes related to image acquisition, dataset creation, and model development to expedite the integration of computer vision in seed testing applications. The authors also propose a concept flow chart to advance computer-assisted seed identification.

Table 2.1: Identification of seed defects using DL techniques

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Corn Seed Defect Detection Based on Watershed Algorithm and Two-pathway Convolutional Neural Networks [50].	Frontiers in Plant Science (2022).	Corn Seed	Presents Corn-seed-Net model which leverages the strengths of both VGG16 and ResNet50. It uses Watershed (segmentation) + CNN (Classification).	Achieved 95.63% average accuracy.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Enhanced Individual Characteristics Normalized Lightweight Rice-VGG16 Method for Rice Seed Defect Recognition [51].	Multimedia Tools and Applications (2023).	Rice Seed	Develop a lightweight version of Rice-VGG16 for the purpose of rice seed defect recognition.	Achieved 99.51% recognition accuracy.
Detection of Cotton Seed Damage Based on Improved YOLOv5 [52].	MDPI-Processes (2023).	Cotton Seed	Images of cotton seeds with three damage levels (undamaged, slightly damaged, seriously damaged) were collected and labeled. Later, it given as input to improved YOLOv5s algorithm, which incorporated the CARAFE upsampling operator and an enhanced loss function for damage identification.	The improved YOLOv5s achieved high accuracy (mAP_0.5 up to 99.5%) and recall rates.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Identification of Defective Maize Seeds Using Hyperspectral Imaging Combined with Deep Learning [53].	Foods-MDPI (2022).	Maize Seed	Collected hyperspectral data from 400 maize seeds and developed CNN-FES for feature selection and CNN-ATM for classification.	Gained accuracy up to 97.50%.
Research on Classification Method of Maize Seed Defect Based on Machine Vision [54].	Journal of Sensors (2020).	Maize Seed	Used CNNs and transfer learning for seed classification, compared with traditional machine learning algorithms.	DL outperforms traditional methods with 95% accuracy.
Detection of Surface Defects for Maize Seeds Based on YOLOv5 [55].	Journal of Stored Products Research (2024).	Maize Seed	Proposed method integrates YOLOv5 framework for image processing and defect detection.	Acheived 95.5% accuracy with 8.8 MB size.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
A Lightweight Method for Maize Seed Defects Identification Based on Convolutional Block Attention Module [56].	Frontiers in Plant Science (2023).	Maize Seed	Integrate CBAM into MobileNetv3 for maize seed defect detection.	Efficient network with superior convergence and accuracy of 93.14%.
Detection of Insect-Damaged Maize Seed Using Hyperspectral Imaging and Hybrid 1D-CNN-BiLSTM Model [57].	Infrared Physics & Technology (2024).	Maize Seed	Hyperspectral imaging (930–1866 nm) was used to capture maize seed data, with the optimal band ratio identified via ANOVA. The 1D-CNN-BiLSTM model integrated both spectral and texture features, achieving optimal classification results with GLCM texture features.	Compared to traditional SVM, the 1D-CNN-BiLSTM model achieved better results.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Enhancing Soybean Classification with Modified Inception Model: A Transfer Learning Approach [58].	Elsevier-Gene (2024).	Soybean Seed	Classify problematic soybean seeds using a modified InceptionV3 model and advanced optimization techniques.	High precision and recall demonstrate the model's effectiveness, achieving 98.73% accuracy in classification.
Online Classification of Soybean Seeds Based on Deep Learning [59].	Elsevier-Engineering Applications of Artificial Intelligence (2023).	Soybean Seed	Utilized MSRCR for image segmentation and SoyNet for classification on NVIDIA Jetson TX2.	Efficient real-time soybean quality assessment with high accuracy and speed.

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Deep Learning Based Soybean Seed Classification [60].	Elsevier-Computers and Electronics in Agriculture (2022).	Soybean Seed	SNet is a lightweight CNN that uses separable convolution blocks, MFR modules, and average pooling combined with Mask R-CNN for segmentation and classification.	SNet achieves 96.2% accuracy in soybean seed classification and surpasses state-of-the-art models with only 1.29M parameters.
Real-time Recognition System of Soybean Seed Full-Surface Defects Based on Deep Learning [61].	Elsevier-Computers and Electronics in Agriculture (2021).	Soybean Seed	Developed a DL-based sorting system for full-surface recognition of soybean seeds using alternate circumrotating exposure and CNN classification.	Achieved 97.84% accuracy with MobileNetV2 on masked datasets, enabling real-time sorting at high precision and speed.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Classification of External Defects on Soybean Seeds Using Multi-Input Convolutional Neural Networks with Color and UV-Induced Fluorescence Images Input [62].	Intelligence, Informatics and Infrastructure (2024).	Soybean Seed	Combines color and UV fluorescence images to improve classification accuracy for soybean seed defects using three pre-trained networks (AlexNet, ResNet-18, EfficientNet).	ResNet-18 achieved the highest accuracy of 93.9%.
Defect Detection and Classification of Soybean Using Convolutional Neural Network [63].	IEEE-7th International Conference on Information and Computer Technologies (2024).	Soybean Seed	Developed an image-processing system using CNNs to detect and classify soybean defects with a Raspberry Pi Camera module.	Slight inaccuracies occurred in distinguishing deformed soybeans from damaged ones, which affected classification.

Wang et al. [50] outline a novel approach for corn seed defect detection, leveraging a watershed algorithm in combination with a two-pathway CNN model which is trained on both RGB and NIR images. The model achieved an average accuracy of 95.63% and outperformed traditional methods. The study explores various parameter settings' impacts on model training and discusses the potential application of the proposed method for high-throughput quality control of corn seeds, which offers an effective. tool for agricultural quality assurance.

Sun *et al.* [51] present an enhanced method named Rice-VGG16 for rice seed defect recognition This approach addresses shortcomings of current approaches such as complex operations and non-normalization processing. Defects in rice seeds are initially classified, and then image enhancement steps are employed to standardize the seed images and develop the datasets. The fifth max-pooling layer is exchanged for an average-pooling layer, and the activation function is altered to Leaky Rectified Linear Units (Leaky-ReLU) to enhance individual features and boost recognition accuracy. Furthermore, a batch normalization layer is included after the last convolution layer of each group, the first fully connected layer is eliminated, the number of neurons in the second fully connected layer is modified to 1024, and the model parameters are optimized for reduced weight. This results in the creation of a normalized lightweight Rice-VGG16 model that improves recognition speed. Hence, by modifying network architecture using the activation function and batch normalization layers, the proposed method achieves improved recognition accuracy and speed. Experimental results showcase high training and recognition accuracies of 99.63% and 99.51%, respectively, with significant parameter reduction compared to traditional VGG16 models, which leads to reduced training and recognition times.

Xu *et al.* [53] develops a fast, non-destructive method for detecting defects using hyperspectral imaging for maize seeds. Raw spectra from 400 maize seeds, comprising 200 healthy seeds and 200 worm-eaten seeds, underwent preprocessing involving detrending and Multiple Scattering Corrections (MSC) to improve the spectral distinctions. The study introduces CNN-FES, a CNN architecture based on feature selection, which outperforms conventional methods like Successive Projections Algorithm (SPA) and Competitive Adaptive Reweighted Sampling (CARS) in capturing essential spectral data. Moreover, the CNN-ATM model, which features an attentional classification mechanism, attained classification accuracy exceeding 90% on both the training and test sets, with accuracy reaching as high as 97.50% in feature wavelength modeling. These results validate the effectiveness of the hyperspectral dataset used for detecting defects in maize seeds, which highlights its significant potential for processing and analyzing complex hyperspectral data. Huang *et al.* [54] used CNN and transfer learning into the seed defect classification domain and compared it against traditional ML algorithms. Experimental results indicated a significant improvement in classification accuracy with DL algorithms, achieving 95% accuracy with GoogLeNet compared to 79.2% accuracy with the SURF+SVM method. Furthermore, the study explored the impact of network depth on classification accuracy, revealing that deeper networks generally resulted in higher accuracy. Visualization techniques were employed to examine the feature maps of each CNN layer and represent the probability distribution of inference results using heat maps. Xia *et al.* [55] propose the YOLOv5 DL framework for detecting Surface irregularities in maize seeds. Initially, a system for capturing maize seed images is established, followed by preprocessing techniques to enhance image quality. The ECA-Improved-YOLOv5S-Mobilenet model is then introduced to improve feature learning and defect detection. Experimental results demonstrate high precision 92.8%, recall rate 98.9%, and mPA0.5 95.5% with a compact model size of 8.8 MB. Overall, this method offers a promising approach to automate seed grading and improve plantation practices, providing a solid foundation for future developments in seed quality assessment. Li *et al.* [56] introduce a lightweight and efficient network for to integrate the Convolutional Block Attention Module (CBAM) into the pre-trained MobileNetv3 to enhance feature extraction by focusing on crucial channel and spatial domain information. Validated with 12,784 images encompassing seven defect types, the proposed network outperforms other pre-trained models. With a true positive rate of 93.14%

and a false positive rate of 1.14%, it demonstrates exceptional convergence with a reduced number of iterations This approach promises improved maize seed defect identification, benefiting food safety and agricultural production. Kahar *et al.* [64] presents an integrated method for recognizing paddy plant leaf diseases and providing recommendations for their control. The research focuses on three prevalent paddy diseases in Malaysia: Bacterial Leaf Blight (BLB), Leaf Blast Disease (LBD), and Bacterial Sheath Blight (BSB). The recognition approach used is a neuro-fuzzy expert system, which integrates the learning capabilities of ANN with the human-like knowledge representation and interpretative strengths of fuzzy logic systems, complemented by a rule-based expert system. A prototype was created to support Malaysian paddy farmers and researchers by providing early detection of diseases and assistance with crop management. Effective crop management is crucial for ensuring crop health and maximizing yield. The recognition accuracy achieved by the system is 74.21%.

Lin *et al.* [65] proposed a soybean image segmentation method named Multi-Scale Retinex with Color Restoration (MSRCR) model to enhance the quality of soybean image with Otsu's segmentation, which achieves 98.05% accuracy. It addresses seed overlapping and adhesion effectively and offers potential for broader agricultural seed classification applications. After image enhancement, author presents SoyNet to perform the classification of soybean seeds which achieves 95.63% accuracy with a 4.92 ms classification time [59]. This state-of-the-art deep learning model is crafted for the online classification of soybean seeds, and incorporates a mix of CONV layers, pooling layers, inception modules, residual blocks, and a fully connected layer. The use of inception modules helps reduce the number of parameters and extract multi-dimensional features, while residual blocks are important for preventing model degradation and simplifying the optimization of weight parameters. These architectural choices enable SoyNet to efficiently process and classify soybean seeds with high accuracy and speed. SoyNet's deployment on the NVIDIA Jetson TX2 platform ensures it meets the requirements for efficient and effective online classification in agricultural applications.

Huang *et al.* [60] developed a soybean network named SNet to predict the classes of soybean seeds. This approach uses the popular object detection approach Mask-RCNN [22] to perform the segmentation of soybean seeds. The SNet is a lightweight CNN designed for the accurate classification of soybean seeds. The architecture is divided into three main sections. The first section comprises seven separable convolution blocks, a Batch Normalization (BN) layer, and a ReLU activation layer. The second section features three separable convolution blocks enhanced with Mixed Feature Recalibration (MFR) modules, which improve the model's ability to emphasize important areas and better capture damaged features. The third section includes an average pooling layer, followed by dense layers for classification. SNet uses a 3×3 kernel size with specific kernel numbers and stride. The full classification pipeline starts with image segmentation using the Mask R-CNN method, followed by classification with SNet. This model achieves a remarkable 96.2% identification accuracy while utilizing only 1.29 million parameters, surpassing six existing state-of-the-art models. Due to its efficiency, SNet is well-suited for the automatic recognition of soybean seeds on resource-constrained platforms, facilitating quality inspection and food safety processes. Gulzar *et al.* [58] employ DL models to classify problematic soybean seeds using a dataset of 5513 images across five classes. The InceptionV3 model was enhanced with five additional layers to improve performance. An initial training accuracy of 88.07% and a validation accuracy of 86.67% were achieved by utilizing techniques such as transfer learning, adaptive learning rate adjustment, and model checkpointing. Further tuning increased accuracy to 98.73%. Evaluation measures that highlighted the efficacy of the model were recall, F1-score, and accuracy (0.9706 to 1.0000). The model's potential for classifying soybean seeds is demonstrated by this study, which advances agricultural technology for crop health evaluation.

Yang *et al.* [66] proposes methods for high-throughput image acquisition, data processing, and analysis of soybean seed. To achieve high-throughput segmentation and classification of soybean seeds, the author used Mask R-CNN with transfer learning in conjunction with synthetic picture synthesis via domain randomization for training. Results indicate the ability to quantitatively assess color and various morphological traits and established a standard for genotype evaluation. Hence, the proposed method effectively segments individual seeds and calculates morphological parameters, proving practical for high-throughput phenotyping with reduced manual annotation costs. Zhao *et al.* [61] introduce a DL-based sorting system that innovatively recognizes the entire surface of soybean seeds. It employs an alternate circumrotating mechanism system that captures comprehensive seed feature information and facilitates precise classification through a trained DL model. Six seed categories were defined, and images were collected under varying brightness and surface conditions to quantify seed defects. Seven CNN models were evaluated, with MobileNetV2 showing the best performance. Visual assessment confirmed the model's capability to detect seed defects across different scales. Optimizations based on these results enhanced classification accuracy, reaching 97.84% on masked datasets. The system operates in real-time on NVIDIA's Jetson Nano.

2.3.2 Variety Identification

Variety identification of soybean seeds refers to the process of determining the specific type or variety of soybean from which the seeds originate. It involves distinguishing between different seed varieties based on their unique genetic, morphological, or biochemical traits. This identification is crucial in agriculture to ensure the correct variety is planted, which influences crop yield, quality, disease resistance, and adaptability to environmental conditions. Table 2.2 mentioned the research related with variety identification of various seed.

Table 2.2: Identification of seed variety using DL techniques

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Corn Seeds Identification Based on Shape and Colour Features [67].	Khazanah Informatika: Jurnal Ilmu Komputer dan Informatika (2020) .	Corn Seed	Performed variety identification of BIMA-20 Good vs. NASA-29 Good corn seed using color+shape features and perform classification through ANN.	Acheived 97% accuracy with both features.
Computer-Vision Classification of Corn Seed Varieties Using Deep Convolutional Neural Network [68].	Journal of Stored Products Research (2021).	Corn Seed	Used CNN for feature extraction and SVM, KNN, bagged tree, ANN and boosted tree for classification.	CNN-ANN combination received 98.1% accuracy.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
RiceSeedNet: Rice Seed Variety Identification Using Deep Neural Network [69].	Elsevier-Journal of Agriculture and Food Research (2024).	Rice Seed	Introduce RiceSeedNet where a neural network is merged with image processing techniques.	Acheived 97% to classify thirteen local varieties of rice seed.
Identification of Rice Seed Varieties Based on Near-Infrared Hyperspectral Imaging Technology Combined with Deep Learning [70].	ACS omega (2022).	Rice Seed	Used various ML and DL approaches to perform rice variety identification using NIR images.	ResNet gain highest accuracy of 86.08%.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Hyperspectral Imaging for Accurate Determination of Rice Variety Using a Deep Learning Network with Multi-Feature Fusion [71].	Elsevier-Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy (2020).	Rice Seed	Utilized HSI, multi-feature fusion, and PCANet for accurate rice variety identification, outperforming traditional machine learning methods.	PCANet achieved 98.57% classification accuracy.
Wheat Varieties Identification Based on a Deep Learning Approach [72].	Elsevier-Journal of the Saudi Society of Agricultural Sciences (2021).	Wheat Seed	Employed CNNs with Transfer Learning on a dataset of wheat grain images.	Gain accuracy upto 95.68%.

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Classification of Bread Wheat Varieties With a Combination of Deep Learning Approach [73].	Springer-European Food Research and Technology (2024).	Wheat Seed	Utilized pre-trained CNN models and hybrid Xception + BiLSTM approach for accurate classification of wheat varieties.	Achieved high classification accuracy of 97.73%.
Quality Assessment of Components of Wheat Seed Using Different Classifications Models [74].	MDPI-Applied Sciences (2022).	Wheat Seed	Employed industrial digital cameras and SVMs to classify wheat seeds based on shape, color, and texture features.	Acheived overall 97.6% accuracy.

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Non-Destructive Discrimination of The Variety of Sweet Maize Seeds Based on Hyperspectral Image Coupled with Wavelength Selection Algorithm[75].	Elsevier-Infrared Physics & Technology (2021).	Maize Seed	Vis–NIR hyperspectral imaging, SG smoothing, FD methods, CARS for feature selection, SVM for classification, compared with multiple algorithms.	Gained 94.07% for nine varieties and 94.86% for germ-up and germ-down.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Research on Maize Seed Classification and Recognition Based on Machine Vision and Deep Learning [76].	MDPI-Agriculture (2022).	Maize Seed	Proposed P-ResNet models is compared with many algorithms and surpasses all.	Outperform other models with an accuracy of 99.70%.
Maize Seed Variety Identification Model Using Image Processing and Deep Learning [77].	Indonesian Journal of Electrical Engineering and Computer Science (2024).	Maize Seed	The proposed hybrid model Gabor, HOG, and CNN-based feature selection identifies Ethiopian maize varieties.	Received 99% accuracy.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Vis-NIR Hyperspectral Imaging Combined with Incremental Learning for Open World Maize Seed Varieties Identification [78].	Elsevier-Computers and Electronics in Agriculture (2022).	Maize Seed	Hyperspectral imaging (HSI) and convolutional autoencoder (CAE) extract features; incremental learning (IL) with RBF-BPR model classifies maize varieties.	Achieved 100% accuracy in distinguishing known and unknown varieties.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Variety Classification of Coated Maize Seeds Based on Raman Hyperspectral Imaging[79].	Elsevier-Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy (2022).	Maize Seed	Raman hyperspectral imaging, variable selection (MCARS, SPA), SVM model is optimized using genetic algorithm.	Accuracy is 96.88%.
Germinative Paddy Seed Identification Using Deep Convolutional Neural Network [80].	Springer-Multimedia Tools and Applications (2023).	Paddy Seed	Utilized deep CNN for germinative seed detection.	Achieved high accuracy; outperformed transfer learning and traditional methods.

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Employing Image Processing and Deep Learning in Gradation and Classification of Paddy Grain [81].	Springer-Artificial Intelligence for Societal Issues (2023).	Paddy Seed	Employ deep learning for paddy seed classification using image processing techniques.	AI transforms agriculture, enhancing grain quality assessment and productivity.
Paddy Seed Variety Identification Using t20-Hog and Haralick Textural Features [82].	Complex & Springer-Intelligent Systems (2022).	Paddy Seed	Develop computer vision system for paddy variety identification using diverse features like T20-HOG.	T20-HOG enhances system performance significantly and gained 99.28% accuracy.

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Varietal Classification of Barley by Convolutional Neural Networks [83].	Elsevier-Biosystems Engineering (2020).	Barley Seed	Nine CNN models were compared for varietal classification based on learning time, computational requirements, and accuracy.	CNN significantly improve barley classification accuracy.
Image Analysis Methods in Classifying Selected Malting Barley Varieties by Neural Modelling [84].	MDPI-Agriculture (2021).	Barley Seed	Utilized AI and neural image analysis to assess barley quality via digital image color data.	Effective model enhances barley quality evaluation for better beer production.

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Nondestructive Identification of Barley Seeds Variety Using Near-Infrared Hyperspectral Imaging Coupled With Convolutional Neural Network [85].	Journal of Food Process Engineering (2021).	Barley Seed	Collected hyperspectral images, preprocessed data, used CNN and traditional models for barley seed variety classification.	CNN outperformed traditional models by achieving over 98% accuracy.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
A Method for Detecting The Quality of Cotton Seeds Based on An Improved ResNet50 Model [86].	Plos one (2023).	Cotton Seed	Enhanced ResNet50 with CBAM and modified FC layer to classify cotton seed using 4419 images.	Achieved 97.23% accuracy, outperforming classical models, fast recognition.
Near-Infrared Hyperspectral Imaging Combined With Deep Learning to Identify Cotton Seed Varieties [87].	MDPI-Molecules (2020).	Cotton Seed	Used NIR hyperspectral imaging, PCA, CNN, ResNet, and various classifiers for cotton seed variety identification.	Deep learning effectively identifies cotton seed varieties with high accuracy.

Title and Reference Number	**Journal Name and Year**	**Seed Type**	**Techniques**	**Remarks**
Cotton-Net: Efficient and Accurate Rapid Detection of Impurity Content in Machine-Picked Seed Cotton Using Near-Infrared Spectroscopy [88].	Frontiers in Plant Science (2024).	Cotton Seed	Preprocessed seed cotton spectral data with SG, SNV, and Normalization; developed Cotton-Net CNN.	Cotton-Net significantly enhances impurity detection accuracy.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
A Deep Learning Image System for Classifying High Oleic Sunflower Seed Varieties [89].	MDPI-Sensors (2023).	Sunflower Seed	CNN AlexNet for classifying sunflower seed varieties.	Achieved high accuracy despite visual similarity of varieties.
Comparative Evaluation of Some Quality Characteristics of Sunflower Oilseeds (Helianthus annuus L.) Through Machine Learning Classifiers [90].	Springer-Food Analytical Methods (2023).	Cotton Seed	Evaluated classification performance using six ML algorithms and multivariate tests.	RF, SVM, and MLP achieved the highest classification accuracy.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
Soybean Variety Identification Based on Improved ResNet18 Hyperspectral Image [91].	Springer-European Food Research and Technology (2022).	Soybean Seed	Enhanced ResNet18 with decomposed convolution kernels, BN layers, and multi-scale feature extraction for soybean variety identification.	Achieved 97.36% accuracy and surpasses Nasnet large and ResNet18 using hyperspectral images.

Title and Reference Number	Journal Name and Year	Seed Type	Techniques	Remarks
A Rapid and Highly Efficient Method for The Identification of Soybean Seed Varieties: Hyperspectral Images Combined With Transfer Learning [92].	MDPI-Molecules (2019).	Soybean Seed	Utilized CNN with hyperspectral images, data augmentation, and transfer learning for soybean variety identification.	Achieved up to 97.2% accuracy and surpasse traditional methods, enabling rapid and accurate seed identification.

Yafie *et al.* [67] introduce a technique in which shape and color features are used for the classification of corn seed using ANN. The identification process involves three primary stages: selection of ROI, feature extraction and classification. Shape features extraction are derived from eccentricity values, while color features are extracted from hue saturation values. Experimental results demonstrate the excellent performance of the model to achieve 89% classification accuracy for poor and good quality BIMA-20 corn seeds and 97% accuracy in distinguishing between BIMA-20 and NASA-29 species. Zhang et al. [93] explored the classification of freeze-damaged corn seeds through hyperspectral imaging paired with a

Deep Convolutional Neural Network (DCNN). Hyperspectral images of corn seeds are captured at five different freezing temperatures across a 400–1000 nm range, with spectra extracted from embryo regions. Four models, including KNN, SVM, ELM, and DCNN, were used to handle the classification of freeze corn seed across five categories. The DCNN model surpassed the other models, reaching accuracy rates of 100% in training, 96.9% in validation, and 97.5% in testing for the five-category classification. Javanmardi *et al.* [68] used a CNN for feature extraction. These features are then classified using various models, including ANN, cubic-SVM, quadratic-SVM, kNN, boosted trees, bagged trees, and Linear Discriminant Analysis (LDA). Compared to models trained solely on simple features, those trained on CNN-extracted features demonstrated superior classification accuracy for corn seed variants. Compared to previous classifiers, the CNN-ANN classifier fared better, identifying 2250 test cases in 26.8 seconds with an F1-score of 98.1%, recall of 98.1%, precision of 98.2%, and classification accuracy of 98.1%.

