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Title:

AgroMedic AI: A Deep Learning Solution for Agricultural Diseases Detection and Severity Estimation.

By:

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Title

AgroMedic AI: A Deep Learning Solution for Agricultural Diseases Detection and Severity Estimation.

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Abstract

Crop diseases represent a major challenge to global agricultural productivity, demanding the creation of more effective detection methods and management strategies. Traditional methods, which depend heavily on manual inspections and chemical interventions, have proven inadequate in meeting the rising demands for food security and sustainable farming practices. This dissertation investigates the application of deep learning models, particularly convolutional neural networks (CNNs) combined with HSV color segmentation, for the detection, classification, and severity estimation of crop diseases.

The primary focus of the research was to develop robust CNN models capable of accurately diagnosing fungal and bacterial diseases across four major crops; Cashew, Cassava, Maize, and Tomato and to quantify disease severity to improve crop management practices. By integrating advanced image segmentation techniques with deep learning models, the study addresses challenges such as variable image quality and environmental noise, which often complicates disease detection in real-world agricultural settings.

The findings demonstrate the significance of AI-driven tools in enhancing the precision of disease management in agriculture. Models such as ResNet152V2 and DenseNet201 achieved high accuracy in detecting and estimating disease severity, surpassing 83% in classification tasks. This research not only adds to the existing body of knowledge but also lays the foundation for future advancements, including the proposed development of "Agromedic AI," a platform designed to deliver advanced disease detection and management solutions to farmers, thereby promoting more sustainable and productive agricultural practices.

Acknowledgments

I wish to express my heartfelt gratitude to my supervisor, Dr. Muhammad Hammad Saleem, for his unwavering guidance, support, and encouragement throughout this research. His expertise and insightful feedback were pivotal in shaping this dissertation. I am profoundly thankful for his patience and commitment, guiding me through each step of the project with care and dedication.

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List of Abbreviations and Acronyms

AI - Artificial Intelligence

CNN - Convolutional Neural Network

IoU - Intersection over Union

PDS - Percentage of Disease Severity

ML – Machine Learning

BCE - Binary Cross-Entropy

ReLU - Rectified Linear Unit

GPU - Graphics Processing Unit

EDA - Exploratory Data Analysis

HSV - Hue, Saturation, Value (colour