The study conducted by Rajalakshmi *et al.* [69] focuses on the classification of regional rice seed varieties from southern Tamilnadu, India, using a neural network called RiceSeedNet in conjunction with conventional image processing methods. The 13,000 RGB images of regional rice seed varieties are collected with 1,000 images for each of the 13 varieties. It makes up the RiceSeed Image Corpus for research purposes. RiceSeedNet is a vision transformer-based architecture designed to automate the varietal identification of rice seeds. The 13 local rice seed varieties were accurately classified using the proposed RiceSeedNet with 97% accuracy. In addition, an evaluation of RiceSeedNet's effectiveness across several rice grain kinds was conducted using a publicly accessible rice grain dataset. In this cross-data validation, RiceSeedNet classified eight different types of rice grains in the public dataset with 99% accuracy. This study addresses crucial agricultural concerns by leveraging advanced technology to ensure seed quality and crop productivity in the region. Jin *et al.* [70] utilize Near-Infrared (NIR) hyperspectral technology with both conventional and DL methods to design accurate identification models for common rice seed types. It employs ML algorithms like SVM, LR, and RF and DL methods (LeNet, GoogLeNet, and Residual Network (ResNet)) to perform variety identification of five common types of rice seeds where the ResNet model achieves the highest 86.8% testing accuracy. An efficient and nondestructive technique for rice seed variety identification is provided by the combination of DL and NIR hyperspectral imaging. Zhang *et al.* [94] developed a double-sided identification and elimination system to identify unclosed-glume rice seeds by simultaneously analyzing images from both sides. Here, to identify the rice seeds with an open glume, feature extraction and tough line detection were applied. Using double-sided image, the system attained an accuracy of 88.1% for regular seeds and 87.7% for unclosed-glumes seeds. CNN and hyperspectral imaging were investigated by Qiu *et al.* [95] as methods for differentiating rice seed types. Four rice seed cultivars were subjected to hyperspectral imaging at two different spectral ranges: 380–1030 nm and 874–1734 nm. Spectral data were extracted from 441–948 nm and 975–1646 nm. Models using KNN, SVM, and CNN were developed with different numbers of training samples. Results showed that models in the 975–1646 nm range performed slightly better. Performance improved with more training samples but plateaued with larger sample sizes. The CNN models generally outperformed KNN and SVM models, highlighting CNN's effectiveness in spectral data analysis. The study concluded that CNNs are a promising method for spectral data analysis and suggested expanding research to include more rice varieties to further validate this approach. Weng *et al.* [71] employed a DL network that combines spectroscopic, texture, and morphological features to identify rice varieties from Hyperspectral Imaging (HSI) images. For comparison, a DL network called Principal Component Analysis Network (PCANet) was used in addition to more conventional ML techniques like KNN and RF. To improve spectral data, methods including Principal Component Analysis (PCA) and multivariate scatter correction were used. PCANet achieved 98.66% correct classification rates for training sets and 98.57% for prediction sets. This technique can be used for other agricultural goods and provides accurate rice variety identification.

Laabassi *et al.* [72] used five CNN architectures to identify the class of wheat seed. It tackles the vital requirement for precise wheat varietal categorization in the grain industry, especially for registration and seed screening. By leveraging transfer Learning, five standard CNN architectures were trained to enhance classification performance. Evaluation of Algerian regions wheat seed demonstrated test accuracies ranging from 85% to 95.68%. Notably, the DensNet201 architecture achieved the highest test accuracy (95.68%), followed closely by Inception V3 (95.62%) and MobileNet (95.49%). These findings affirm the accuracy and reliability of the proposed approach. A pre-trained hybrid model based on a CNN is presented by Yasar *et al.* [73] to categorize bread wheat varieties. Using transfer learning and fine-tuning on the CNN model that was previously trained, the images were classified. The integration of a bidirectional long short-term memory algorithm with Xception CNN improved classification accuracy and achieved the greatest classification success rate of 97.73%. These findings demonstrate the effectiveness of the proposed approach in automatically classifying bread wheat varieties and highlight the potential of utilizing such methods in systems designed for bread wheat variety classification, aiding in the production of pure wheat varieties efficiently. Fazel *et al.* [74] evaluates the potential of ML algorithm equipped with industrial digital cameras for identifying and categorizing seven-grain groups in wheat seed samples. An examination of 21,000 individual grains was conducted with an emphasis on texture, color, and shape variables using three SVM and two statistical models. The relief method ranked 91 features, with shape features being the most significant, followed by texture and color. The quadratic-SVM with the top 35 features attained the highest classification accuracy. Independent data testing demonstrated accuracy ranging from 90.7% to 100% across various grain types, with an average accuracy of 97.6%. This research underscores the effectiveness of machine vision systems, particularly when combined with QSVM or non-linear discriminant analysis, in evaluating wheat seed visual qualities for cereal seed quality control. Olgun *et al.* [96] propose an automated system capable of accurately classifying wheat grains. Dense Scale Invariant Features (DSIFT) performance is evaluated using SVM classification. Histograms of features are used to represent images in DSIFT features, which are first clustered using k-means clustering to create the Bag of Words (BoW) of visual words. The efficacy of the suggested approach in classifying wheat grains is confirmed by experimental findings on a customized dataset, which show an overall accuracy rate of 88.33%.

Zhou *et al.* [75] presents a novel method of utilizing HSI for the identification of sweet maize seed varieties. It captures Vis-NIR hyperspectral images of nine varieties with germ orientations up and down. To emphasize the distinctions between seed varieties, the Savitzky–Golay (SG) smoothing and First Derivative (FD) techniques were used. The Competitive Adaptive Reweighted Sampling (CARS) approach was then used to extract effective wavelengths, which were subsequently used to build an SVM-based variety classification model. The performance of this model was compared with six other feature extraction methods and six classification algorithms (NB, KNN, ANN, DT, LDA, LR). Results demonstrated that the SG + FD + CARS + SVM model achieved the highest classification accuracy, with 94.07% and 94.86% accuracy for germ up and germ down orientations, respectively. This method shows promise for accurately discriminating sweet maize seed varieties. Xu *et al.* [76] introduces a rapid classification method using machine vision and deep learning. After gathering 8080 maize seeds altogether from five different types, the data was enhanced and the sets of seeds were split into training and validation (80:20 ratios). To recognize and classify maize seeds using transfer learning, an enhanced network architecture called P-ResNet is developed. The results show that P-ResNet achieved the highest classification accuracy at 99.70%, with model loss around 0.01. Other models (AlexNet, VGGNet, GoogLeNet, MobileNet, DenseNet, ShuffleNet, EfficientNet) showed high accuracy as well, ranging from 96.44% to 98.28%. The accuracy for BaoQiu, ShanCu, XinNuo, LiaoGe, and KouXian varieties reached over 99.6%. The experimental findings show how well the suggested CNN model classifies maize seeds, and they also serve as a guide for the identification of other crop seeds and agricultural applications in the food sector. Gebeyehu *et al.* [77] present an optimal model for the identification of Ethiopian maize varieties. For training and testing purposes, images of every type of maize were gathered from the Adet Agriculture and Research Center (AARC) in Ethiopia. It employs two feature extraction techniques: (i) CNN and (ii) Histogram of Oriented Gradients (HOG) + gabor filters while SVM is used to perform classification Experimental analysis states that a combination of CNN, HOG and SVM achieves the highest accuracy of 99%. This research underscores the feasibility of deep learning for maize seed identification and proposes the hybrid model as a valuable tool for variety selection and inspection. Zhang *et al.* [78] addresses challenges in the authentication of maize seed varieties in the Chinese market, where frequent additions, eliminations, and fake varieties complicate the identification process. Hyperspectral imaging incorporated with incremental learning is proposed to tackle this issue. Hyperspectral images of five maize seed varieties were analyzed using a Convolutional Autoencoder (CAE) to extract features. A novel Radial Basis Function-Biomimetic Pattern Recognition (RBF-BPR) model is introduced and compared favorably with other models. This approach achieves 100% correct acceptance and rejection rates and surpasses other models. This method supports IL without old class data and can adapt to government updates on maize varieties. Liu *et al.* [79] introduce a novel method for classifying coated maize seed varieties using a Raman hyperspectral imaging system. Evaluating 760 maize seeds from four varieties, Raman spectral data were extracted and preprocessed. Modified Competitive Adaptive Reweighted Sampling (MCARS) and Successive Projections Algorithm (SPA) were utilized for variable selection, with MCARS being newly introduced as a stable search technology. RF and Back-Propagation Neural Network (BPNN) models were compared with SVM models optimized using the Genetic Algorithm (GA). Based on Raman data, the MCARS-GA-SVM model produced predictions with a precision of 100% and a calibration accuracy of 99.29%. With a 96.88% accuracy on the validation set, the method shows strong potential for real-time, high-accuracy classification of seed varieties.

As paddy cultivation is essential for ensuring food security, but still the traditional approach used for the selection of paddy seed which is used for cultivation is a costly and time-consuming process. Islam *et al.* [80] propose a novel framework utilizing deep CNN for automatic germinative seed detection. They collect seed images in open environments, which pose illumination and scale challenges. To mitigate this, images are converted to HSV format and applied normalization techniques. Experiments on a dataset of three paddy varieties demonstrated the framework's high accuracy of 99.50%). Compared to transfer learning techniques and traditional feature-based methods. Hence, the proposed model provides a non-invasive approach for detecting germinative paddy seeds and making it well-suited for implementation in both the industrial sector and for farmers. Its application promises to boost paddy cultivation by increasing both yield and operational efficiency. Ranjan *et al.* [81] used DL algorithms and focuses on detecting and classifying paddy grain seeds based on morphological characteristics such as size, color, surface, and thickness. Various image processing techniques are employed for data pre-processing, including image preparation, feature extraction, acquisition, filtering, and linearization. The dataset comprises 570 images of binary-scaled paddy grain samples, with RGB color division and mathematical feature extraction. ROI boundary detection enhances feature extraction for training a multi-class CNN. The model's accuracy is evaluated based on overall classification performance. This research underscores AI's potential for revolutionizing agricultural practices and benefiting society. Uddin *et al.* [82] developed a novel method for paddy variety identification using a feed-forward NN model. This model is trained with various heterogeneous features which are extracted by T20-HOG features and haralick to significantly improve performance. The proposed system exhibits superior accuracy compared to previous works, indicating its potential for efficient application in both industry and agricultural settings.

Computer vision algorithms shows promising results to replace human expertise in detection of defective grains and recognizing barley varieties. However, traditional classification methods based on color, texture, and morphology which achieved less than 75% accuracy. Kozlowski *et al.* [83] examines performed the classification of barley seed using nine CNN layers. The comparison encompasses DL models and transfer learning approaches and assesses their learning time, classification times, computational demands, and classification accuracy. The findings demonstrate that using CNN can achieve barley classification accuracy exceeding 93%, significantly improving over traditional methods and highlighting the potential for DL to enhance quality control in the brewing industry. Quality evaluation is crucial in production, including beer brewing and its ingredients like hops, yeast, and malting barley. Pilarskar *et al.* [84] focuses on assessing malting barley quality for malt production, utilizing AI and neural image analysis to identify grain varieties, contamination levels, and other visual characteristics. The study found that digital image color data effectively identifies barley quality. The Multi-Layer Perceptron (MLP) neural network, trained on color data from digital images, proved to be the best model for recognizing malting barley varieties. This method promises to enhance malthouse operations and beer production quality in the future. Singh *et al.* [85] used NIR-HSI to discriminate barley seed varieties rapidly and nondestructively. A dataset consisting of 35,280 seeds from 35 different Indian barley varieties, including 29 hulled and 6 naked varieties, was collected. HSI. images were acquired in the 900–1700 nm range, and mean spectra were extracted and pretreated using six techniques, including Standard Normal Variate (SNV) and Savitzky–Golay smoothing. Both raw and preprocessed spectral data were fed into CNN and traditional models such as PLS-DA, KNN, and SVM. The end-to-end CNN model using raw spectral data outperformed other models by using preprocessing techniques and traditional methods. This approach achieves over 98% accuracy on the test set. This study highlights that NIR-HSI, combined with CNN, offers a fast, accurate, and non-destructive approach to identifying barley seed varieties and make it a powerful tool for agricultural applications.

Ensuring precise detection of cotton seed quality is vital for sustaining cotton farming. Du *et al.* [86] present the incorporation of a CBAM into ResNet50 to enhance feature extraction by learning channel and spatial information for classify cotton seeds. Modification of the fully connected layer and implementation of an improved activation function streamline the model training process. Training on 4419 cotton seed images yields an impressive average detection accuracy of 97.23%, processing images in just 0.11s. Comparative analysis against other models demonstrates superior feature extraction capabilities and accuracy. The Impro-ResNet50 model proves adept at swiftly and accurately identifying cotton seed quality, meeting the demands of modern cotton farming effectively.The comparative analysis demonstrates superior feature extraction capability and accuracy compared to other models. Jamuna *et al.* [97] employs ML techniques to classify seed quality at varying development stages of the cotton crop. The models were trained by three ML techniques—Naive Bayes (NB), Decision Tree (DT), and MLP. Features were extracted from a dataset of 900 records across various categories. The performance of the models was assessed through 10-fold cross-validation. The findings revealed that the DT and MLP demonstrated similar levels of accuracy in classifying seed cotton yield. However, the MLP took more time to build the model compared to the DT. This research demonstrates the effectiveness of ML in improving the assessment of cotton seed quality. Cotton seed production in Xinjiang, China, faces resource wastage due to inefficient distribution. Niu *et al.* [98] propose a hierarchical classification method to optimize spatial suitability based on climate, land, water resources, infrastructure, production risk, and planting history. Suitable areas for Early-Maturing Cotton, Early-Medium-Maturing Cotton, and Long Staple Cotton are identified. The western Tarim Basin is identified as the most suitable region for cotton seed production, whereas the western and northern parts of the Tarim Basin are considered sub-suitable. This method aids in selecting optimal production bases, considering market factors. Zhu *et al.* [87] utilized near-infrared HSI to identify seven cotton seed varieties. Pixel-wise PCA score images revealed differences among varieties. Effective wavelengths were selected via PCA loadings. Classification models were established using a custom CNN and ResNet. Partial Least Squares Discriminant Analysis (PLS-DA), LR, and SVM were employed as direct classifiers, and full spectra and effective wavelengths were used. Furthermore, models using PLS-DA, LR, and SVM were assessed with deep features extracted by CNN and ResNet.The custom CNN outperformed ResNet slightly. Full spectra models showed higher accuracy, with most models achieving over 80% accuracy across calibration, validation, and prediction sets. This study demonstrates the feasibility of using near-infrared hyperspectral imaging with deep learning for cotton seed variety identification. The widespread use of machine-picked cotton in China has significantly increased seed cotton impurities, affecting the valuation and the quality of processed products. Traditional semi-automated impurity testing is inefficient and inadequate for purchasing needs. A technique for quickly acquiring Near-Infrared Spectral (NIRS) data for seed cotton spectral data is presented by Li *et al.* [88]. Data preprocessing was done using three pretreatment algorithms: Standard Normal Variate Transformation (SNV), Normalization, and Savitzky-Golay convolutional Smoothing. A one-dimensional CNN, Cotton-Net, was developed to improve impurity content prediction accuracy. Ablation experiments with SELU, ReLU, and Sigmoid activation functions found that Cotton-Net with SELU and normalized data performed best, achieving a correlation coefficient of 0.9063 and an RMSE of 0.0546. The LSSVM model, enhanced by Normalization and the Random Frog algorithm, also performed well with a correlation coefficient of 0.8662 and an RMSE of 0.0622. This method shows potential for advancing rapid detection instruments for seed cotton impurities.

Sunflower seeds are renowned for their oil and oleic acid content, making them highly nutritious and resilient to arid climates. Barrio *et al.* [89] explores the efficacy of DL algorithms in the classification of sunflower seeds. 6000 seeds from six different types of sunflowers were photographed using a Nikon camera and an image acquisition setup with controlled illumination. Using the CNN AlexNet model, classification accuracies reached 100% for two classes and 89.5% for six classes. To Evaluate the physico-chemical properties of sunflower seeds for their classification and quality assessment. DT, RF, SVM, Multiple Linear Regression (MLR), NB, and MLP are the six ML methods used by Ccetin *et al.* [90] to categorize six sunflower oilseed types. Multivariate tests, including MANOVA, and discriminant analysis were conducted to analyze the seeds' characteristic properties. RF, SVM, and MLP exhibited the highest accuracy rates, while NB demonstrated the lowest mean absolute error. MANOVA underscored significant variations in the physical attributes of the sunflower varieties, with Colombi and Transol showing similar characteristics.

In horticulture, fruit classification demands expert knowledge, prompting the need for an automated system. Younis Gulzar [99] addressed fruit classification issues in the horticulture sector by utilizing MobileNetv2. This study used a dataset of 26,149 images of 40 fruit types, split into a 3:1 training-test ratio.The TL-MobileNetV2 model, which makes advantage of transfer learning, was developed by augmenting the MobileNetV2 architecture with a five-layer customized head. TL-MobileNetV2 achieved 99% accuracy, outperforming MobileNetV2 by 3% and surpassing AlexNet, VGG16, InceptionV3, and ResNet. The model also achieved 99% precision, recall, and F1-score, demonstrating that transfer learning and dropout techniques effectively improve performance and reduce overfitting. Recent advancements in agricultural research have introduced computational technologies to enhance farming practices, particularly in seed quality classification. Traditional methods, reliant on visual inspection of seed characteristics like color, shape, and texture, are labor-intensive and time-consuming. Hamid *et al.* [100] proposes an automated seed classification system using CNN and transfer learning to classify 14 common seed varieties. The system employs advanced DL techniques, including decayed learning rate, model checkpointing, and hybrid weight adjustment, and applies symmetry in image sampling for consistent feature extraction. The model achieved 99% classification accuracy on both training and test sets, significantly outperforming previous studies. This research demonstrates the potential of computational intelligence to improve efficiency in agricultural seed sorting.

Liu *et al.* [91] present a novel method for soybean variety identification using an improved ResNet18 model on hyperspectral images. The method enhances feature extraction by decomposing large convolution kernels and incorporating a multi-scale feature extraction module to improve the perception of soybean hyperspectral images. The proposed method achieves a recognition accuracy of 97.36%, outperforming the standard ResNet18 and NasNet Large models. Zhu *et al.* [92] utilized CNN with hyperspectral imaging to identify ten soybean varieties. It collected reflectance data from 1200 seeds, augmenting it to create 9600 images split into training, validation, and test sets. Pretrained CNN models like AlexNet, ResNet18, Xception, InceptionV3, DenseNet201, and NASNetLarge were fine-tuned via transfer learning. Here, validation accuracy reached 91%, while test accuracies ranged from 90.6% to 97.2%, which performs on par with traditional methods reliant solely on hyperspectral reflectance. This approach demonstrates CNN effectiveness in rapidly and accurately identifying soybean seed varieties and suggests broader applicability for efficient crop seed identification in agricultural contexts.

Upon reviewing the current literature on DL applications in agriculture, significant advancements are noted in crop disease detection, yield prediction, and seed classification across various crops. These studies highlight the efficacy of CNN and ML algorithms for the accurate prediction of seeds which enhances quality control and agricultural productivity. Despite these achievements, challenges persist. Some research lacks pre-processing techniques before classification, while others apply them without specifying model weights. Moreover, seed classification typically involves four to five classes, with specific focus on crops like corn, rice, barley, wheat, cotton, sunflower, camellia, and maize. There remains a need for further research dedicated to addressing the unique challenges of soybean seed classification, ensuring comprehensive coverage of its distinct characteristics in agricultural contexts. The limitations of defect and variety identification in soybean seed are mentioned in the article [101] and in this report, efforts were made to address these limitations.

2.4 Summary

This chapter covers the fundamentals of image classification and explores various ML algorithms and DL models used for seed classification. Initially, section 2.2 is divided into two subsections which inform about the fundamentals of ML and DL. The subsection 2.2.1 gives an idea about the four basic types of ML algorithms and then explores popular algorithms like KNN, LR, NB, RF, and SVM with their respective pros and cons. However, section 2.2.2 gives an idea about the basic architecture of CNN and the working of various layers. While section 2.3 reviewed various state-of-the-art methods for defect and variety identification of seeds like rice, barley, wheat, maize, corn etc using neural network architecture.

Chapter 3

COLLECTION OF GOOD AND DEFECTIVE SOYBEAN SEED DATASET

3.1 Introduction to Dataset Collection

A dataset is a collection of data or observations that are organized for analysis. It typically consists of structured or unstructured data, such as numbers, text, images, or other types of information. Datasets are used in various fields for research, analysis, modeling, and ML tasks. They can range from small and simple datasets with a few entries to large and complex datasets containing millions or even billions of records. Datasets are essential for training and assessing machine learning models, as well as for generating insights and supporting data-driven decision-making across various fields. An image dataset is a collection of images that are used to train, validate, and test machine learning models, particularly neural networks, for image classification tasks. Image datasets are essential for several reasons:

1. **Training Neural Networks:** Image datasets provide the necessary input data to train neural networks for image classification tasks. Through exposure to a wide variety of images, the neural network learns to identify patterns and features that differentiate between various classes or categories.

2. **Model Evaluation:** Image datasets are crucial for evaluating the performance of trained models. Once training is complete, the model is evaluated

on a distinct subset of the dataset to measure its accuracy, specificity, sensitivity, and other performance metrics.

3. **Generalization:** A diverse and comprehensive image dataset helps neural networks generalize well to unseen data. It ensures that the model can accurately classify images it hasn't encountered during training.

4. **Bias Detection:** Image datasets also help in identifying and mitigating biases in the model. By analyzing the distribution of images across classes, researchers can detect biases and take corrective measures to ensure fair and unbiased classification. Image datasets play a crucial role in training, assessing, and enhancing the performance of neural networks for image classification tasks. They enable the development of robust and accurate models that can effectively classify images across various domains and applications.

3.2 Proposed Dataset

In DL endeavor, dataset play an important role. For the proposed research work, we present our soybean seed dataset. The details steps are explained in subsection 3.2.1 and Subsection 3.2.2.

3.2.1 Data Collection

Initially, soybean seeds are gathered from a specific geographic location, Rajnapur Khinkhini, Taluka Murtijapur, in the Akola district with precise coordinates for this village 20.716954212 latitude and 77.540011783 longitude. Total 500 to 600 seeds of varied varieties and defects are collected. Utilizing a NIKION D800 camera, 1000 photos of soybean seeds are captured and categorized into 10 distinct classes, guided by agricultural experts and farmers insights. These classes comprise seven defective seed categories and three variety classifications. Each class encompasses 100 soybean image samples, and various training-testing ratios are employed for model training. Defective seed images encompass cracked, wrinkled, broken, purple, damaged, insect-bitten, and green seeds. Table 3.1 mentions the definition of defective soybean seeds. This meticulously curated dataset forms the foundation for training the deep learning model, ensuring robust performance in soybean seed classification tasks.

Table 3.1: Defective Soybean Seed Classes with Definitions

Sr. No.	**Seed Class Name**	**Definition**
1	Broken soybean	Soybean with an incomplete body shape.
2	Green soybean	Soybean that is infected by a pathogen, causing the surface to turn green.
3	Damaged soybean	Affected by various fungal diseases, brown to black or small, irregular grey areas with black specks.
4	Insect-bitten soybean	Soybean with long, wide cracks in the epidermis caused by insect bites.
5	Wrinkled soybean	When seed is exposed to high temperature and alternating wet and dry conditions.
6	Purple seeds soybean	Affected by Cercospora Leaf Spot.
7	Cracked soybean	Soybean with a slight crack on the surface due to external force.

3.2.2 Experimental Setup

The NIKON D800 camera is used to capture images of both good quality and defective soybean seeds. Two 11-watt lamps are placed from two sides of the table at a height of 12 inches from the table and the same height camera is used to capture the pictures. The camera photographed each image of soybean samples placed on the white cloth from a distance of 12 inches and an angle ranging between 60° to 90° with the cloth. For each seed of soybean, pictures are captured from all possible sides. While some images are captured to depict soybean clusters containing 5 to 10 seeds, captured of size 7360*4912 pixels with a vertical and horizontal resolution of 300 dpi. Figure 3.1 shows the experimental setup to capture the soybean dataset while Figure 3.2, Figure 3.3 and Figure 3.4 shows the sample image and all side view of all ten classes of soybean seed.

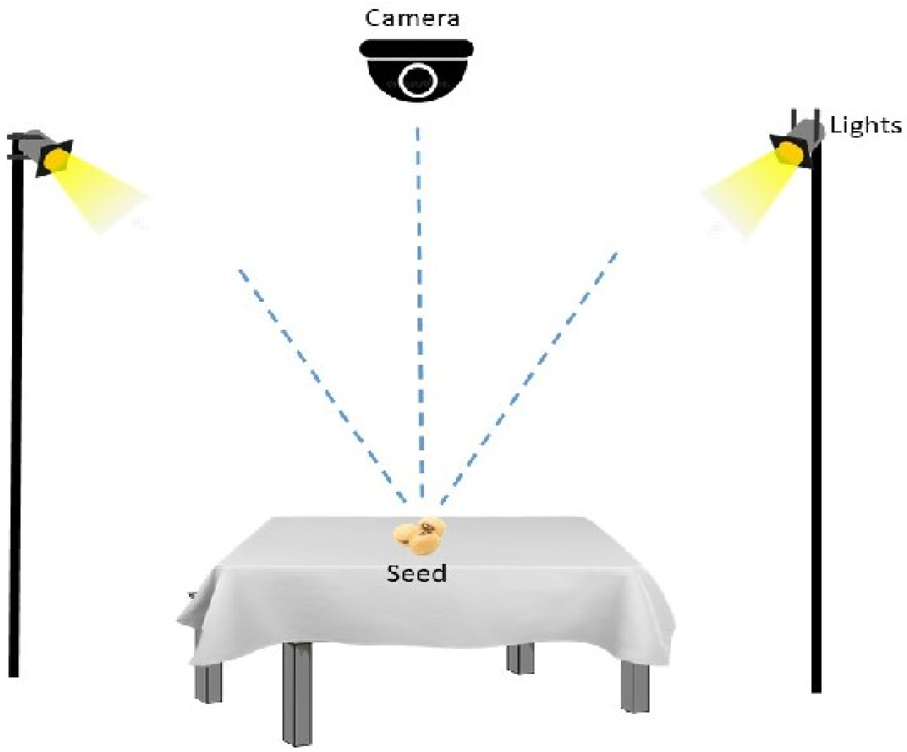

Figure 3.1: Experimental setup to capture images of soybean seed dataset.

3.3 Existing Dataset

In 2023 Lin *et al.* present Soybean Seeds Classification Dataset on kaggle [59]. The dataset contains 5 types of soybean seed images with 5,513 samples. The five categories present in dataset are are intact, spotted, immature, broken, and skin-damaged. These images are resized to 227×227 pixels, and were derived from original 3072×2048 pixel images using an image-processing algorithm[1].

[1]Soybean Seeds Classification Dataset, available at `https://www.kaggle.com/datasets/aryashah2k/soybean-seedsclassification-dataset`.

(a) JS335 Seed

(b) S9305 Seed

(c) KDS726 Seed

Figure 3.2: Sample image and all side view of soybean seed variety.

(a) Broken Seed

(b) InsectBitten Seed

(c) Crack Seed

(d) Damaged Seed

Figure 3.3: Sample image and all side view of soybean seed defects.

(a) Green Seed

(b) Purple Seed

(c) Wrinkle Seed

Figure 3.4: Sample image and all side views of soybean seed defects.

3.4 Summary

This chapter discusses the development of a soybean seed dataset, a critical step for training, validating, and testing ML and DL models. The soybean seeds were collected from Rajnapur Khinkhini, Taluka Murtijapur, in the Akola district, with 500-600 seeds of different varieties and defects gathered. Using a NIKON D800 camera, 1000 photos were taken and categorized into 10 classes (7 defective seed categories and 3 variety classifications) with 100 images each, guided by agricultural experts. Images were captured from all possible sides of each seed, with clusters of 5-10 seeds also photographed at a resolution of 7360x4912 pixels and 300 dpi. This high-quality, diverse dataset ensures robust performance in soybean seed classification tasks.

Chapter 4

PREPROCESSING OF SOYBEAN SEEDS IMAGE DATASET

4.1 Introduction to Pre-processing Step of Soybean Seed Dataset

Image-based analysis of agricultural products, particularly soybean seeds, has become increasingly important for ensuring quality and optimizing yield. It is essential to pre-process the image dataset effectively to facilitate advanced image-based analysis. Pre-processing converts raw images into a format optimized for analysis, improving the accuracy and efficiency of later steps like feature extraction and classification. This involves a series of steps including image normalization, noise reduction, segmentation, and enhancement.

The objective of this work is to develop a comprehensive pre-processing pipeline for a soybean seeds image dataset. By systematically addressing common issues such as varying lighting conditions, background noise, and inconsistent seed orientations, we aim to create a standardized dataset that can be used for robust and reliable image analysis. This chapter is derived from the article [1]. This pre-processed dataset will serve as a foundational resource for machine learning models and other analytical techniques aimed at improving agricultural practices and

[1] Amar V. Sable, Parminder Singh, and Avinash Kaur, Present paper in the International Conference on VLSI, SIGNAL PROCESSING, POWER ELECTRONICS, IOT, COMMUNICATION AND EMBEDDED SYSTEM (VSPICE) Springer, 2023 on the topic "Classification of Soybean Seed using Support Vector Machine with Image Enhancement Techniques"

outcomes. As the agricultural industry increasingly adopts digital and automated technologies, the importance of high-quality image data cannot be overstated. A well-prepared image dataset ensures that the analytical models can perform at their best, ultimately contributing to better crop management and higher yields.

To enhance the quality of the soybean seed image, we proposed a seed-based contour detection (SCD) algorithm that performs pre-processing operations on the seed. This algorithm is a comprehensive process designed to identify and isolate soybean seeds accurately. This approach follows a carefully designed sequence of steps to systematically process and analyze visual data.

4.2 Seed Contour Detection Algorithm

Preprocessing images is a vital first step in image analysis and computer vision. It consists of applying various techniques to raw images to improve their quality and make them suitable for subsequent processing and analysis. The purpose of image pre-processing is to enhance the visual quality of images by reducing noise and emphasizing key features, which helps algorithms more effectively carry out tasks like object detection, classification, and segmentation. In this study, Seed Contour Detection (SCD) Algorithm is proposed to enhance the quality of the soybean seed dataset. Figure 4.1 shows the Sequence Flow Diagram (SFD) of SCD algorithm.

The SCD algorithm used RGB images from the dataset. Each image serves as the foundation for subsequent processing stages. Initially, it isolates the red component from the RGB image to enhance features specific to soybean seeds, as they often exhibit distinct characteristics in this color channel. In mathematical terms, for a given pixel at coordinates (x, y) in an RGB image represented as R (x, y), G (x, y), and B (x, y) (denoting red, green, and blue color channels respectively), the extraction of the red component (R (x, y)) can be expressed as per Equation 4.1.

$$R_{(x,y)} = \text{Red Channel of Pixel at}(x, y) \tag{4.1}$$

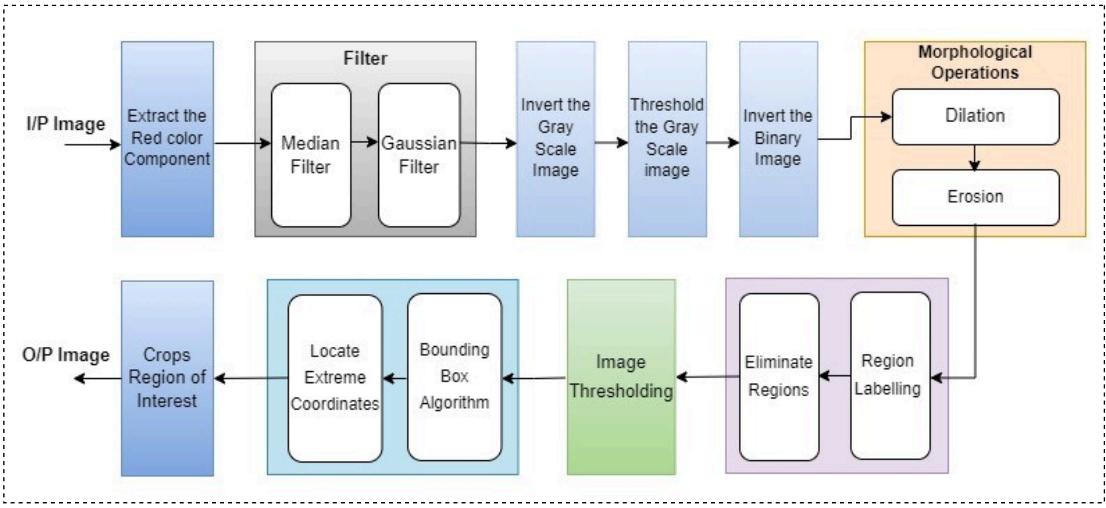

Figure 4.1: SFD of SCD algorithm.

This operation essentially involves retaining the intensity values from the red channel while disregarding the green and blue components, resulting in an image where each pixel's value represents only the red channel information. This can be symbolically represented in Equation 4.2.

$$R_{(x,y)} = \text{Intensity of Red Channel at } (x, y) \tag{4.2}$$

The median filter is a non-linear image processing technique that is used to reduce noise in an image dataset. It works by replacing each pixel value with the median value of its neighbors within a defined window (e.g., 3x3 or 5x5). To mitigate noise and irregularities within the image, a median filter of 3x3 window size is applied. This filtering process smoothens the image while preserving essential details. Applying a median filter with a 3x3 window to an image involves sorting the pixel values within the window and selecting the median value as the new value for the center pixel. The process for a 3x3 median filter at a specific pixel location (x, y) is shown in Equation 4.3.

$$\begin{aligned} I'_{\text{new}}(x, y) = \text{median}\big(&I(x-1, y-1), I(x, y-1), I(x+1, y-1), \\ &I(x-1, y), I(x, y), I(x+1, y), \\ &I(x-1, y+1), I(x, y+1), I(x+1, y+1)\big) \end{aligned} \tag{4.3}$$

To reduce noise and blur the image slightly to prepare it for subsequent analysis gaussian filter is used. A Gaussian filter is a linear filter used in image processing to blur an image and reduce noise. It works by applying a Gaussian function, which assigns weights to neighboring pixels based on their distance from the center. The result is that nearby pixels have more influence than distant ones, creating a smoothing effect. The Gaussian filter is widely used for edge-detection pre-processing and noise reduction. Here, at each pixel location (x, y) in the image, the filter operation computes a weighted average of the pixel values in the neighborhood defined by the Gaussian kernel using Equation 4.4.

$$I'_{(x,y)} = \sum_{i=-k}^{k} \sum_{j=-k}^{k} G_{(i,j)} \cdot I_{(x-i,y-j)} \tag{4.4}$$

where $I'_{(x,y)}$ is the new value of the pixel at position (x, y) after applying the Gaussian filter. $I_{(x,y)}$ represents the intensity value of the pixel at position (x, y) in the original image. $G_{(i,j)}$ is the Gaussian kernel value at position (i, j) within the filter. The sums are performed over the Gaussian kernel window, typically covering a region around the pixel (x, y) and k determines the extent of the Gaussian kernel window, often related to the standard deviation.

By subtracting the filtered image from 255, the algorithm inverts the image. This inversion step sets the groundwork for binarization by applying a threshold to the inverted image. A threshold value of 128 is set to create a binary image, separating soyabean seeds from the background. The resulting binarized image undergoes another inversion. This step readies the image for morphological operations to refine seed boundaries further. To ensure the consistency of the background binary image is inverted. During this tiny regions or holes within regions of interest became evident. Though these holes are potentially small, they hinder the accurate identification of seed boundaries and need addressing. Morphological operations play a vital role in preserving the shapes within images, especially in the context of binary images. In our process, four essential morphological operations were employed: dilation, closing, erosion, and opening. Morphological operations, specifically dilation followed by erosion, were employed to fill these holes. The concept here is simple: dilation expands the white regions, thereby filling small black holes, and erosion then shrinks them back to preserve the general shape but without the holes. We utilized a 7x7 window called a Structuring Element (SE), to ensure effective filling even for slightly larger holes also. SE is a matrix or kernel used to modify the pixels of an image based on their neighbors A significant point to mention is the choice of closing areas for post-dilation. By restricting the area to 50,000 pixels, we effectively maintained the integrity of our region of interest and ensured that there is no over-extension. Let's represent the input image and the SE is a small matrix or kernel that defines the neighborhood used for morphological operations dilation, erosion, opening, and closing denotes from Equation 4.5 to Equation 4.10.

Dilation Operation (SE is a 7x7 window):

$$I_{\text{dilated}}(x, y) = \max_{(i,j)\in SE} I_{(x+i,y+j)} \tag{4.5}$$

Erosion Operation (SE is a 7x7 window):

$$I_{\text{erosion}}(x, y) = \min_{(i,j)\in SE} I_{(x+i,y+j)} \tag{4.6}$$

Opening Operation (Combination of Erosion followed by Dilation):

$$I_{\text{opened}}(x, y) = \text{dilate}\left(\text{erode}(I)\right) \tag{4.7}$$

$$I_{\text{opened}}(x, y) = \max_{(i,j)\in SE} \left[\min_{(k,l)\in SE} I_{(x+k+i,y+l+j)} \right] \tag{4.8}$$

Closing Operation (Combination of Dilation followed by Erosion):

$$I_{\text{closed}}(x, y) = \text{erode}\left(\text{dilate}(I)\right) \tag{4.9}$$

$$I_{\text{closed}}(x, y) = \min_{(i,j)\in SE} \left[\max_{(k,l)\in SE} I_{(x+k+i,y+l+j)} \right] \tag{4.10}$$

Label Regions operation in image processing assigns unique labels or identifiers to different connected components or regions within an image. This process is performed using connected-component labeling algorithms. Here, connected pixels are identified by scanning the entire image and marking neighboring pixels belonging to the same region. After an extensive experiment, we finalized the value of the threshold is 1000 and eliminated small regions or components in an image that are smaller than a prede-fined threshold. It filters out small, insignificant areas to refine and focus on larger, more substantial elements within the image. This process helps in reducing noise or eliminating minor structures that might not be of interest for analysis or identification. Thresholding the image creates a mask essential for handling multiple seeds within an image. This process prepares for the next step of identifying bounding boxes. It gives a clear distinction between foreground and background elements, aiding in segmentation and feature extraction.

A bounding box algorithm is employed to precisely delineate the boundaries around individual soyabean seeds. This crucial step provides a visual reference for accurate seed identification. The process involves finding the extreme coordinates (top-left and bottom-right corners) for each identified region. This bounding box delineates the spatial extent of the identified area, aiding in subsequent analysis or visualization. In the case of cracked, damaged and insect-bitten seeds labelled regions were more than one since the upper shell or coat of seeds is broken. Due to this, a single seed is differentiated into many small neighbouring regions or rectangles. In the case of a single region of interest, we cropped the region corresponding to the upper-left coordinate and bottom-right coordinate of the bounding box. For multiple bounding boxes, we se-lect the top left and bottom right bounding boxes. Then top left coordinates of the former bounding box and the bottom right coordinates of the bottom right bounding box were used to extract the region of interest. As cracked, damaged and insect-bitten seeds contain more than one bounding box, the remaining classes demonstrate the single bounding box as shown in Figure 4.2. Using the coordinates obtained from the previ-ous step, the algorithm crops individual seed images. These cropped images contain isolated soybean seeds, crucial for detailed analysis and further processing. Figure 4.3 represents the output of the SCD algorithm on a single insect-bitten seed image with three bounding boxes and Figure 4.4 indicates the output of the SCD algorithm for multiple Seeds and their bounding boxes. For our research work, we used single seed images for further process. The meticulous execution of each step within the Seed Contour Detection Algorithm ensures that noise is minimized, seed boundaries are accurately delineated, and resulting images contain individual soybean seeds with clear bound-ing boxes, facilitating precise identification and analysis.

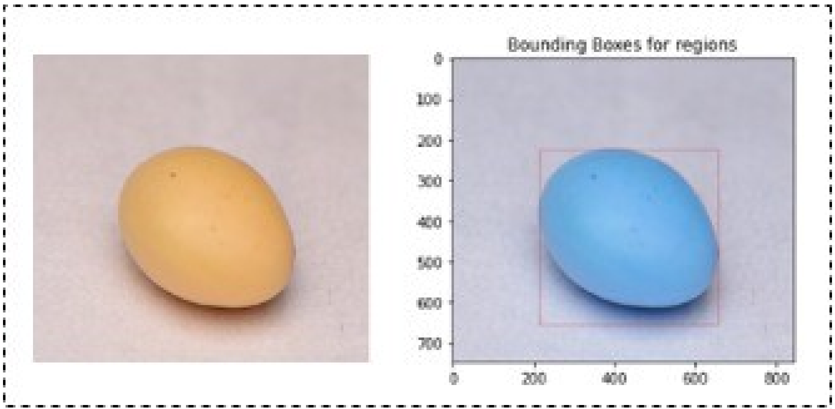

Figure 4.2: Output of SCD algorithm for single regions (1 bounding box) in a single seed.

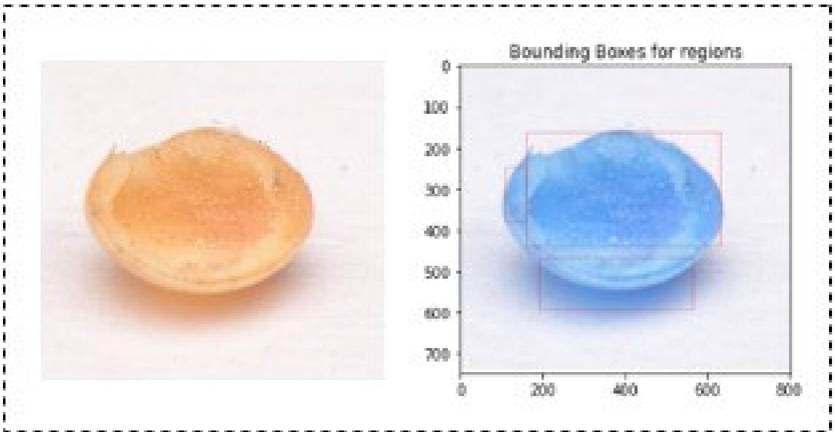

Figure 4.3: Output of SCD algorithm for multiple regions (3 bounding boxes) in a single seed.

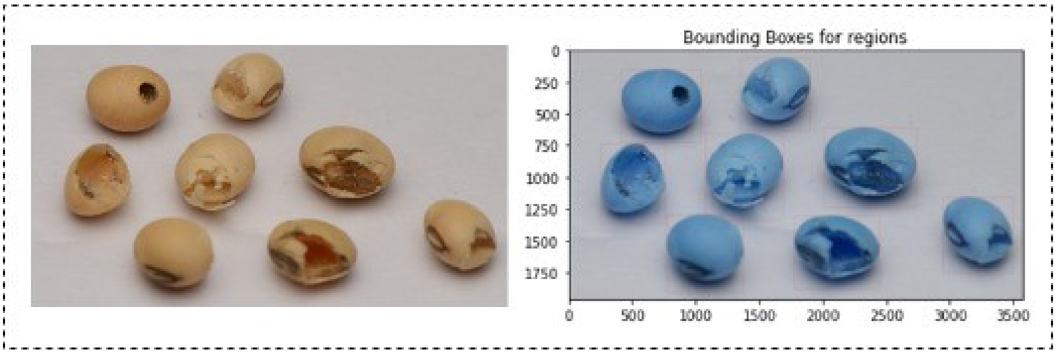

Figure 4.4: Output of SCD algorithm for multiple seeds and their bounding boxes.

4.2.1 SCD algorithm

Algorithm 1 represents the step-by-step execution of the SCD algorithm.

Algorithm 1: SCD Algorithm for Soybean Seed Image Pre-processing

Data: Soybean Seed Dataset

Result: Cropped Seed Image with Bounding Box around seed in an image

SCD_A ← Input (Soybean dataset);

SCD_B ← `Extract_R`(*(SCD_A)*);

SCD_C ← `Apply_Median_Filter`(*(SCD_B)*);

SCD_D ← `Apply_Gaussian_Filter`(*(SCD_C)*);

SCD_E ← `Invert`(*(SCD_D)*);

SCD_F ← `Binarize`(*(SCD_E)*);

SCD_G ← `Invert`(*(SCD_F)*);

SCD_H ← `Morphological_operation`(*(SCD_G)*);

SCD_I ← `Label_Regions`(*(SCD_H)*);

SCD_J ← `Eliminate`(*(SCD_I)*);

SCD_K ← `Threshold`(*(SCD_J)*);

SCD_L ← `Apply_Bounding_Box_Algorithm`(*(SCD_K)*);

SCD_M ← `Locate_BB_Coordinates`(*(SCD_L)*);

SCD_N ← `Crop`(*(SCD_M)*);

In the above algorithm, various variables are utilized to store intermediate results and facilitate specific operations. These variables serve as placeholders for data transformations and enable the algorithm to progress through its preprocessing steps effectively.

i **SCD_A**: Represents the input image obtained from the Soybean Seed Dataset. This serves as the starting point for the algorithm, encapsulating the raw image data of soybean seeds.

ii **SCD_B**: As the algorithm progresses, subsequent variables are assigned to store different stages of image processing. For instance, SCD_B is used to hold the red channel (R) extracted from the input image, isolating important information regarding the seed characteristics.

iii **SCD_C**: Following this, SCD_C retains the outcome of applying a median filter to the red channel image. This filter helps reduce noise present in the image, ensuring a smoother and clearer representation.

iv **SCD_D**: Continuing the preprocessing pipeline, SCD_D stores the result of applying a Gaussian filter. This operation further refines the image by smoothing it and diminishing noise, contributing to improved feature detection.

v **SCD_E**: The variable SCD_E is designated to contain the inverted image, a step often employed to enhance contrast or prepare for subsequent processing.

vi **SCD_F** and **SCD_G**: Subsequently, SCD_F and SCD_G respectively hold the binarized and inverted binary versions of the image. These transformations simplify the image into a binary representation, facilitating subsequent analysis.

vii **SCD_H**: Further processing involves morphological operations, with SCD_H capturing the outcomes of dilation and erosion applied to the binary image. These operations enhance or suppress features based on the image's structures within a specified window.

viii **SCD_I** through **SCD_K**: As the algorithm progresses, variables such as SCD_I through SCD_K are utilized to store results including labeled regions, eliminated noise, and thresholded images. These steps help prepare the image for subsequent analysis.

ix **SCD_L** and **SCD_M**: Towards the end of the preprocessing pipeline, SCD_L and SCD_M respectively store the results of applying a bounding box algorithm and locating extreme coordinates of each bounding box. These steps are crucial for precisely delineating the positions and extent of individual seeds.

x **SCD_N**: Finally, SCD_N represents the cropped seed images, serving as the output of the algorithm. Through these sequential operations and variable assignments, the algorithm systematically preprocesses soybean seed images, ensuring they are ready for further analysis and classification.

Through this systematic preprocessing pipeline, the SCD Algorithm ensures that soybean seed images are suitably prepared for subsequent analytical tasks, contributing to improved accuracy and efficiency in crop detection and classification. Figure 4.5 and Figure 4.6 show the output of all stages of the SCD algorithm for a variety and defects class of soybean seed.

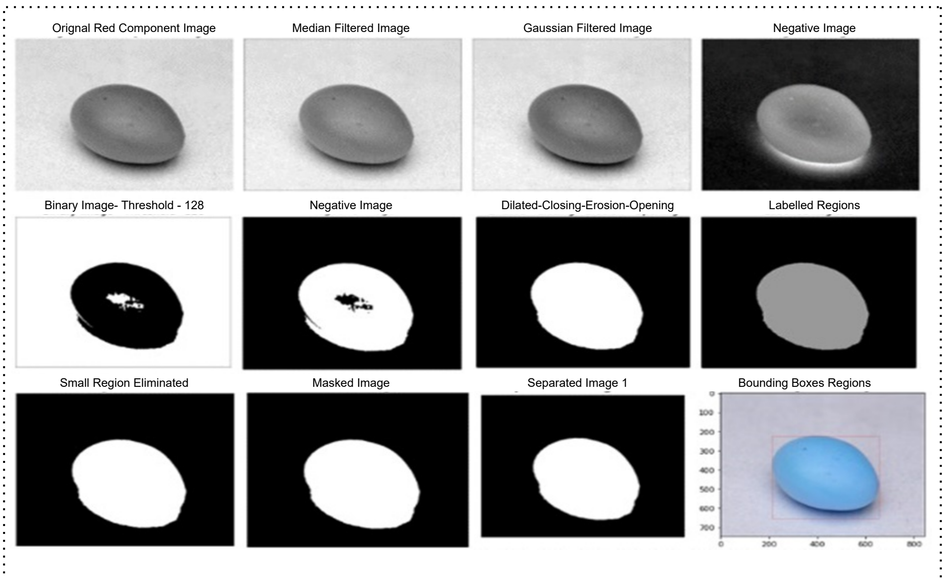

Figure 4.5: Each stage output of SCD algorithm for a soybean seed (variety).

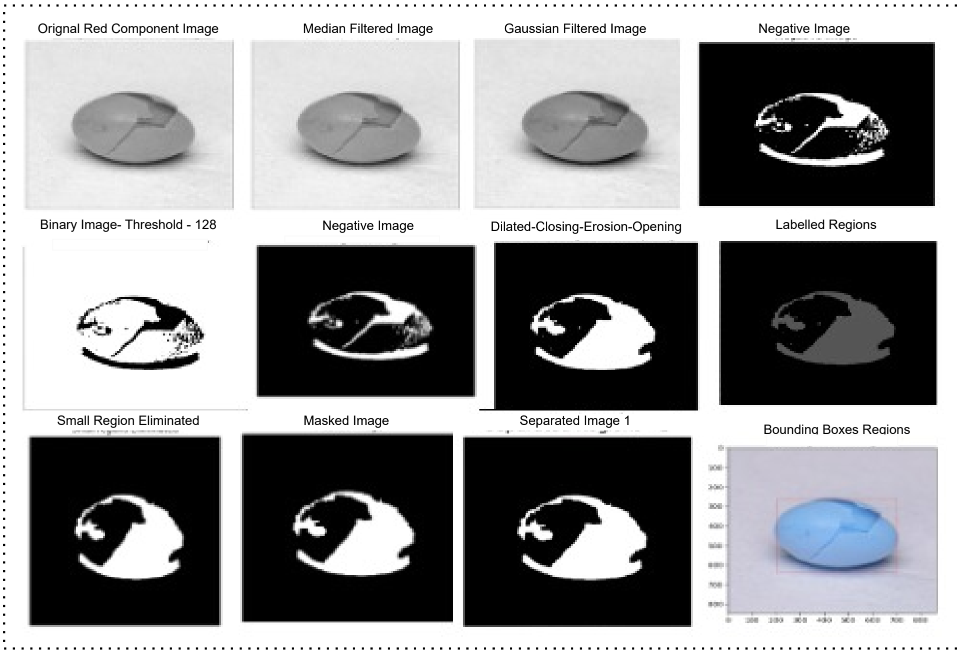

Figure 4.6: Each stage output of SCD algorithm for a soybean seed (defects).

4.3 Summary

This chapter presents objective 2 “ To pre-process soybean seeds image dataset ” of research work. Preprocessing is pivotal in data analysis, ensuring data quality and optimizing models. In this chapter, a Seed Contour Detection algorithm (SCD) is proposed to enhance the quality of soybean seed. The enhanced soybean dataset is used as input for subsequent stages. Overall, preprocessing lays the groundwork for effective modeling and insights generation by preparing data for subsequent analysis, improving model accuracy, and enabling robust predictions. Present one conference paper and one journal paper on this objective.

Chapter 5

SOYBEAN SEED DEFECT IDENTIFICATION

5.1 Introduction to Defect Identification Model

Soybean is a native crop growing in East Asia for its edible bean [102]. As a major leguminous crop, soybeans are a fundamental component of the global food system to fulfill the dietary needs of humans and animals. They can be consumed in various forms, including whole soybeans or in the form of tofu, tempeh, soy milk, soy sauce, and soybean oil [103]. Beyond their nutritional value, soybeans have numerous industrial applications [12]. However, environmental factors like droughts or excessive rainfall can significantly impact crop health and yield. Additionally, improper pest and disease management practices can compromise bean quality. Harvesting methods that are not properly executed may cause physical damage to the beans, further reducing their quality. The degradation of soybean quality can have widespread economic, nutritional, and environmental effects [104]. Reduced nutritional value raises concerns for both human and animal consumption and leads to deficiencies in essential nutrients which impacts overall health. This chapter is derived from the article [1].

Economically, farmers, distributors, and processors incur substantial losses due to decreased market value, increased production costs, and the potential rejection

[1] Sable A, Singh P, Kaur A, Driss M, Boulila W. "Quantifying Soybean Defects: A Computational Approach to Seed Classification Using Deep Learning Techniques". Agronomy. 2024; 14(6):1098. https://doi.org/10.3390/agronomy14061098, Journal Rank:JCRQ1 (Plant Sciences), CiteScore- Q1 (Agronomy and Crop Science) with Impact Factor: 3.3; 5-Year Impact Factor: 3.7. SJR:- 0.69

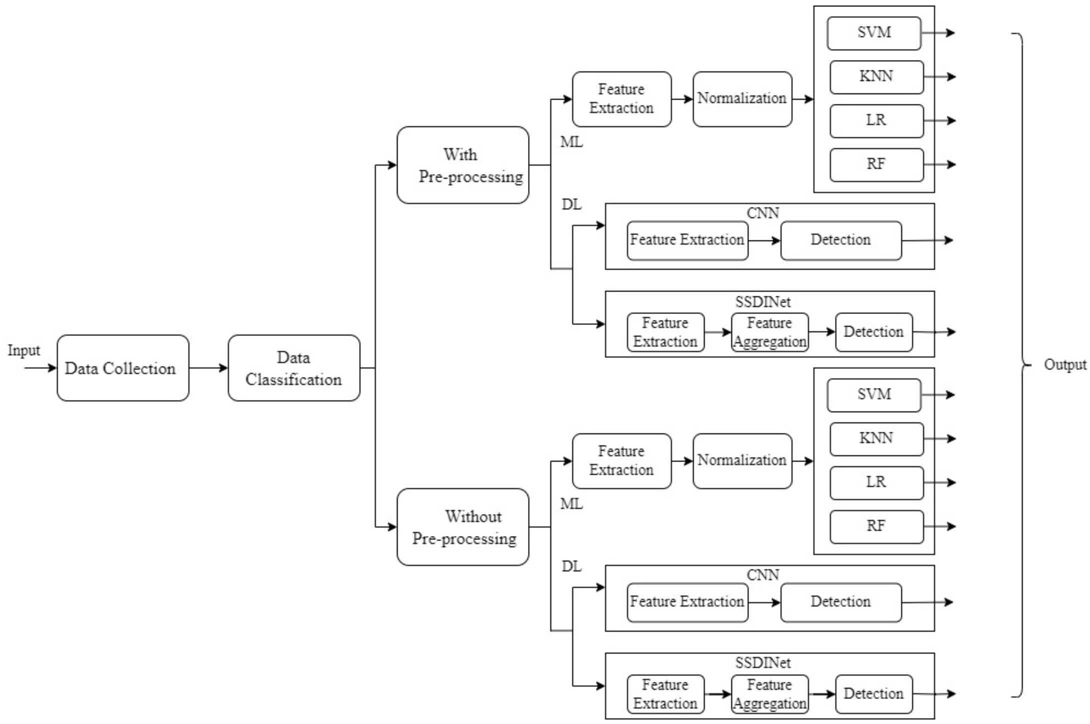

Figure 5.1: Sequence Slow Diagram of Seed Defect Identification.

of inferior batches. These losses can disrupt livelihoods and worsen food insecurity, especially in areas where soybeans are a staple crop or key protein source. Therefore, it is essential to separate low-quality soybean seeds from high-quality ones. Traditionally, visual inspection is used to identify visible signs of damage, discoloration, or mold. Screening or sieving mechanisms are also employed to sort beans based on size and shape, as damaged beans often exhibit different physical characteristics. However, this traditional method relies heavily on subjective human judgment, leading to inconsistency and misidentification of degraded beans. Manual inspection is also labor-intensive and time-consuming, affecting production costs and slowing down processing speeds [105]. Since soybean seed damage is primarily visible on the surface, computer vision methods are crucial for effectively classifying affected soybean seeds. Implementation of the DL model offers a more efficient and automated solution for quickly and accurately processing large volumes of soybeans. DL algorithms are highly effective in image recognition and classification tasks [66]. These advanced techniques aim to improve accuracy and reliability and they significantly reduce the likelihood of false positives or missed defects compared to traditional methods. From a cost perspective, automated DL-based defect detection systems can lead to long-term savings by decreasing the reliance on manual labor and minimizing losses from undetected defects. With the increasing global demand for soybeans, the need for efficient and precise quality control measures is growing. Developing advanced computational methods for soybean defect quantification addresses this need and aligns with industry goals of enhancing efficiency and quality. This thesis provides a comprehensive approach to perform defect identification of soybean seed using ML and DL approaches. Figure 5.1 shows the sequence flow diagram of seed defect idenification module where initial step of data collection and classification is explained in Chapter 3 while pre-processing is explained in Chapter 4.

5.2 Feature Extraction

Feature extraction is a technique of converting raw data into a set of attributes that can be effectively used in ML models. It involves the identification and isolation of relevant information from the data that contributes to the predictive power of the model. It also reduces the complexity of the data while retain essential patterns. The need for feature extraction arises because raw data often contains noise, irrelevant information, and redundancies that can negatively affect model performance. By using informative features, feature extraction improves the model's accuracy, efficiency, and generalizability. It enables models to learn from data more effectively by highlighting key characteristics and reducing dimensionality, which also addres the issue of overfitting. To detect the class of defective soybean seed efficitively, feature extraction plays crucial role. To extract good quality spatial features from images, this thesis used the following feature extraction algorithm.

1. **Wavelet based feature:** Features are extracted using 6 types of wavelets which are bior 3.1, bior 3.5, bior 3.7, db3, sym3 and haar wavelet. It extract 4 feature from single wavelet, hence it extracts 24 features from 6 wavelets.

2. **Grey-level co-occurrence matrix (GLCM):** GLCM extracts the statistical features of soybean image. It creates a matrix representing the frequency of pixel pairs with specific intensity values and directions. Key parameters include the direction and distance between pixel pairs. The GLCM is normalized to form a probability distribution, from which statistical features such as contrast, correlation, energy, and homogeneity are extracted. These features form a vector representing the image texture. GLCM reduces data complexity and enhances machine learning model performance.

3. **Local binary pattern-based feature and histogram of gaussian-based feature :** Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG) are powerful feature extraction techniques used in image processing. LBP captures texture information by comparing pixels with their neighbors and converts these comparisons into binary codes, and generating a histogram of these codes to form a feature vector. This method is efficient, robust to illumination changes, and widely used in tasks like texture classification and face recognition. On the other hand, HOG focuses on the shape and structure of objects by computing the gradients of the image, creating histograms of gradient directions within small regions, and normalizing these histograms. The resulting feature vector represents the image's edge and gradient structures, making HOG particularly effective for object detection, such as identifying pedestrians and vehicles. Both LBP and HOG enhance machine learning models' ability to analyze and classify images based on texture and shape, respectively, making them essential tools in computer vision.

Using the above feature extractor 7536 statistical and fine features are extracted from soybean images. 24 features from the wavelet-based feature, 6 from GLCM, 512 from LBP, 324 from HOG, 2601 from LBP texture feature and 4096 from the wavelet-based texture feature and at last all features are concatenated to generate a features.csv file. This file contains the complete 7536 features of the soybean seed image. For defective seed, the value in the truth table is zero and for good quality seed, it is 1.

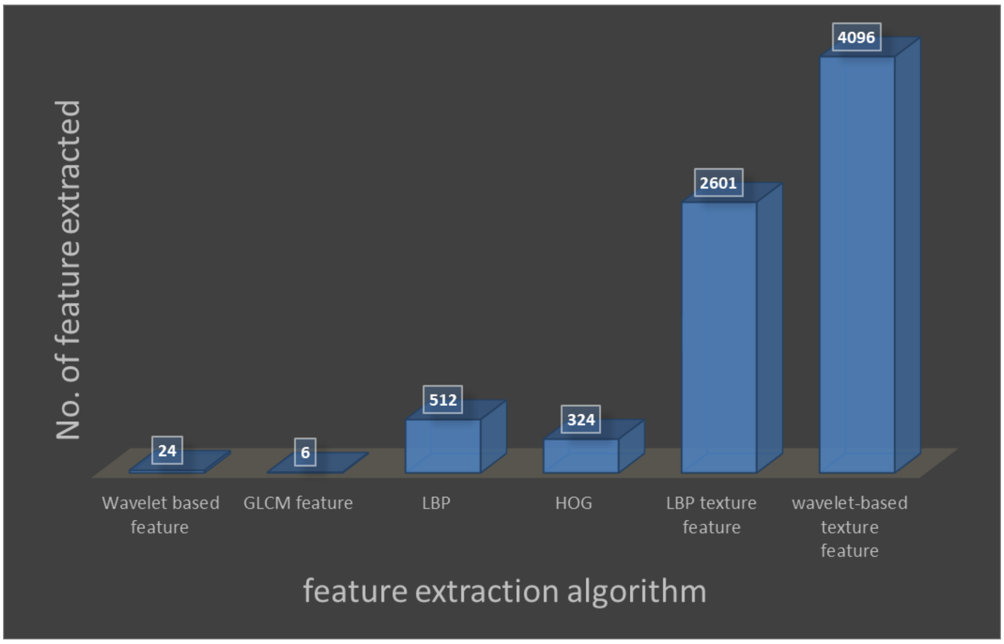

Figure 5.2: Count of Extracted Features.

5.2.1 Normalization

Data normalization, is the process of arranging data entries so that they appear uniform across all fields and records and hence simplifies the procedure of finding, gathering, and analyzing information. Normalization after feature extraction is an essential step to feed input to machine learning models. It ensures that different features, which varying in scales and range, are brought to a similar scale to prevent any single feature from disproportionately influencing the model. This consistency is crucial for the stability and efficiency of optimization processes, especially for gradient descent-based algorithms, which converge faster with normalized features. Normalization also enhances the interpretability of model coefficients, making it easier to understand each feature's influence. Furthermore, it can improve model accuracy for algorithms sensitive to feature scales, such as KNN, and SVM. By reducing computational complexity, normalization leads to more efficient training and prediction processes. Ultimately, it ensures that features contribute equally to the model, preventing those with larger scales from dominating and leading to more balanced and fair predictions. In our normalization process, the data in features.csv is converted into standard form. Firstly, we identify the maximum value in each column and then divide by that maximum value to the entire column. So that the column contains either 0 or 1 entry for each feature and this updated features.csv file is fe to different models of ML.

5.3 ML Model

To predict 7 defective (Cracked, Wrinkled, Broken, Purple, Damaged, Insect-Bitten, and Green Seed) and one good-quality soybean seed, this thesis used the following ML algorithms:-

5.3.1 KNN

KNN is a non-parametric ML approach used for classification and regression. It assigns data points to a class by evaluating the majority label among their nearest neighbors in the feature space, where proximity is calculated using distance measures such as Euclidean or Manhattan distance. In my research work, the KNN model is created with k=3 neighbors, which specifies that the algorithm will consider the three nearest data points to make predictions. The Manhattan distance is employed as the distance metric in this context. The model is subsequently trained using the fit method, with X_train and Y_train denoting the features and labels of the training dataset, respectively.

5.3.2 LR

LR is a statistical method used for classification tasks. It is set to classify seeds into different categories including cracked, wrinkled, broken, purple, damaged, insect-bitten green seeds and good-quality seeds. LR models the probability that a seed belongs to each category using a logistic function. During training, LR learns the optimal coefficients for each feature to predict the probability of a seed being defective.

5.3.3 RF

RF models are ensemble learning methods that combine the predictions of several decision trees during the training process. RF combines predictions from these trees (mode for classification, mean for regression) to achieve robust and accurate results. By randomly selecting features at each node and utilizing bagging, RF mitigates variance and improves generalization compared to individual decision trees. It's effective for various applications, providing insights into feature importance and performing well in high-dimensional data scenarios where complex interactions need to be captured with minimal parameter tuning.

5.3.4 SVM

SVM with a Radial Basis Function (RBF) kernel are effective for non-linear classification tasks. The RBF kernel maps the data into a higher-dimensional space and measures the similarity between data points through a Gaussian function. SVMs then find the optimal hyperplane that maximizes the margin between classes. This method is advantageous in scenarios where data is not linearly separable, as it allows SVMs to create complex decision boundaries in the transformed feature space. The regularization parameter (C) plays a key role in managing the balance between increasing the margin and reducing classification errors, which is essential for preventing overfitting. SVMs that utilize RBF kernels perform exceptionally well in a range of applications, including image recognition, text classification, and bioinformatics, where it's crucial to capture complex relationships among features. However, tuning parameters like C and the kernel parameter gamma γ is crucial for optimizing SVM performance and generalization to new data, ensuring robust model performance across different domains.

5.4 DL Model

In DL model to identify the class of defective soybean seed, we used CNN and developed SSDINet which is explained as follows:

5.4.1 CNN

The CNN model consists of 12 layers which is used to detect the defects of soybean seed. The network starts with five convolutional blocks, each block containing a convolutional layer (with 32, 64, 128, 256, and 512 filters respectively, all of size 3x3), followed by batch normalization, ReLU activation, and max pooling. Figure 5.3 shows the architecture of CNN model.

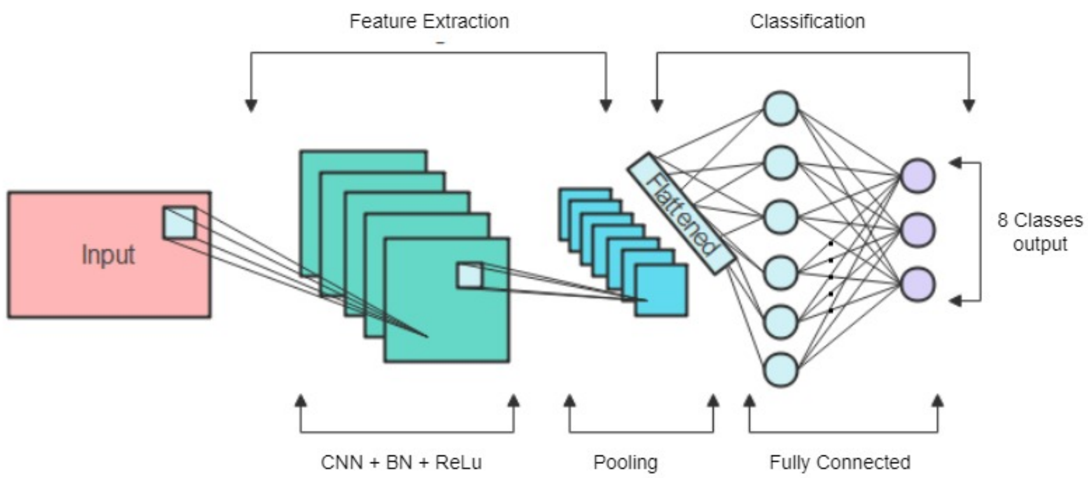

Figure 5.3: Architecture of CNN.

The CNN layers are responsible for performing feature extrection in the images by applying filters to detect patterns such as edges, textures, and more complex structures in deeper layers. Batch normalization stabilizes and accelerates training by normalizing the outputs of the convolutional layers. The ReLU activation function allows to learn complex patterns to network. Max pooling reduces the spatial dimensions of the feature maps while retains the most important information and makes the computation more efficient. After these convolutional blocks, the model has a flattened layer to convert the feature maps into a single vector, followed by a dense layer with 128 neurons, batch normalization, and ReLU activation. The final output layer is a dense layer with 8 neurons and a softmax activation function, which produces a probability distribution over 8 classes, effectively classifying the input images into one of these classes.

5.4.2 SSDINet

To recognize defective soybean seeds, this thesis proposed the Soybean Seed Defect Identification Network (SSDINet) which is a lightweight and fast model. It is composed of CNN layers, max-pooling layers, parallel executable depthwise convolution blocks, and squeeze-and-excitation blocks, followed by an average pooling layer and a flattened layer. For seed classification, the network employs four fully connected layers. Initially, features are extracted through the CONV layer, which uses swish activation and BN. BN helps to mitigate overfitting and is followed by a max-pooling layer, as illustrated in Figure 5.4 and Table 5.1 indicates model architecture with input and output shapes and operations. To reduce parameters and perform channel-wise recalibration, Depthwise Separable Convolution blocks (DSep-conv) and Squeeze-and-Excitation Networks (SENet) are used simultaneously. Features extracted by DSep-conv and SENet are merged to effectively obtain high-quality spatial features. After the feature combination, an average pooling layer and a flattened layer are applied. Finally, four dense layers are employed for seed classification, which incorporates ReLU activation, BN, and drop out. The last dense layer uses SoftMax for defects classification which transforms logits into probability distributions across classes. Algorithm 2 details the steps of SSDINet.

In SSDINet, DSep-conv and SENet serve distinct yet complementary functions in the feature extraction process. DSep-conv reduces the number of parameters efficiently while captures spatial hierarchies in the input features. It uses K_d as depthwise filters, and Z represents the depthwise convolution result, as described using Equation 5.1.

$$Z_{i,j,k} = \sum_{m,n} X_{(i \cdot s+m),(j \cdot s+n),k} \cdot K_{d,m,n,k} \tag{5.1}$$

Algorithm 2: Soybean Seed Defect Identification Network (SSDINet)

Require: Enhanced Soybean seed dataset

Ensure: Classification of Soybean seed

1: $Z_{\text{CONV}} = \text{Convolution}(X, \text{swish\_activation}, \text{batch\_normalization})$ {Feature Extraction through CONV Layer}

2: $Z_{\text{MaxPool}} = \text{MaxPooling}(Z_{\text{CONV}})$ {Max Pooling Layer}

3: $Z_{\text{DSep\_conv}} = \text{DepthwiseSeparableConv}(Z_{\text{MaxPool}})$ {Depthwise Separable Convolution Blocks (Deeps-conv)}

4: $Z_{\text{SENet}} = \text{SqueezeAndExcitation}(Z_{\text{MaxPool}})$ {Squeeze-and-Excitation Networks (SENet)}

5: $Z_{\text{Merged}} = \text{Concatenate}(Z_{\text{DSep\_conv}}, Z_{\text{SENet}})$ {Merge Features from DSep-conv and SENet}

6: $Z_{\text{AvgPool}} = \text{AveragePooling}(Z_{\text{Merged}})$ {Average Pooling Layer}

7: $Z_{\text{Flatten}} = \text{Flatten}(Z_{\text{AvgPool}})$ {Flatten Layer}

8: $Z_{\text{Classif}} = \text{FullyConnectedLayers}(Z_{\text{Flatten}})$ {Four Fully Connected Layers}

9: $Y = \text{Softmax}(Z_{\text{Classif}})$ {Softmax Activation for Multi-Class Classification}

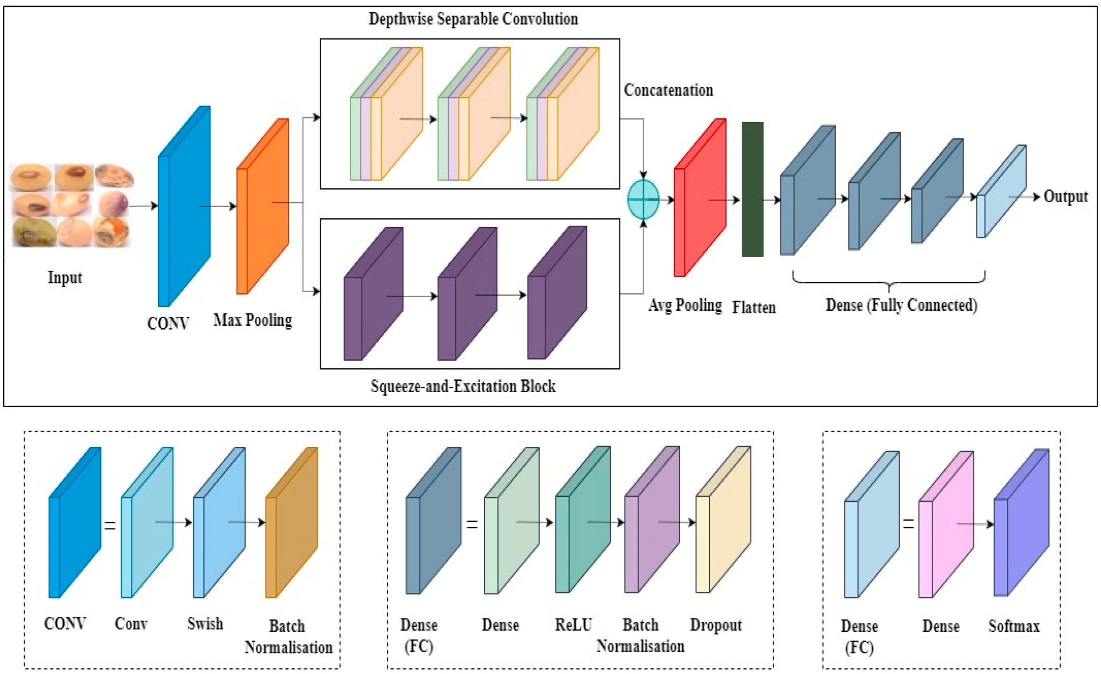

Figure 5.4: Architecture of SSDINet.

Where s represents the stride, i, j denote spatial indices, k denotes the channel index of the input feature map, m, n represent convolution kernel indices, and $K_{d,m,n,k}$ signifies the depthwise convolution filter. Depthwise convolution performs a separate convolution operation for each channel in the input feature map, with

Table 5.1: Model architecture of SSDINet with input and output shapes and operations

Layer Name	Input Shape	Operation	Output Shape	Kernel/Filter	Stride
Input Layer	(224, 224, 3)	Input	(224, 224, 3)	-	-
Conv2D	(224, 224, 3)	Conv2D(32 filters, 3x3, padding='same')	(224, 224, 32)	32, 3x3	1
BatchNormalization	(224, 224, 32)	Batch Norm	(224, 224, 32)	-	-
Activation (Swish)	(224, 224, 32)	Swish	(224, 224, 32)	-	-
MaxPooling2D	(224, 224, 32)	MaxPooling2D(2x2)	(112, 112, 32)	2x2	2
DepthwiseConv2D	(112, 112, 32)	DepthwiseConv2D(3x3, padding='same')	(112, 112, 32)	32, 3x3	1
BatchNormalization	(112, 112, 32)	Batch Norm	(112, 112, 32)	-	-
SE Block	(112, 112, 32)	SE (2 Dense layers)	(112, 112, 32)	Global Pool -¿ Dense	-
Concatenate	(112, 112, 32)	Concat (Depthwise + SE)	(112, 112, 64)	-	-
AvgPooling2D	(112, 112, 64)	AvgPooling2D(2x2)	(56, 56, 64)	2x2	2
Flatten	(56, 56, 64)	Flatten	(200704,)	-	-
Dense (1st layer)	(200704,)	Dense(256)	(256,)	256	-
Dense (2nd layer)	(256,)	Dense(128)	(128,)	128	-
Dense (3rd layer)	(128,)	Dense(64)	(64,)	64	-
Dense (4th layer)	(64,)	Dense(32)	(32,)	32	-
Output Layer	(32,)	Dense(8)	(8,)	8	-

spatial dimensions determined by the stride s. In Pointwise Convolution, K_p serves as a pointwise filter, yielding Y as the final output feature map shows in Equation 5.2.

$$Y_{i,j,l} = \sum_{k} Z_{i,j,k} \cdot K_{p,k,l} \tag{5.2}$$

Where l denotes the output channel index. The pointwise convolution integrates outputs from depthwise convolution across channels, performing a 1x1 convolution to blend and transform features. This approach significantly reduces parameters compared to traditional convolutions. Leveraging DSep-conv, the model sustains expressive power with fewer parameters, crucial for lightweight and faster models, enhancing both computational efficiency and mitigating overfitting. Figure 5.5 illustrates the DSep-conv structure. Therefore, the operation of DSep-conv is summarized as follows:

$$Y = \text{Pointwise Conv}(\text{DepthwiseConv}(X, K_d), K_p) \tag{5.3}$$

Here, DepthwiseConv(X, K_d) denotes depthwise convolution and Pointwise Conv(, K_p) represents pointwise convolution. This structure optimizes SSDINet for computational efficiency and suitability in lightweight models.

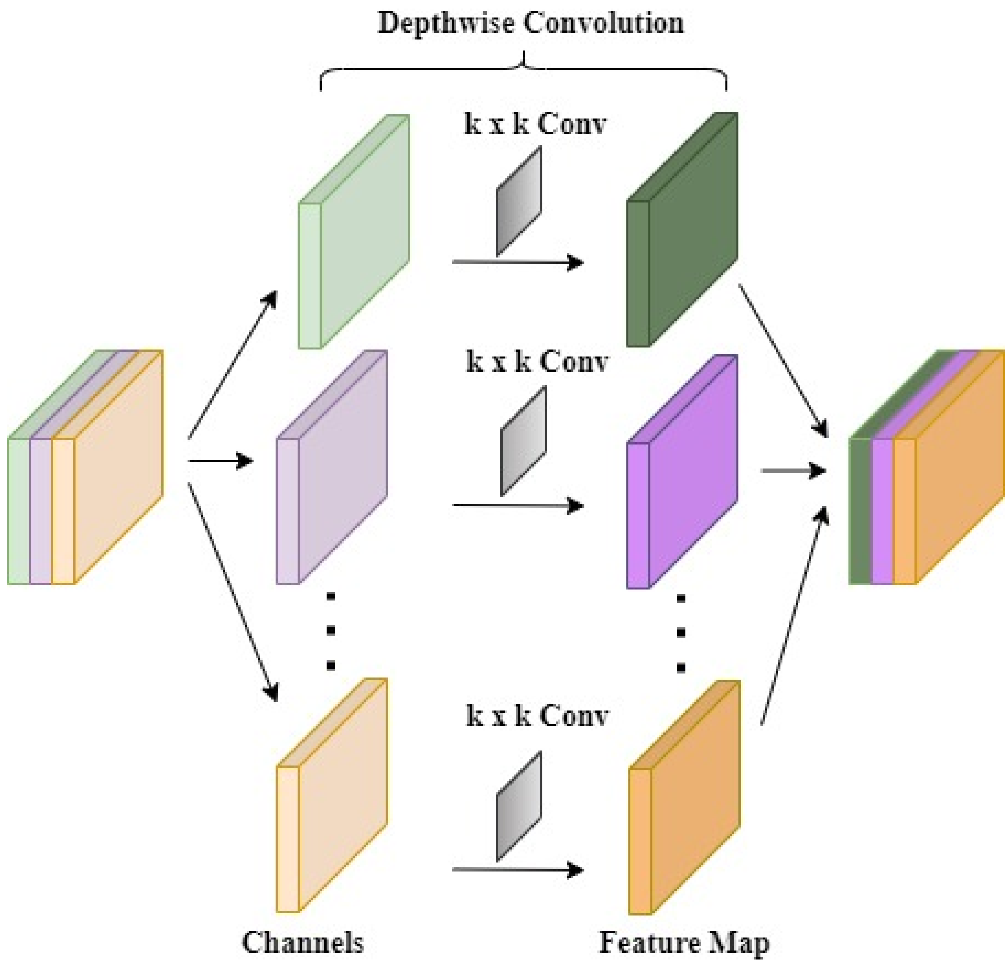

Figure 5.5: Architecture of depthwise separable convolution block (DSep-conv).

The role of SENet is to enhance channel-wise recalibration of feature responses, prioritizing important information while suppressing less informative channels. SENet introduces an attention mechanism that dynamically recalibrates feature maps. Here, X represents the input feature map with dimensions $H \times W \times C$, where H and W are height & width of image and C is the number of channels. It begins with a squeeze operation (global average pooling) to derive channel-wise statistics shows in Equation 5.4, followed by an excitation operation (fully connected layers) to model inter-dependencies between channels represented by Equation 5.5

$$Z_k = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_{i,j,k} \quad \text{(Squeeze operation)} \tag{5.4}$$

$$S_k = \sigma(W_2 \cdot \text{ReLU}(W_1 \cdot Z_k)) \quad \text{(Excitation operation)} \tag{5.5}$$

Here, Z_k represents the channel-wise statistic or squeezed feature for the k-th channel, S_k denotes the excitation weight for the k-th channel, W_1, W_2 are learnable parameters, and σ denotes the sigmoid activation function. The output is then multiplied element-wise with the input feature maps. SENet enables the model to focus on relevant features by assigning varying weights to channels based on their importance. This adaptive recalibration enhances the network's representational power, facilitating better discrimination among different seed defects. The overall operation of SENet is summarize in Equation 5.6:

$$Y = \text{Scale}(X, \text{Excite}(\text{Squeeze}(X))) \quad \text{(SENet operation)} \tag{5.6}$$

Here, Y represents the final feature map after adaptive recalibration through the Squeeze-and-Excitation mechanism. The architecture of SENet is shown in Figure 5.6.

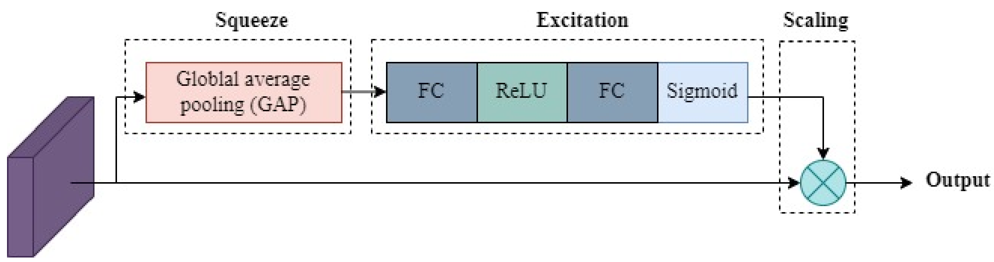

Figure 5.6: Architecture of squeeze-and-excitation networks (SENet).

5.5 Evaluation Metrics

To predict the class of soybean seed, the following evaluation metrics are used:

1. **Confusion Matrix (CM):** - A confusion matrix plays a key role in assessing the performance of classification models within ML and DL frameworks. It helps in understanding the performance of a model by comparing the actual target values with those predicted by the model as shown in Figure 5.7 where

   - True Positive (TP): The count of positive instances that are accurately identified as positive by the classification model.
   - True Negative (TN): The count of negative instances that are accurately identified as negative by the classification model.
   - False Positive (FP): the count of negative instances that are incorrectly identified as positive by the classification model.
   - False Negative (FN): the count of positive instances that are incorrectly identified as negative by the classification model.

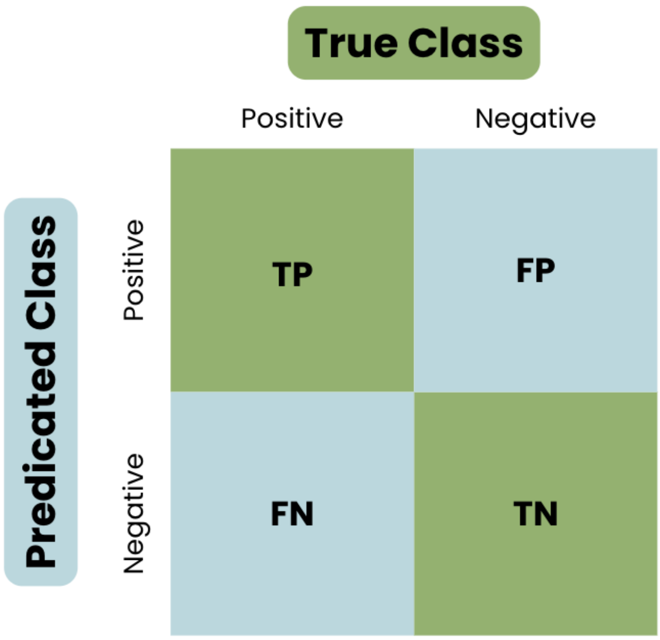

Figure 5.7: Structure of Confusion Matrix.

2. **Accuracy (A):** - Accuracy is defined as the proportion of correctly predicted instances to the total number of instances in a dataset.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.7}$$

3. **Precision (P):** - Precision is the ratio of correctly predicted positive instances to the total number of instances that were predicted as positive.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5.8}$$

4. **Recall (R):** -Recall, also referred to as sensitivity, is the ratio of correctly predicted positive instances to the total number of actual positive instances.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5.9}$$

5. **F1-score (F1):** - The F1 score is the harmonic mean of precision and recall, offering a single metric that balances the two, reflecting both the accuracy of positive predictions and the model's ability to identify all relevant instances.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5.10}$$

5.6 Experimental Result

This section entails the details of syatem requirement to build neural network, training & testing ratio of soybean classes and comparison of ML and DL moules.

5.6.1 System Requirements

To run the neural network model effectively, a system with specific hardware and software requirements is necessary which is mentioned as follows :-

1. **Software requirements:** To implement ML and DL models, system uses Windows 11 operating system with GPU acceleration NVIDIA T4 and P100. Python 3.11 is used, along with TensorFlow 2.0 or later, which includes Keras as part of its API. The CUDA Toolkit and cuDNN should be installed, and compatible with the TensorFlow version. The latest NVIDIA drivers are necessary to ensure compatibility with the GPU and CUDA versions. Basic requirement to implement neural network architectures is explained in the Table 5.2.

Table 5.2: Software requirements

Software Requirements	**Description**
Operating System	Windows 11
Python	Python 3.9 or later
TensorFlow	TensorFlow 2.0 or later (includes Keras)
CUDA Toolkit	Version compatible with TensorFlow (e.g., CUDA 10.1)
cuDNN	Version compatible with CUDA Toolkit
NVIDIA Drivers	Latest drivers compatible with GPU and CUDA version
Other packages	OpenCV 4.1, Seaborn 0.11, Pycocotools 2.0.6, tqdm 4.64 etc.

2. **Hardware requirements: -** A multi-core processor such as an Intel i5 or AMD Ryzen 5 (or higher) is recommended. An NVIDIA GPU with CUDA support (e.g., NVIDIA GTX 1080 or RTX 20xx series) significantly accelerates the training process. At least 16 GB of RAM is required, with 32 GB or more being preferable for handling large datasets and models. An SSD with at least 100 GB of free space ensures faster read/write operations. A reliable power supply unit is essential to support the GPU and other hardware components. Basic hardware requiremnt is mentioned in Table 5.3.

5.6.2 Dataset Split

To accurately identify the class of soybean seed, the dataset plays a crucial step. It serves as the foundation for the model's learning process, enabling it to recognize

Table 5.3: Hardware requirements

Hardware Requirements	**Description**
CPU	Multi-core processor (e.g., Intel i5, AMD Ryzen 5 or higher)
GPU	NVIDIA GPU with CUDA support (e.g., NVIDIA GTX 1080, RTX 20xx series)
RAM	At least 16 GB, preferably 32 GB or more
Storage	SSD with at least 100 GB free space
Power Supply	Reliable power supply unit to support GPU and other components

patterns and features unique to each seed class. We collect samples of 500-600 soyabean seeds where we have 250 samples of good quality seed and the remaining are defective soyabean samples which are further divided into 7 different classes. To train the neural network efficiently after applying the SCD algorithm, for experimental analysis dataset is split into three split ratios (80:20, 85:15, and 90:10) and their performances are observed mentioned in Table 5.4. From an experimental analysis, it is noted that an 80:20 ratio gives promising results, So for further investigation, we prefer an 80:20 ratio.

Table 5.4: Soybean seed classes and split ratios for training and testing

Soybean Seed Classes	80:20		85:15		90:10	
	Training	Testing	Training	Testing	Training	Testing
Good seeds	200	50	212	38	225	25
Broken seeds	87	22	92	17	98	11
Crack seeds	88	22	93	17	99	11
Damaged seeds	92	24	98	18	104	12
Insect-bitten seeds	90	23	96	17	101	12
Green seeds	76	20	81	15	86	10
Purple seeds	76	19	80	15	85	10
Wrinkled seeds	88	23	94	17	99	12

5.6.3 Comparison of ML Models

In the context of soybean seed defect classification, the selection of ML models such as KNN, RF, LR, and SVM depends on their distinct capabilities and suitability for addressing the complexities inherent in the classification task.

Firstly, KNN is chosen for its simplicity and effectiveness in scenarios where the decision boundaries between different seed defect classes may not be linear. By relying on local similarity measures, KNN can discern patterns in the data and make predictions based on the majority vote of its nearest neighbors. This makes KNN particularly useful for exploratory analysis and smaller datasets where it can capture intricate local patterns that other models might overlook. On the other hand, RF leverages ensemble learning to aggregate predictions from multiple decision trees. This approach enhances the model's robustness against noisy data and outliers, which is advantageous in real-world agricultural datasets where variability and imperfections are common. RF excels in handling high-dimensional feature spaces, making it well-suited for scenarios where comprehensive classification across multiple seed defect classes is required.

LR offers interpretability through its straightforward coefficients, which allows researchers and domain experts to understand the influence of each feature on the classification outcome. This transparency is invaluable in agricultural applications, where insights into the factors contributing to seed defect classification can inform agricultural practices and interventions effectively. SVM especially when equipped with nonlinear kernels, excels in capturing complex relationships within data and defining clear decision boundaries between different seed defect classes. SVM are particularly useful when the classification problem requires class separation that may not be linearly separable in the original feature space, that offers a powerful tool for achieving high classification accuracy. Hence, the choice to utilize KNN, RF, LR, and SVM in soybean seed defect classification is grounded in their ability to address diverse challenges such as nonlinear decision boundaries, interpretability of results, robustness to noise, and scalability to handle large datasets. By employing these models in combination, our research works conducts comprehensive analyses that yield reliable insights into identifying and categorizing seed defects, which supports advancements in agricultural quality assessment and management.

Table 5.5: Performance of ML algorithms

Algorithms	Precision (%)	Recall (%)	F-1 score (%)	Accuracy (%)
RF	82.21	78.08	78.29	78.38
KNN	86.43	78.58	78.54	79.28
LR	85.96	81.78	79.37	81.98
SVM	**92.93**	**90.79**	**91.85**	**91.89**

The Table 5.5 presents the performance metrics of different ML algorithms—RF, KNN, LR, and SVM which is evaluated on a soybean seed defect classification task.Here, SVM achieves the highest precision of 92.93% with recall 90.79%, F-1 score 91.85%, and accuracy of 91.89% among the algorithms evaluated. SVM ability to define clear decision boundaries and handle complex relationships within data contributes to its superior performance in accurately classifying soybean seed defects. Figure 5.8 shows the confusion metrics of SVM. LR also performs well with a precision of 85.96%, recall of 81.78%, F-1 score of 79.37%, and accuracy of 81.98%. LR's interpretability and straightforward coefficients make it effective in understanding the influence of different features on seed defect classification. Figure 5.9 indicates the confusion metrics of LR. KNN achieves a precision of 86.43%, recall of 78.58%, F-1 score of 78.54%, and accuracy of 79.28%. KNN's reliance on local similarity measures and its simplicity contribute to its competitive performance, although it shows slightly lower recall and F-1 scores compared to SVM and LR. Figure 5.10 denotes the confusion metrics of KNN. RF exhibits the lowest performance metrics among the algorithms, with a precision of 82.21%, recall of 78.08%, F-1 score of 78.29%, and accuracy of 78.38%. RF's ensemble learning approach helps in handling noise and complex relationships, but in this case, it shows slightly lower accuracy compared to SVM, LR, and KNN. Figure 5.11 shows the confusion metrics of RF. Hence, SVM emerges as the top-performing algorithm for soybean seed defect classification based on the provided metrics among ML algorithms. It achieves the highest scores across precision, recall, F-1 score, and accuracy, indicating its effectiveness in accurately identifying and categorizing seed defects. LR and KNN also demonstrate competitive performance, while RF shows slightly lower performance metrics in this specific classification task.

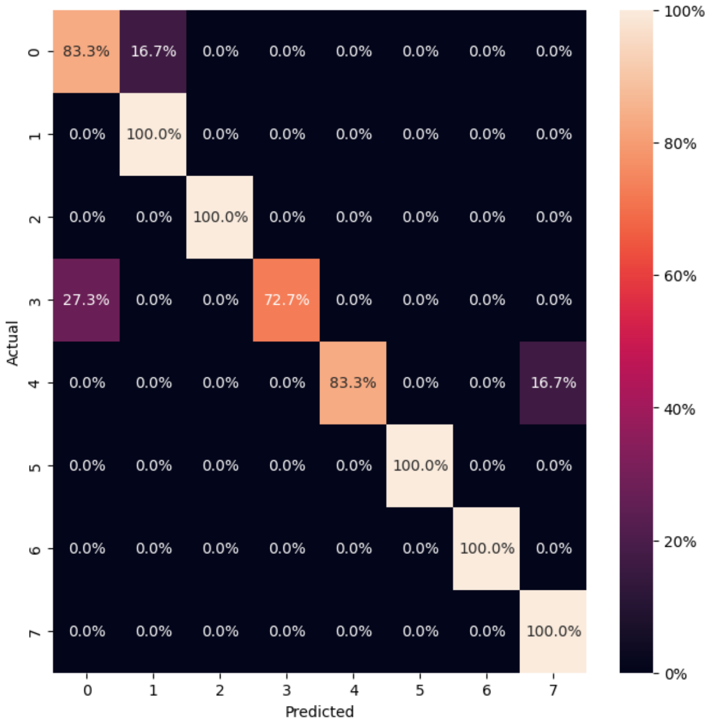

Figure 5.8: CM of SVM.

5.6.4 Comparison of ML Models with DL Models

To train SSDINet on the soybean dataset, we employed a categorical cross-entropy loss function used for the diverse nature of the soybean dataset. This loss function was paired with the softmax function in the final layer that transformed the raw model outputs into a probability distribution. The categorical cross-entropy loss then measured the dissimilarity between this predicted distribution and the true distribution of the classes. The initial CNN layer utilized the swish activation function and the dense layers employed the ReLU function, which is widely used due to its efficiency and effectiveness in DL models. For optimization Adam optimizer with a learning rate of 0.0001, weight decay of 0.0005, and a momentum of 0.9 is used. The SSDINet is trained with a batch size of 4 over 50 epochs. These

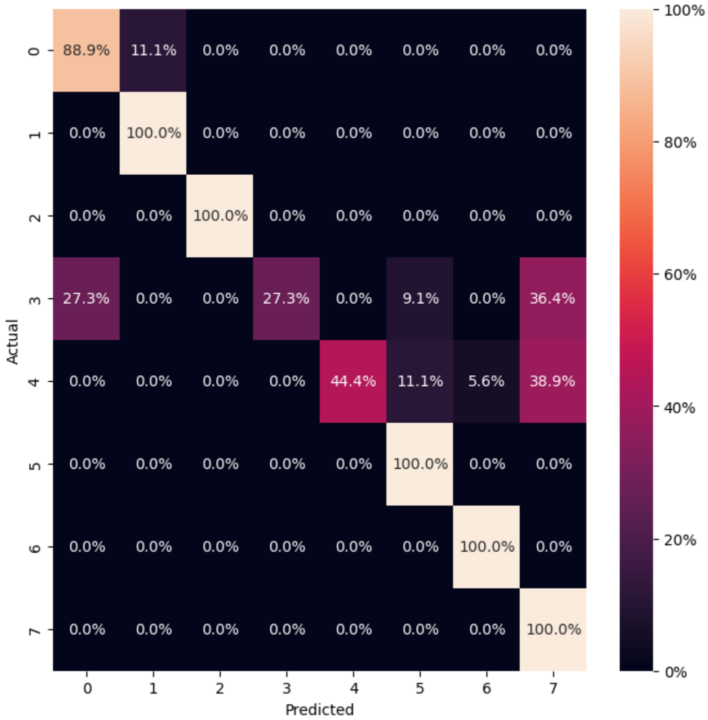

Figure 5.9: CM of LR.

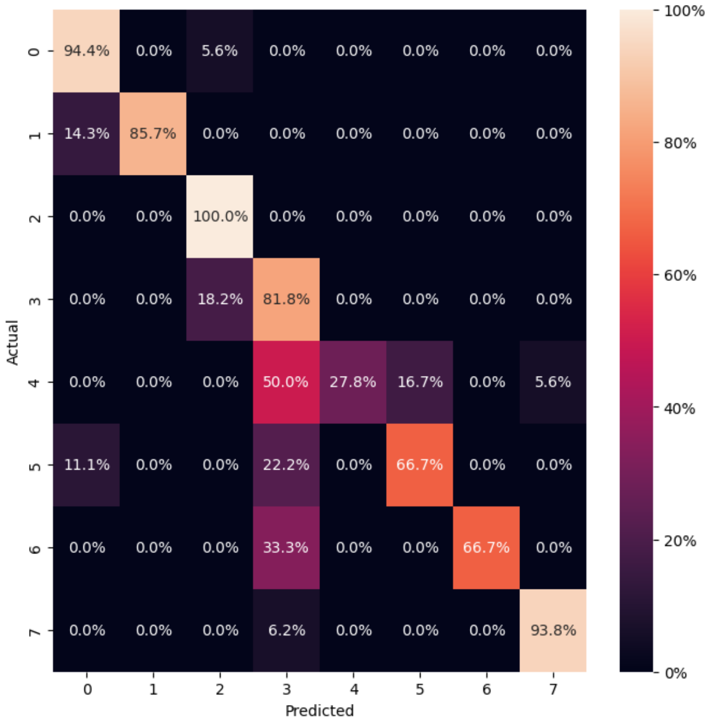

Figure 5.10: CM of KNN.

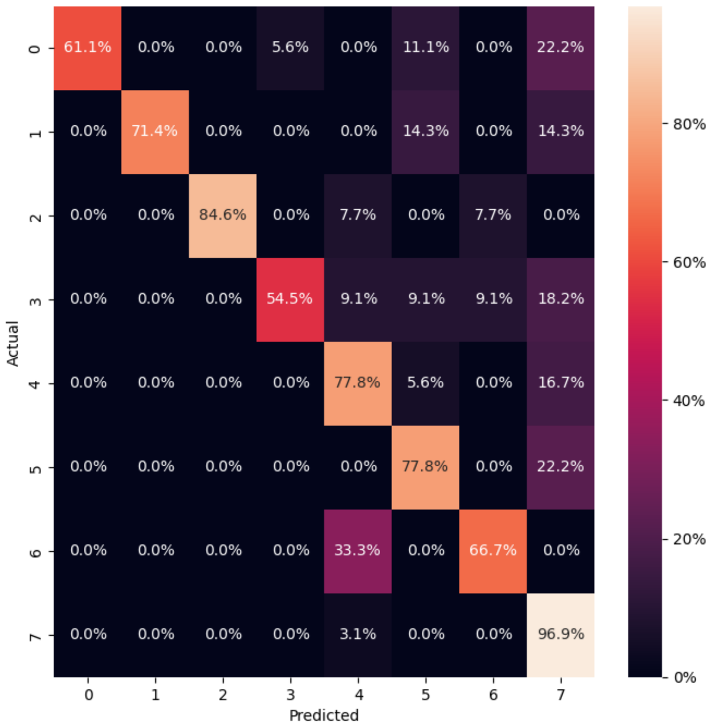

Figure 5.11: CM of RF.

hyperparameters were chosen to ensure stable and efficient training. Figure 5.12 illustrates the increase in accuracy and the reduction in loss for the SSDINet model during the training and testing phases which demonstrate the effectiveness of the chosen training setup. Figure 5.13 indicates the CM of SSDINet.

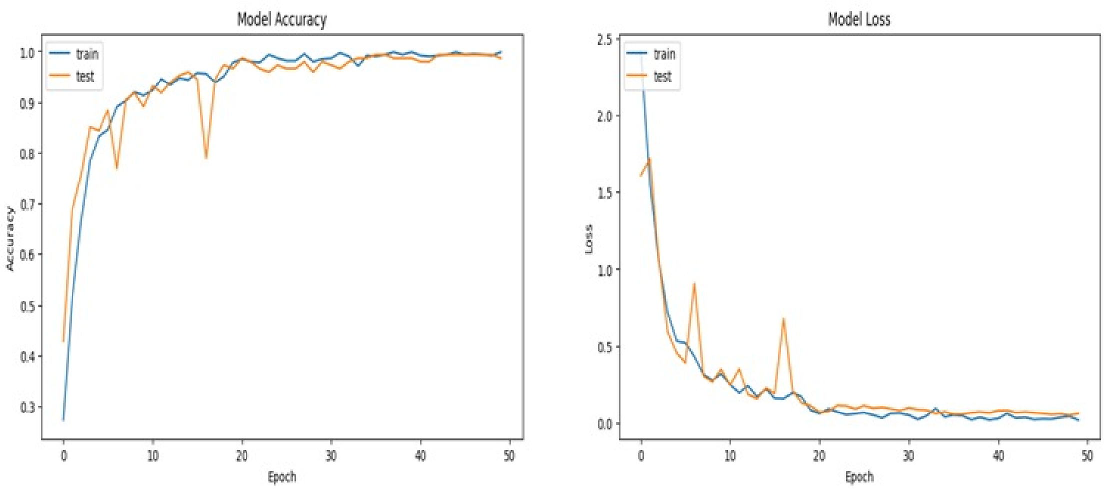

Figure 5.12: Performance of SSDINet in terms of epoch Vs accuracy and epoch Vs loss.

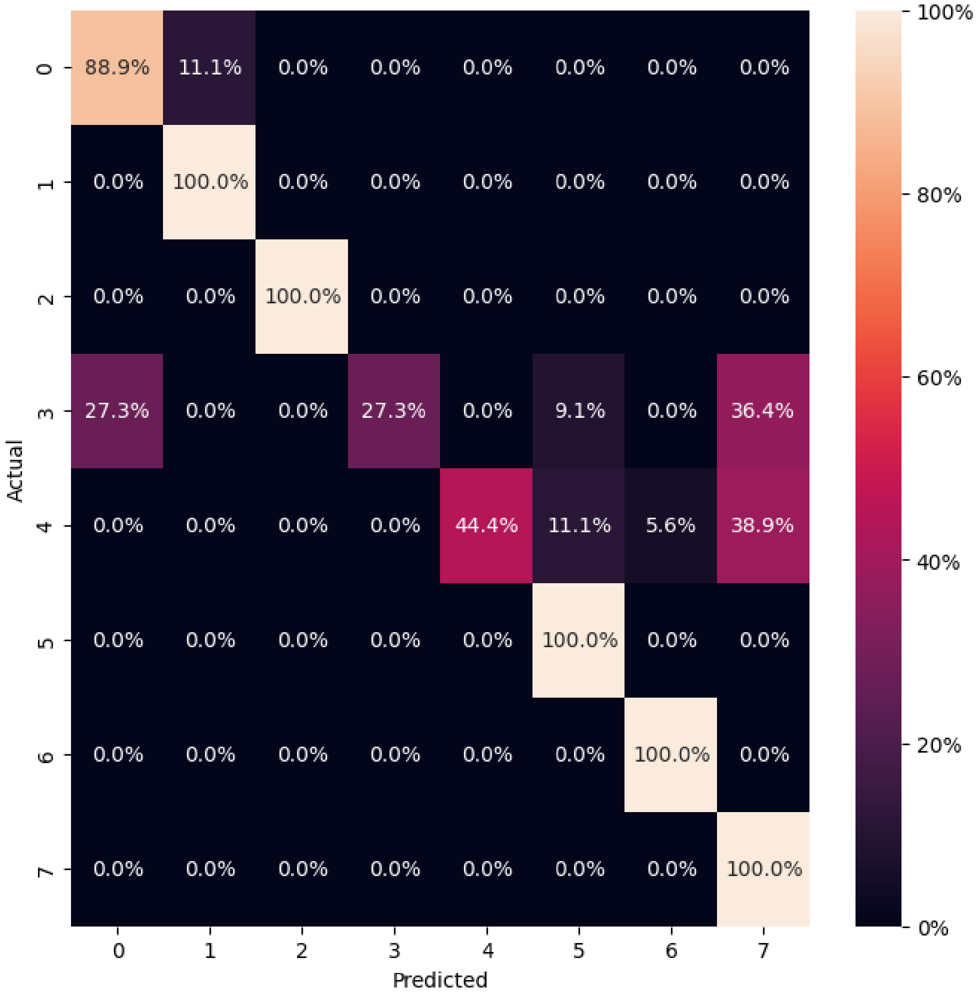

Figure 5.13: CM of SSDINet.

Table 5.6 presents the results of SSDINet for dataset split ratios of 80:20, 85:15, and 90:10. Initially, the soybean dataset was processed through the SCD algorithm, after which the images were divided according to the specified split ratios and the network was trained. Notably, the 80:20 split ratio yielded the most promising results after applying the SCD algorithm. When comparing the performance on raw data images to those processed with the SCD algorithm, there was a notable 3% increase in accuracy with the latter. Therefore, the proposed SCD algorithm not only enhanced the quality of the soybean seed images but also improved the classification accuracy.

Table 5.6: Performance metrics for SSDINet models with and without SCD algorithm at different dataset split ratios.

Dataset split ratio	Model	Precision (%)	Recall (%)	F-1 score (%)	Accuracy (%)
80:20	**SSDINet without SCD algorithm**	**95.01**	**96.66**	**96.82**	**95.23**
85:15		94.23	95.36	92.01	94.36
90:10		92.15	93.20	91.89	92.10
80:20	**SSDINet with SCD algorithm**	**98.74**	**97.64**	**95.66**	**98.64**
85:15		95.54	94.93	93.63	95.63
90:10		94.57	94.86	92.19	94.93

For the SSDINet model without the SCD algorithm, the performance metrics show a consistent decrease in performance as the dataset split ratio becomes more imbalanced. At the 80:20 split ratio, the model achieves a Precision of 95.01%, Recall of 96.66%, F-1 score of 96.82%, and Accuracy of 95.23%. With a 85:15 split ratio, these metrics decrease slightly, with Precision at 94.23%, Recall at 95.36%, F-1 score at 92.01%, and Accuracy at 94.36%. At the most imbalanced 90:10 split ratio, the model's performance drops further, achieving a Precision of 92.15%, Recall of 93.20%, F-1 score of 91.89%, and Accuracy of 92.10%. In contrast, the SSDINet model with the SCD algorithm demonstrates superior performance across all split ratios. At the 80:20 split ratio, the model with the SCD algorithm significantly outperforms the one without it, achieving a Precision of 98.74%, Recall of 97.64%, F-1 score of 95.66%, and Accuracy of 98.64%. Even as the data becomes more imbalanced, the SCD-enhanced model maintains higher performance metrics: at the 85:15 split ratio, it achieves a Precision of 95.54%, Recall of 94.93%, F-1 score of 93.63%, and Accuracy of 95.63%. At the 90:10 split ratio, it still performs better than the model without SCD, with a Precision of 94.57%, Recall of 94.86%, F-1 score of 92.19%, and Accuracy of 94.93%. Figure 5.14 shows a graphical comparison of the SSDINet model across various data splits ratios.

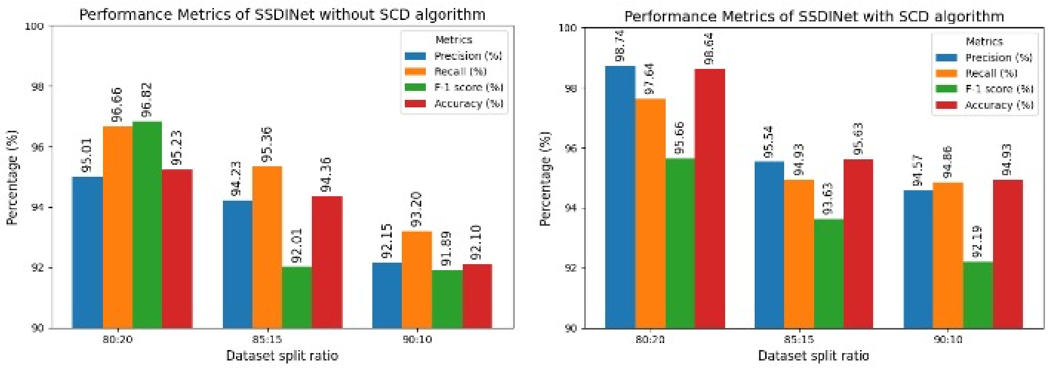

Figure 5.14: Performance of SSDINet (a) without SCD, (b) with SCD.

The Table 5.7 shows a comparison of the performance metrics for various ML and DL algorithms applied to a classification task. The algorithms assessed RF, KNN, LR, SVM, CNN, and SSDINet. Among ML algorithms, SVM performs better while CNN, as a deep learning model, further improves upon the metrics achieved by SVM, with a precision of 94.90%, recall of 92.67%, F-1 score of 93.50%, and accuracy of 93.69%. CNN's superior performance highlights the strength of deep learning models in handling complex datasets, with its robustness in classification tasks evidenced by its high accuracy. Figure 5.15 indicates confusion metrics of CNN. Among all models, SSDINet achieves the highest performance across all metrics, with a precision of 98.74%, Recall of 97.64%, F-1 score of 98.66%, and Accuracy of 98.64%. SSDINet's exceptional performance is a testament to its advanced architecture and capability in accurately identifying and classifying the data, outperforming all other algorithms evaluated.

Table 5.7: Performance of ML and DL algorithms

Algorithms	Precision (%)	Recall (%)	F-1 score (%)	Accuracy (%)
RF	82.21	78.08	78.29	78.38
KNN	86.43	78.58	78.54	79.28
LR	85.96	81.78	79.37	81.98
SVM	92.93	90.79	91.85	91.89
CNN	94.90	92.67	93.50	93.69
SSDINet	**98.74**	**97.64**	**98.66**	**98.64**

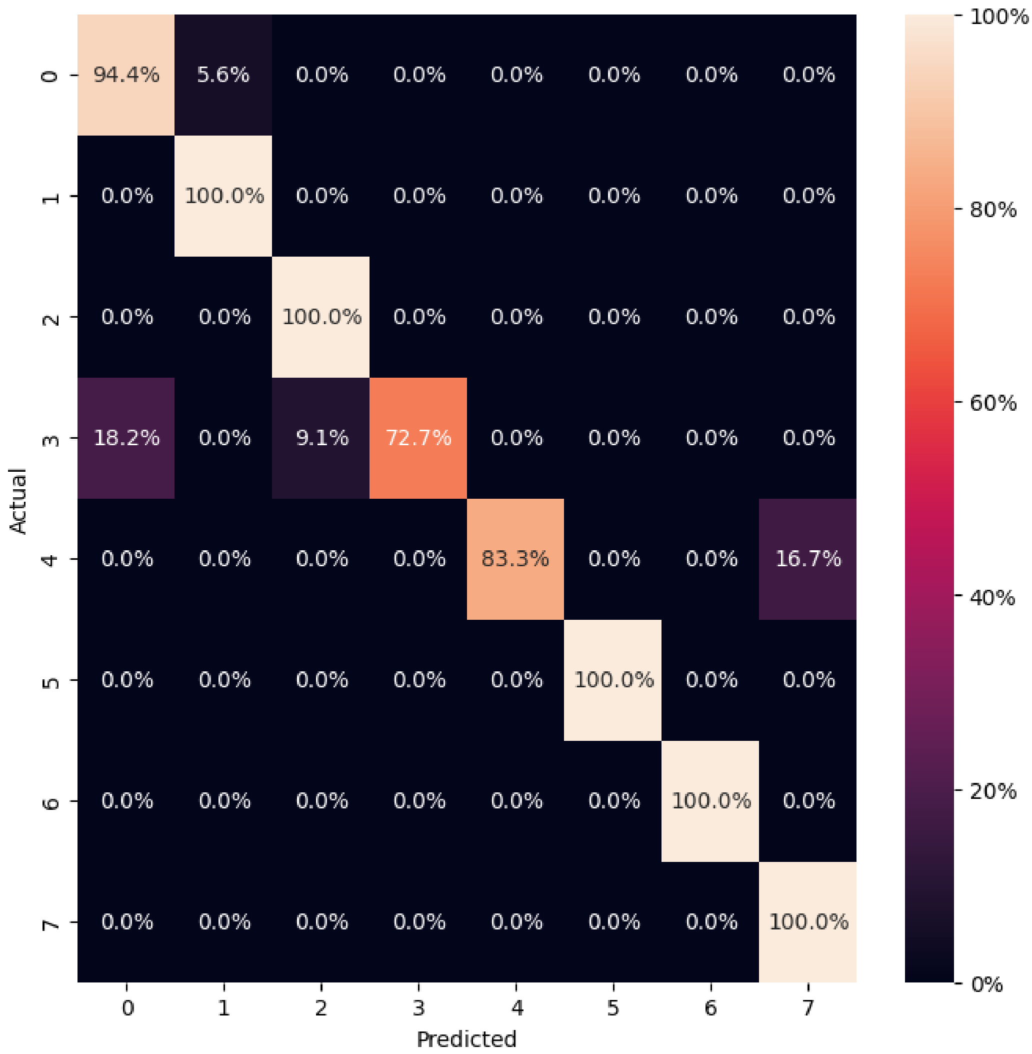

Figure 5.15: CM of CNN

The classification performance of SSDINet in identifying various soybean seed classes is summarized in Table 5.8 (Values in brackets indicate the classes). The categories of cracked seed, damaged seed, insect-bitten seed, green seed, purple seed, and wrinkled seed all exhibited 100% accuracy, followed by the good seed and broken seed categories. Figure 5.16 denotes a graphical representation of SSDINet output using the SCD algorithm for each class.

Table 5.8: Result of SSDINet with SCD algorithm for each class.

Soyabean Seed Classes	Precision (%)	Recall (%)	F-1 score (%)	Accuracy (%)
Good seeds (7)	100	98	99	97.7
Broken seeds (0)	100	96	98	96
Crack seeds (1)	92	100	94	100
Damaged seeds (2)	100	100	100	100
Insect-bitten seeds (3)	100	100	100	100
Green seeds (4)	100	100	100	100
Purple seeds (5)	93	100	95	98
Wrinkled seeds (6)	100	100	100	100
Overall	**98.74**	**97.64**	**95.66**	**98.64**

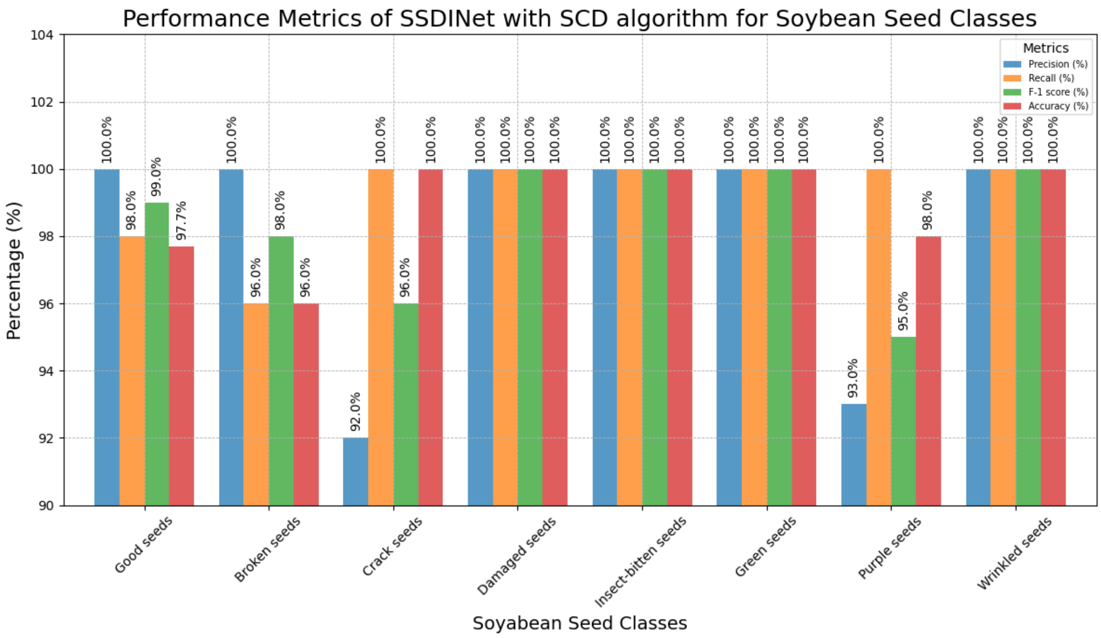

Figure 5.16: Graphical representation of SSDINet output using the SCD algorithm for each class.

The proposed SSDINet is also tested on Soybean Seeds Classification Dataset, available on Kaggle from 2023 [59]. Figure 5.17 shows the confusion metrics of SSDINet on the available dataset. The Table 5.9 summarizes the classification performance of a model applied to different classes of soybean seeds which includes Spotted, Damaged, Intact, Immature, and Broken soybean seeds. The Intact class achieved the highest accuracy 99.6%, while Broken seeds had the lowest 62.5%, which indicates greater difficulty in identifying this class. Overall accuracy and

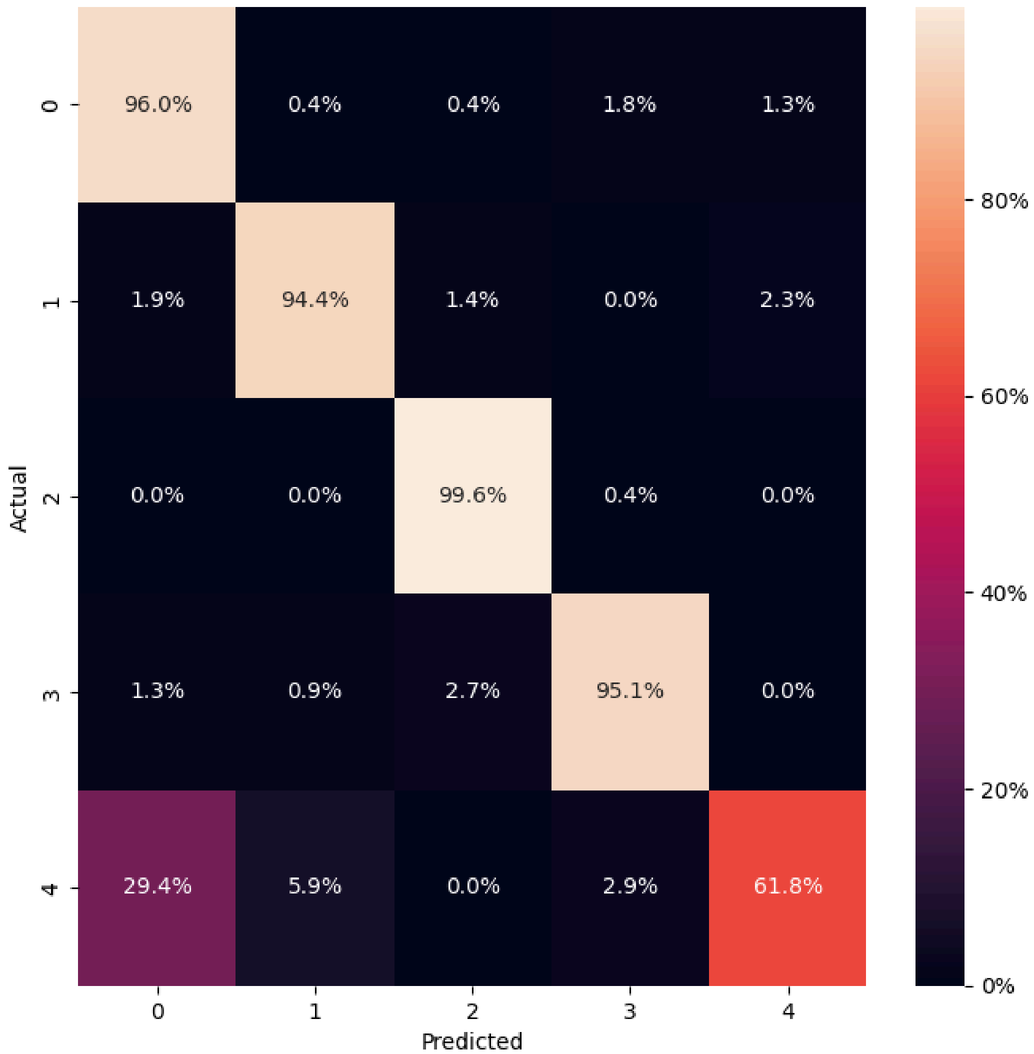

Figure 5.17: CM of SSDINet on Kaggle dataset.

average metrics across all classes are 96.77% for accuracy, 95.97% for precision, 96.07% for recall, and 95.95% for the F1-score, showing strong overall model performance despite variability across specific seed classes.

Table 5.9: Soybean Seed Classification Results on available Dataset

Seed Class	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F-1 Score (%)**
Spotted (0)	96.9	96	97	96
Damaged (1)	95.3	97	95	96
Intact (2)	99.6	95	100	97
Immature (3)	97.3	98	97	98
Broken (4)	62.5	84	62	71
Overall	**96.77**	**95.97**	**96.07**	**95.95**

5.7 Summary

This thesis presents a thorough methodology for identifying defects in soybean seeds, ML and DL techniques. The study begins with an exploration of traditional ML algorithms KNN, SVM, RF and LR detailing their application in seed classification. It then transitions to advanced DL approaches, focusing on Convolutional Neural Networks (CNNs) and SSDINet. The thesis also incorporates techniques like transfer learning, adaptive learning rate adjustment, and model checkpointing to enhance model performance. By using both ML and DL strategies, this research offers a robust solution for the accurate and efficient identification of soybean seed defects, ultimately contributing to improvements in agricultural technology and crop health management. In summary, SSDINet emerges as the top-performing algorithm, demonstrating superior capability with the highest precision, recall, F-1 score, and accuracy. CNN and SVM also perform notably well, with CNN leading among the deep learning models and SVM excelling among the traditional ML algorithms. This research includes a detailed analysis of the performance of different models, evaluates their effectiveness in real-world scenarios, and discusses the potential for implementation in industrial settings. Through this approach, the thesis aims to contribute to the advancement of agricultural technology and improve the overall quality and marketability of soybean seeds.

Chapter 6

SOYBEAN SEED VARIETY IDENTIFICATION

6.1 Introduction to Seed Variety identification Model

India is a top agricultural producer because of its diversified climate and soil types. Soybeans is renowned for their high protein content, due to which it is an important source of plant-based protein and are used to produce various food products like soy milk, tofu, tempeh, miso and soy sauce [12]. Soybean oil, extracted from soybeans, is one of the most commonly consumed vegetable oils worldwide. They contain all the essential amino acids and are rich in essential nutrients such as dietary fiber, vitamins (especially B vitamins), minerals (iron, calcium, magnesium), and phytonutrients (isoflavones) [102]. However, environmental factors which include adverse weather conditions like droughts or excessive rainfall during cultivation significantly impact the health and yield of soybean crops [106]. Likewise, insufficient management practices for pests and diseases result in compromised bean quality. Hence, the identification of suitable soybean seed varieties is a pivotal aspect of maximizing agricultural productivity and sustainability, particularly in regions with unique climatic and soil conditions like Vidarbha in Maharashtra. This process is essential for ensuring that the selected soybean varieties are well-adapted to local conditions, which can significantly influence yield, pest resistance, and overall crop health.

In Vidarbha, where the agro-climatic conditions include specific challenges such as irregular rainfall, high temperatures, and varying soil types, selecting the right soybean variety can make a substantial difference. The choice of soybean variety affects multiple factors, including growth duration, which must align with the local growing season to avoid periods of adverse weather. Additionally, resistance to local pests and diseases is critical, as it can reduce the need for chemical interventions and lower production costs. Identifying the soybean seed variety involves thorough research and trials to evaluate how different varieties perform under the specific conditions of Vidarbha. Moreover, the adaptability of soybean varieties to the region's soil type is another crucial factor. Vidarbha's soil can range from fertile black cotton soil to less fertile red soil, and each type can affect the growth and productivity of different soybean varieties differently. By selecting varieties that are well-suited to the prevalent soil conditions, farmers can optimize nutrient uptake and improve plant health.

In this thesis, three soybean seed varieties are detected using ML and DL techniques. In ML techniques KNN, RF, LR and SVM are used while in DL modified GoogleNet is developed named modified GoogleNet for Variety Identification (MGVI) which are summarized in next section.

6.2 ML Model

To predict 3 varieties (JS335,KDS726 and JS9305) of soybean seed, this thesis used KNN, RF, LR and SVM algorithms which is explained in detail in Section 5.3.

6.3 DL Model

To recognize the variety of soybean seeds, this thesis presents Modified GoogleNet for Variety Identification(MGVI) which uses pre-trained Inception-V1(GoogleNet) [17]. It employs parallel convolutional paths of varying receptive field sizes, which

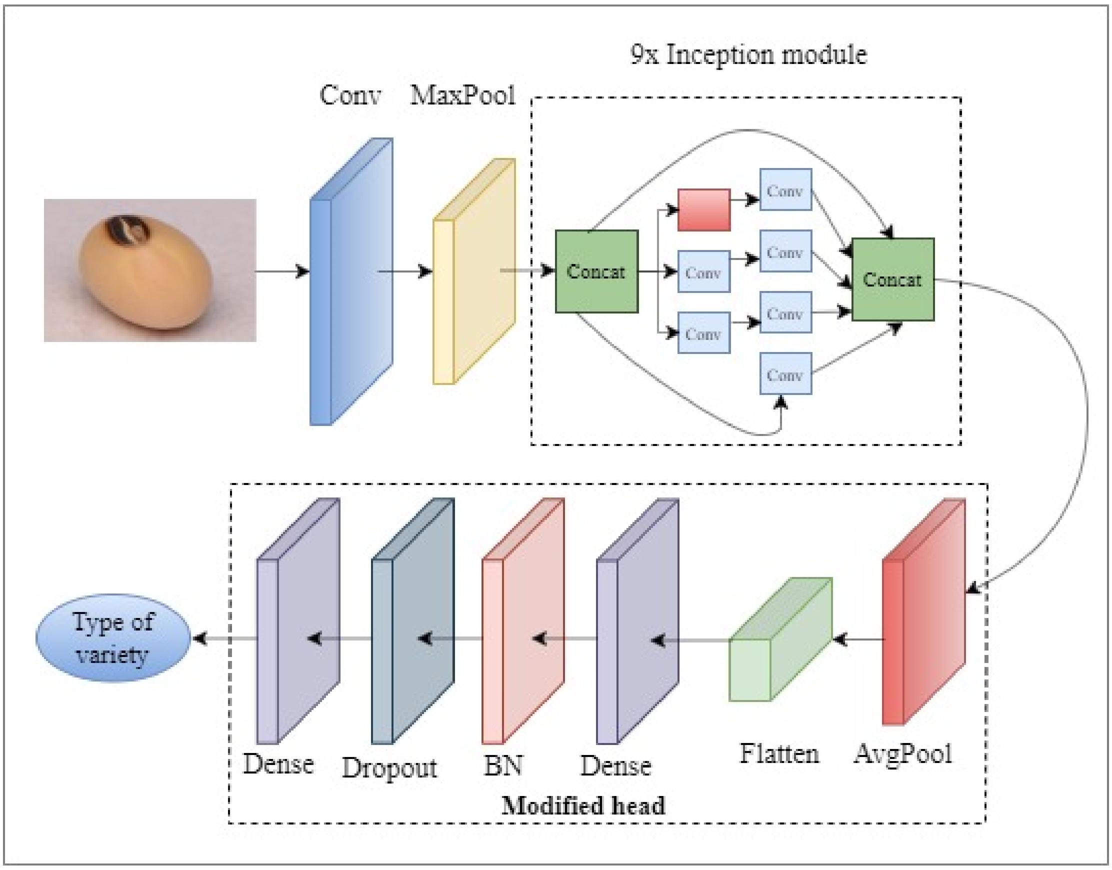

Figure 6.1: Architecture of MGVI.

enables the network to capture local features effectively and exhibits better results for variety identification. The initial part of the network consists of several convolutional layers with small filter sizes (e.g., 7x7, 3x3) with ReLU activation function. These layers perform basic feature extraction while reducing the spatial dimensions of the input. The core building block of GoogleNet is the inception module. Each inception module contains multiple parallel CNN branches with varying filter sizes like 1x1, 3x3, 5x5, Max Pooling (MP), and 1x1 CNN layers for dimensionality reduction. The outputs of these branches are concatenated along the channel dimension and allow the network to capture features at multiple scales within the same layer. Inception Modules (IM) are stacked together to form the main body of the network. As inception modules extract coarse and fine features efficiently from similar images it prove beneficial for the identification of soybean seed variety. Throughout the network, max-pooling layers are used to reduce the spatial dimensions of feature maps and introduce translational invariance. After the Inception modules, GAP calculates the average value of every feature map across the dimensions, which results in a fixed-size feature vector and also prevents overfitting. Figure 6.1 shows the proposed architecture of the MGVI module and Table 6.1 denotes input and output shapes and operations.

Table 6.1: Model architecture of MGVI with input and output shapes and operations

Layer	Input Shape	Operation	Kernel/Filter	Stride	Output Shape
Input	224×224×3	-	-	-	224×224×3
Conv Layer 1	224×224×3	Conv (64 filters, ReLU)	7×7	2×2	112×112×64
MP-1	112×112×64	MP	3×3	2×2	56×56×64
Conv Layer 2	56×56×64	Conv (192 filters, ReLU)	3×3	1×1	56×56×192
MP-2	56×56×192	MP	3×3	2×2	28×28×192
IM-1	28×28×192	Inception (1×1, 3×3, 5×5, MP)	Varies	1×1	28×28×256
IM-2	28×28×256	Inception (1×1, 3×3, 5×5, MP)	Varies	1×1	28×28×480
MP-3	28×28×480	MP	3×3	2×2	14×14×480
IM-3	14×14×480	Inception (1×1, 3×3, 5×5, MP)	Varies	1×1	14×14×512
IM-4	14×14×512	Inception (1×1, 3×3, 5×5, MP)	Varies	1×1	14×14×512
MP-4	14×14×512	MP	3×3	2×2	7×7×512
Average Pooling	7×7×512	GAP	7×7	-	1×1×512
Flatten	1×1×512	Flatten	-	-	512
Dense Layer 1	512	Fully Connected (ReLU)	-	-	256
Dropout Layer	256	Dropout (0.2)	-	-	256
Batch Norm Layer	256	Batch Normalization	-	-	256
Dense Layer 2	256	Fully Connected	-	-	3
SoftMax Output	3	Classification (SoftMax)	-	-	Probabilities

After experimentation, this module consists of Inception-V1 and the modified head. The modified head contains 1) Pooling layer, ii) Flatten layer, iii) Dense layer, iv) BN and v) Dropout layer. Here, the Pooling Layer reduces the spatial dimensions of the input feature maps and preserves information. Flatten prepares the data for fully connected layers while a fully connected layer learns complex patterns from the flattened input. BN normalizes the previous layer's activations and stabilizes and accelerates training. The dropout rate determines the proportion of neurons to drop during each training iteration with a value of 0.2. Lastly, a dense layer with SoftMax function determines the variety of soybean seeds.

The presented MGVI model stands out due to its use of Inception-V1 with parallel convolutional paths of varying receptive field sizes that enable to capture fine and coarse features simultaneously. This features play a crucial role for distinguishing soybean seed varieties. Its lightweight design leverages 1x1 convolutions for dimensionality reduction that reduces parameters while preserves feature richness. The GAP layer prevents overfitting and improves generalization, while BN and dropout regularize the model for better training. MGVI's efficiency, scalability, and robustness to positional variations make it ideal and outperforms traditional models in both accuracy and resource efficiency which is shown in section 6.4.

6.4 Result and Analysis

The architecture of MGVI consists of modified GoogleNet which is used for seed variety identification. The performance of MGVI in terms of accuracy and loss is shown in Figure 6.2. Here, the training accuracy of the MGVI model starts from 50% and reaches 99% after 50 epochs. In the case of testing accuracy, it begins at 50%, meanwhile, after 2 iterations it falls to 35% and then suddenly starts increasing and achieves the highest 97%. Figure 6.3 also showcases the proposed modules' training loss, indicating a discernible pattern during the training phase. Initially, the training loss exhibits a noticeable peak due to the model's unfamiliarity with the data. However, as the training proceeds, the model begins to ingest and encode the images, leading to a gradual decline in the training loss. Here, the initial training loss is higher than defect identification, it diminishes progressively over subsequent iterations. Eventually, it stabilizes at a training loss of 0.20, underscoring the model's proficiency in distinguishing between different varieties present in the dataset.

The reduction in training loss serves as a testament to the model's efficacy in learning intricate patterns and features essential for both defect and variety identification tasks. Figure 6.4 shows the confusion metrics of modules. These matrices illustrate the classification accuracy by showing the TP rates for all class and confirm the high efficacy of MGVI. The Table 6.2 summarizes the performance metrics of ML-DL algorithms, which entails their precision, recall, F-1 score, and

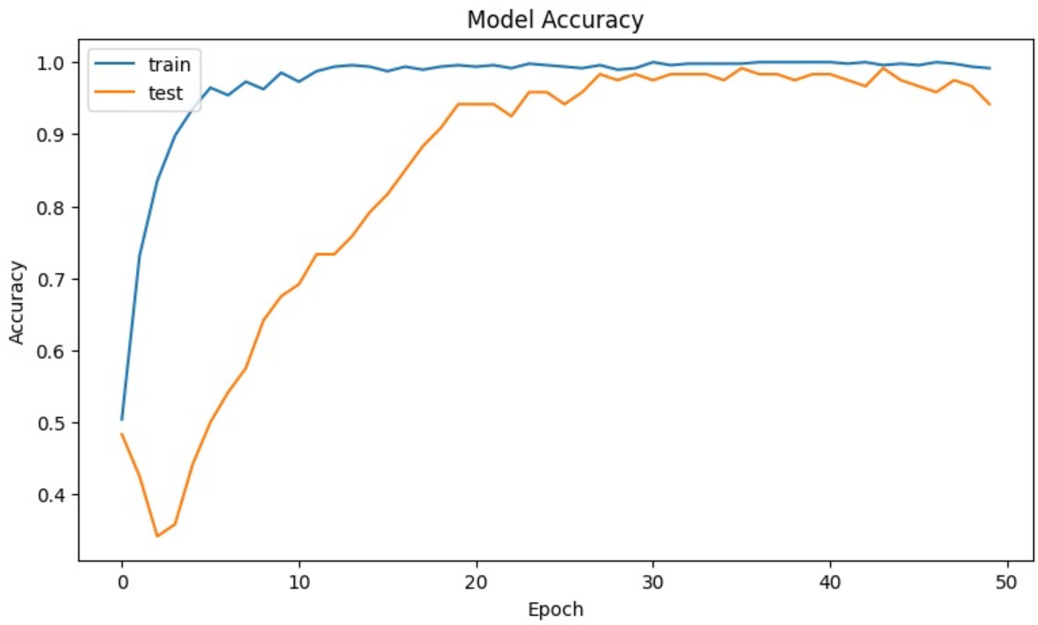

Figure 6.2: Accuracy Vs epoch performance of MGVI model at 50 epochs.

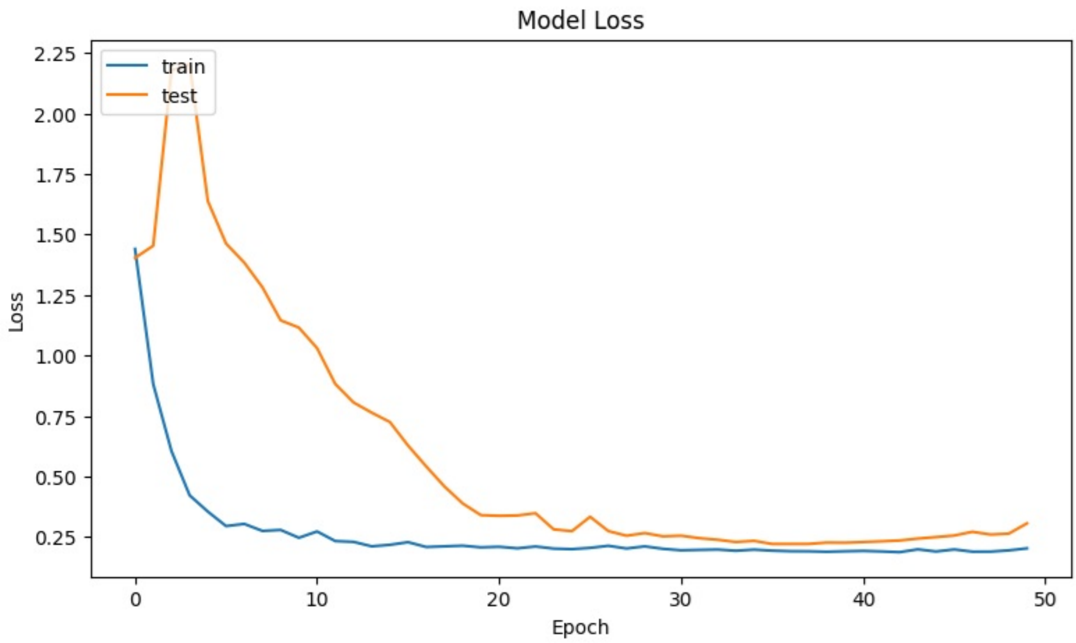

Figure 6.3: Accuracy Vs loss performance of MGVI model at 50 epochs.

accuracy. Each metric offers a unique perspective on the algorithm's effectiveness. The RF algorithm exhibits good performance with precision around 83%, and an accuracy of 83.87%. This suggests that RF is fairly effective in predicting both

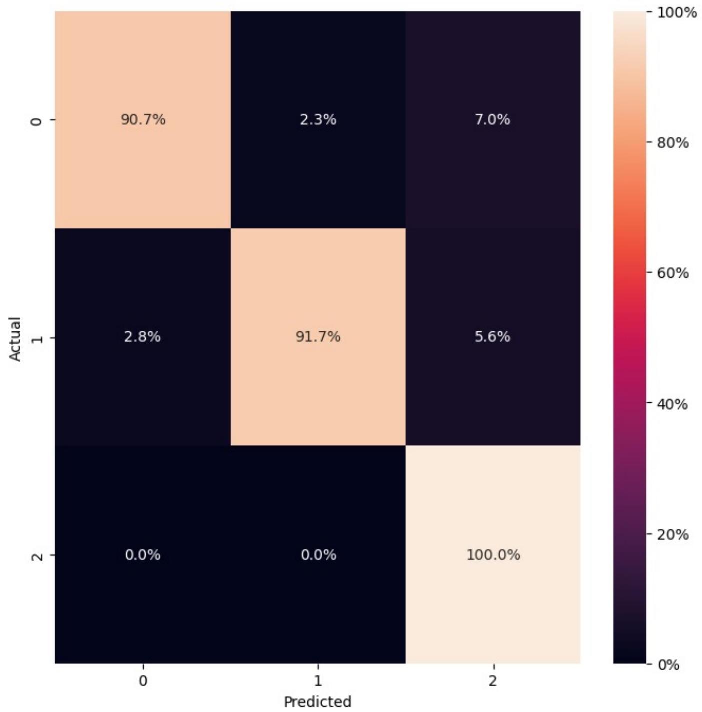

Figure 6.4: CM of MGVI.

positive and negative instances. Figure 6.5 indicates the confusion metrics of RF. KNN has a slightly higher precision at 84.84%, indicating fewer false positives compared to RF, but its recall is lower at 81.80%, which might result in missing some positive instances. Figure 6.6 indicates the confusion metrics of KNN. The F-1 score and accuracy for KNN are also a bit lower than RF, at 82.86% and 82.80% respectively. LR significantly outperforms both RF and KNN with a precision of 90.37%, recall of 89.32%, F-1 score of 90.30%, and accuracy of 89.32%. Figure 6.7 indicates the confusion metrics of LR. This indicates that LR is highly effective in making balanced predictions. SVM performs slightly better than LR, with precision at 90.90%, recall at 90.12%, an F-1 score of 90.15%, and accuracy of 90.32%. This suggests that SVM is a very effective model, offering both high precision and recall. Figure 6.8 indicates the confusion metrics of SVM. Lastly, the MGVI which is a deep learning algorithm has the highest performance metrics across all categories. Its precision and recall are both around 97%, with an F-1 score of 96.81% and an accuracy of 97.90%. These results indicate that MGVI is the most effective model among those listed, providing highly accurate and reliable predictions. Hence, RF and KNN provide decent performance, they are outperformed by LR and SVM. Among all, MGVI stands out as the best-performing algorithm, delivering the highest scores in all metrics, which reflects its superior prediction capabilities.

Table 6.2: Performance of ML and DL algorithms

Algorithms	Precision (%)	Recall (%)	F-1 score (%)	Accuracy (%)
RF	83.81	82.92	83.22	83.87
KNN	84.84	81.80	82.86	82.80
LR	90.37	89.32	90.30	89.32
SVM	90.90	90.12	90.15	90.32
MGVI	**96.91**	**97.37**	**96.81**	**97.90**

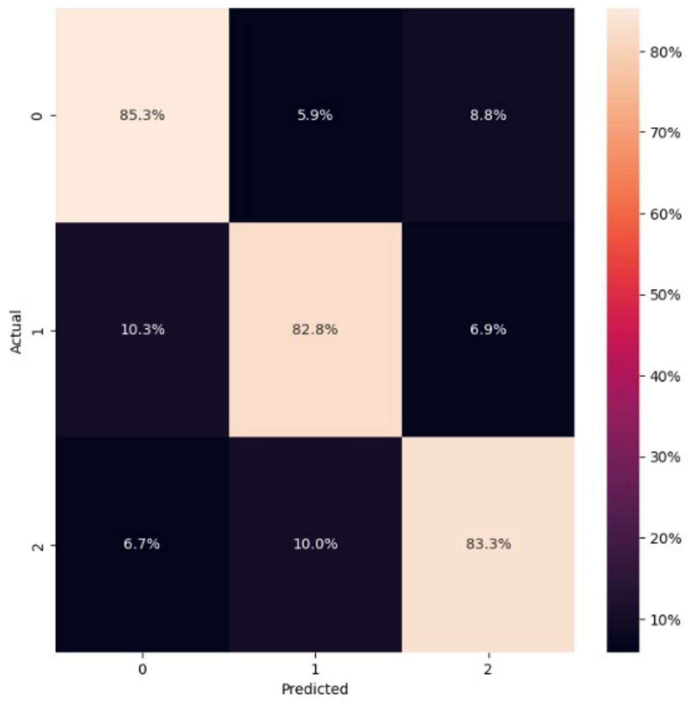

Figure 6.5: CM of RF.

Table 6.3 represents per class performance of variety across various evaluation metrics. Here, JS335 (class 0) and JS9305 (class 2) achieve the highest accuracy of 100% followed by KDS726 (class 1) with 92.5%. By combining all three classes the accuracy of seed variety identification module is 97%. However, the performance of MGVI across all seed classes is impressive, with average metrics showing the

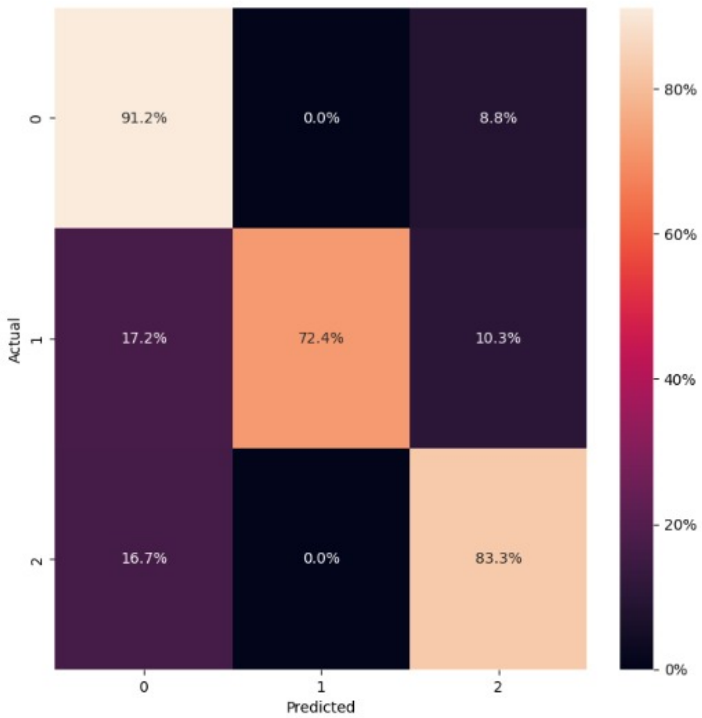

Figure 6.6: CM of KNN.

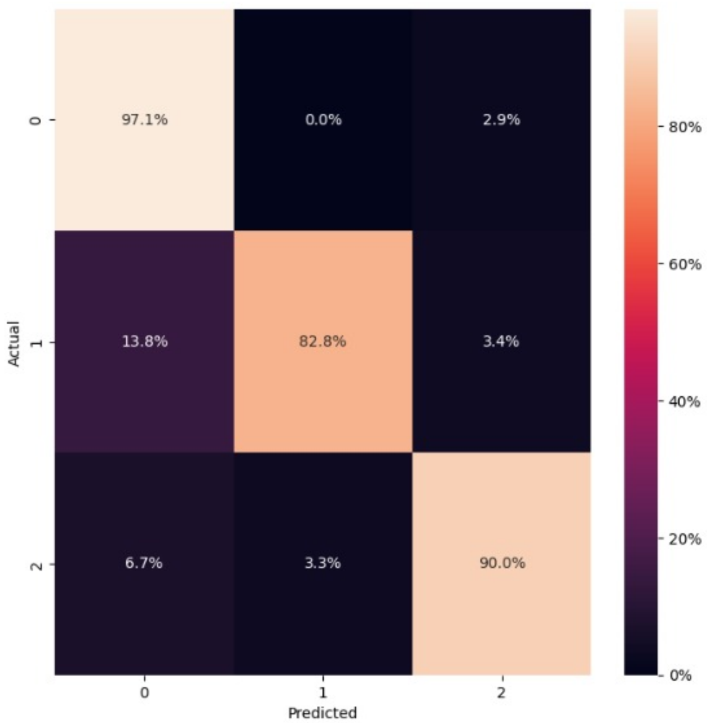

Figure 6.7: CM of LR.

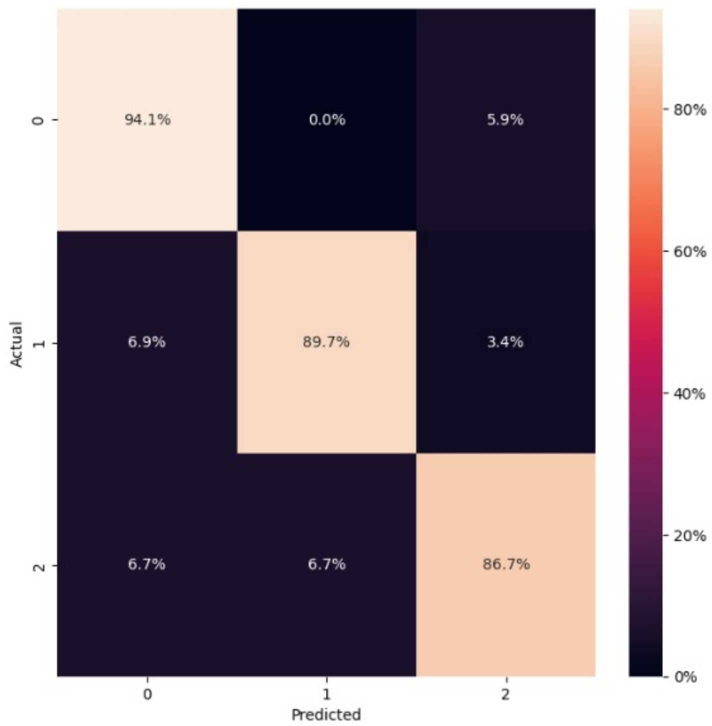

Figure 6.8: CM of SVM.

Table 6.3: Result of MGVI with SCD algorithm for each class of variety.

Soyabean Seed Classes	Precision (%)	Recall (%)	F-1 score (%)	Accuracy (%)
JS335 (0)	98	100	99	100
KDS726 (1)	93	93	93	92
JS9305 (2)	95	100	97	100
Overall	**96.91**	**97.37**	**96.81**	**97.90**

overall accuracy of MGVI is 97.90%, with a precision 96.91%, 97.37 % recall and 96.81% F1 score.

6.5 Publication

1. Submitted paper to SN Computer Science journal with title DVINet: A Transfer Learning-Based Framework for Defect and Variety Identification in Soybean Seeds"

6.6 Summary

Identifying suitable soybean seed varieties is vital for optimizing agricultural productivity and sustainability in Vidarbha, Maharashtra. The region's unique climatic conditions, including irregular rainfall, high temperatures, and varied soil types, necessitate careful selection of soybean varieties to ensure high yield, pest resistance, and crop health. This thesis provides, ML and DL approaches to recognize soybean seed variety. KDS726, JS335 and JS9305 are widely cultivated seeds in Vidarbha Maharashtra. This thesis identifies these varieties using RF, KNN, LR and SVM which are popular ML techniques. Among these four techniques SVM surpasses other techniques in terms of various evaluation metrics. Later, this thesis provides novel DL techniques named MGVI which outperformed all and acheive 97.90% accuracy. Hence, effective identification of variety leads to enhanced crop resilience, higher yields, and improved profitability,it also contributes to the sustainability of soybean farming in Vidarbha. By selecting the right varieties, farmers can achieve economic stability, meet market demands, and maintain the health of their land and resources.

Chapter 7

COMPARISON WITH EXISTING METHODOLOGY

7.1 Introduction

The development and evaluation of DL models in the domain of soybean seed classification have become increasingly crucial due to the growing need for accurate, efficient, and resource-friendly systems. In this chapter, we present an in-depth analysis of the proposed SSDINet and MGVI model. These models are compared against state-of-the-art DL models, which includes SNet, SoyNet, and improved ResNet-18, to highlight their superiority in terms of accuracy, model size, precision, recall, and classification time.

SSDINet is designed as a faster and lightweight model, optimized for both high performance and resource efficiency. It achieves a remarkable accuracy of 98.64%, which surpasses other models while maintaining a smaller model size and faster inference time. Similarly, MGVI demonstrates superior performance in variety identification, achieving the highest accuracy of 97.90%. This chapter provides a comprehensive comparative analysis of these models across key performance metrics, underscoring the effectiveness of the proposed approaches in soybean seed classification tasks. Through this evaluation, SSDINet and MGVI emerge as robust solutions for enhancing the classification of soybean seed varieties and defects which offers an optimal balance between accuracy and computational efficiency.

7.2 SSDINet

The presented faster and lightweight SSDINet model is evaluated against the state-of-the-art DL models SNet and SoyNet as presented in Table 7.1. In terms of accuracy, SSDINet achieves 98.64%, surpassing both SNet and SoyNet. Notably, SSDINet maintains high performance with a smaller model size (1.15 M Params) compared to SNet and SoyNet, which have 1.29 M and 7.26 M parameters, respectively, which demonstrate its efficiency in resource utilization. Furthermore, SSDINet exhibits competitive inference times of 4.70 ms, which is comparable to SoyNet's 4.92 ms and significantly faster than SNet's 9.67 ms. This comprehensive evaluation underscores SSDINet's effectiveness, efficiency, and superiority over the other models, making it an optimal choice for soybean seed classification in terms of both performance and resource efficiency.

Table 7.1: Comparison with state-of-the-art approaches

Model	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)	Size (Params)	Time
SNet [60]	97.0	94.0	95.5	96.2	1.29 M	9.67 ms
SoyNet [59]	96.69	96.71	96.69	95.63	7.26 M	4.92 ms
SSDINet (Proposed)	98.74	98.64	98.64	98.64	1.15 M	4.70 ms

7.3 MGVI

Table 7.2 provides a comparative analysis of three models—SNet, SoyNet, and improved ResNet-18 with MGVI (proposed model) across various performance metrics. Precision, which indicates the % of TP predictions among all positive predictions, is highest for MGVI at 96.91%, slightly surpassing SNet's 97.0% and SoyNet's 96.69%. In terms of recall, MGVI again leads with 97.37%, significantly higher than SNet's 94.0% and slightly better than SoyNet's 96.71% which highlights MGVI's effectiveness in identifying all positive cases. In terms of accuracy, which represents the percentage of correctly predicted instances out of the total instances, MGVI achieves the highest accuracy at 97.90%, surpasses SNet at 96.2%, SoyNet at 95.63% and improved ResNet-18 at 97.36%. Hence, the higher accuracy signifies MGVI's enhanced capability in correctly classifying both positive and negative cases. It indicates that MGVI works well among all existing methodologies and classifies seeds effectively. Figure 7.1 indicates the graphical comparison of the proposed MGVI with other state-of-the-art methods.

Table 7.2: Comparison with existing methodology

Model	**Precision (%)**	**Recall (%)**	**F-1 score (%)**	**Accuracy (%)**
SoyNet [59]	96.69	96.71	96.69	95.63
SNet [60]	97.0	94.0	95.5	96.2
Improved ResNet-18 [91]	–	–	–	97.36
MGVI (Proposed)	**96.91**	**97.37**	**96.81**	**97.90**

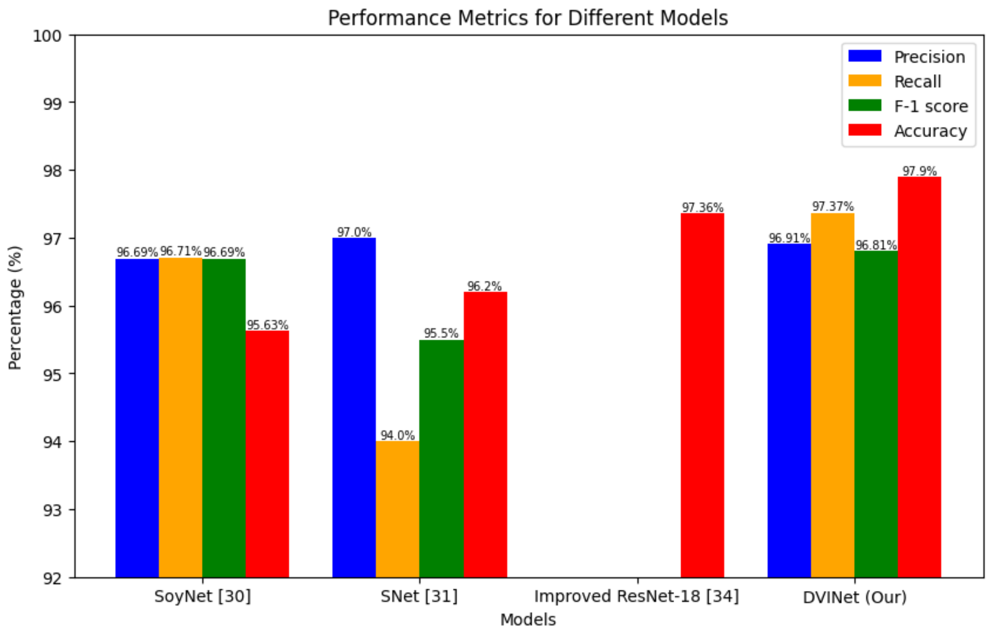

Figure 7.1: Graphical comparison of MGVI with existing methods.

7.4 Summary

This chapter evaluates the performance of the proposed SSDINet and MGVI models in comparison to state-of-the-art deep learning models, SNet and SoyNet, focusing on various performance metrics such as accuracy, model size, classification time, precision, recall, and F1 score. SSDINet achieves an impressive accuracy of 98.64%, outperforming both SNet and SoyNet. It also demonstrates efficient resource utilization with a model size of only 1.15 million parameters, which is smaller than SNet's 1.29 million and SoyNet's 7.26 million. Furthermore, SSDINet shows competitive inference times, processing data in 4.70 milliseconds, faster than SNet's 9.67 milliseconds and comparable to SoyNet's 4.92 milliseconds. These results highlight SSDINet's effectiveness in terms of both performance and resource efficiency, making it a superior choice for soybean seed classification.

The chapter also presents the MGVI model, which surpasses its competitors in several key performance areas. MGVI achieves the highest accuracy, at 97.90%, outclassing SNet (96.2%), SoyNet (95.63%), and the improved ResNet-18 (97.36%). MGVI also excels in precision, recall, and F1 score, with a recall rate of 97.37%, indicating its strong ability to identify positive cases. The improved performance metrics across all categories confirm MGVI's robustness and efficiency in correctly classifying soybean seeds. Overall, both SSDINet and MGVI prove to be highly effective and resource-efficient models for soybean seed classification, significantly improving upon existing methodologies.

Chapter 8

CONCLUSION AND FUTURE SCOPE

8.1 Conclusion

Soybean is a crucial crop globally, valued not only for its high protein content but also for its versatility in various products, from animal feed to biodiesel. As a staple in the agricultural sector, optimizing soybean cultivation is essential for food security and economic stability. In this context, the identification of defects and selection of high-performing soybean seed varieties become pivotal. Advanced deep learning models play a significant role in this process, enabling precise classification and prediction of soybean seed quality and characteristics. This thesis introduced SSDINet and MGVI, a novel defect and variety identification network designed for soybean seeds that leverages transfer learning techniques.

In this thesis, the researcher divides the challenges into four aspects *(i)* dataset generation *(ii)* dataset pre-processing *(iii)* defect identification and *(iv)* variety identification. The researcher performed the methodological literature review, propose solutions, developed mechanisms, and simulated the techniques to escalate the current state-of-the-art in these areas. In particular, Chapter 1 explains the details of the objective of this thesis and describes the contribution of the presented study. It also defines the structure of the thesis.

Chapter 2, a methodological survey carried out for existing research on the problem addressed in this research work. Here, the survey is split into two parts, the first part explains the technological background while the second part is further split into papers of variety identification and defects identification. Papers of variety/defects identification explain the methodology and remarks of state-of-the-arts approaches.

Chapter 3 entails the details of dataset formation. Initially when the research work started soybean seed dataset is not publicly available. Later, the samples of soybean seed are collected and further process of dataset preparation is explained in this Chapter. After dataset collection, Chapter 4 performs the pre-processing operation on images using propose SCD algorithm. It also helps in better yield predictions and research, promoting sustainable farming practices. For farmers in Vidarbha cultivating soybeans, such an algorithm can significantly boost planting accuracy, reduce production costs, and support sustainable and profitable farming.

Chapter 5 explains the various ML and DL algorithms that are used to identify defects of soybean seeds. In ML, RF, KNN, LR and SVM are used to identify defects where SVM outperformed all other ML algorithms in terms of all evaluation metrics. This thesis also proposes a novel algorithm named SSDINet to identify 7 defects and one good-quality soybean seed. In comparison, deep learnings SSDINet outperformed RF, KNN, LR, SVM, and CNN. The same strategy is applied for variety identification in Chapter 6 where proposed MGVI outperformed all other algorithms. At Last, Proposed SSDINet and MGVI are compared with state-of-the-art methods in Chapter 7.

The proposed models SSDINet and MGVI, contribute to future advancements in agricultural technology by enhancing seed defect and variety identification using DL. These models provide accurate, efficient, and automated solutions for quality control in the soybean industry. SSDINet's lightweight design and fast processing time enable real-time defect identification, while MGVI's advanced Inception-V1 architecture improves variety classification accuracy. As agricultural systems increasingly rely on precision technology, these models can significantly optimize crop management, reduce losses, and ensure higher-quality production that supports sustainable agriculture and food security.

8.2 Future Scope

DL approaches play a pivotal part in the identification of seeds. Although the technology has been around for decades, recent innovations and advancements have sparked renewed interest. ML and DL-based analytics solutions operate in real-time, introducing a new dimension to the agriculture industry. While these models continue to provide valuable insights and reports to senior decision-makers, real-time analytics empower frontline industry to enhance performance. The following section explains the future directions in this field.

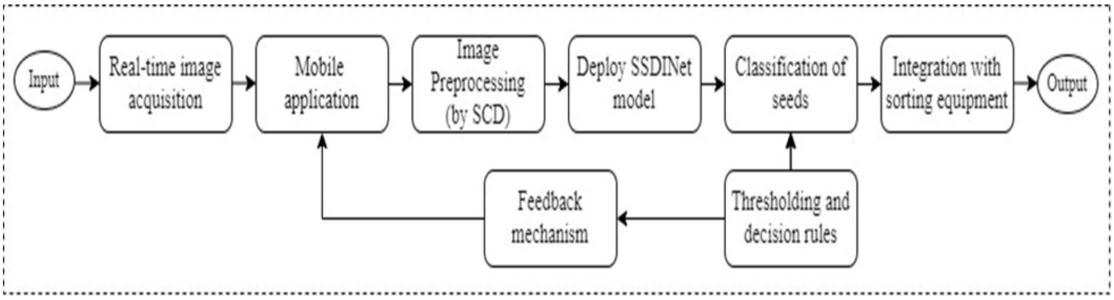

Figure 8.1: Flow chart of real-time system.

In the future, this thesis provide a solution to sort seeds in real-time into different categories. As this is our future scope, Figure 8.1 indicates the flow chart. The potential approach to perform real-time classification of soybean seeds is as follows:

1. Real-Time Image Acquisition: - Implement a high-speed camera system to capture images of soybean seeds as they pass along a conveyor belt or through a sorting mechanism.

2. Mobile Application Interface: - Develop a user-friendly mobile application interface that allows operators to input data and control the seed sorting process in real-time.

3. Wireless Connectivity: - Enable wireless connectivity between the mobile application and the seed sorting system to facilitate real-time communica-

tion and data exchange. This is achieved using Wi-Fi, Bluetooth, or other wireless communication protocols according to system requirements.

4. Image Preprocessing: - Apply SCD algorithm to eliminate noise from captured images and make them for classification.

5. Deep Learning Model Integration: - Deploy a deep learning model SSDINet to optimized for real-time performance and capable of classifying soybean seeds into seven predefined categories.

6. Thresholding and Decision Rules: - Define thresholding criteria and decision rules based on the output probabilities or confidence scores generated by the deep learning model. These rules should be optimized to accurately categorize seeds into the seven predefined categories in real-time.

7. Feedback and Control: - Incorporate feedback mechanisms into the mobile application to provide operators with real-time feedback on the classification results. Operators can review the sorted seeds' categories and make adjustments to the sorting parameters or initiate reclassification if necessary.

8. Integration with Sorting Equipment: - Integrate the real-time seed classification system with seed sorting equipment, such as pneumatic or mechanical sorters, to automate the sorting process based on the classification results. This integration should ensure seamless coordination between the classification system and the sorting mechanism to achieve accurate and efficient seed sorting.

9. Testing and Validation: - Conduct rigorous testing and validation of the real-time sorting system under various operating conditions like defect types, and conveyor speeds. Validate the system's performance against ground truth data to ensure consistent and reliable sorting results.

By addressing these aspects, this thesis aims to bridge the gap between research innovation and practical implementation, thereby maximizing the impact of our work in real-world applications within the soybean industry.

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Appendix A

List of publications

1. Sable A, Singh P, Kaur A, Driss M, Boulila W. "Quantifying Soybean Defects: A Computational Approach to Seed Classification Using Deep Learning Techniques". Agronomy. 2024; 14(6):1098. https://doi.org/10.3390/agronomy14061098, Journal Rank: JCR - Q1 (Plant Sciences) /CiteScore- Q1 (Agronomy and Crop Science) with Impact Factor: 3.3; 5-Year Impact Factor: 3.7. SJR :- 0.69.

2. Sable A, Singh P, Singh J, Hedabou M. A Survey on Soybean Seed Varieties and Defects Identification Using Image Processing. in International Semantic Intelligence Conference (IHIC-2021). Proceedings are published in Advances in Computational Intelligence, its Concepts & Applications (ACI 2022).

3. Amar V. Sable, Parminder Singh, and Avinash Kaur, Present paper in the International Conference on VLSI, SIGNAL PROCESSING, POWER ELECTRONICS, IOT, COMMUNICATION AND EMBEDDED SYSTEM (VSPICE) Springer, 2023 on topic "Classification of Soybean Seed using Support Vector Machine with Image Enhancement Techniques". Proceedings are published in Lecture notes in the electrical engineering series of SPRINGER.

4. Amar V. Sable, Parminder Singh, and Avinash Kaur Submitted paper to SN Computer Science journal with title “DVINet: A Transfer Learning-Based Framework for Defect and Variety Identification in Soybean Seeds”.

5. One copyright on the topic “Precision Agriculture: Deep Learning-Based Soybean Seed Varieties and Defect Identification”.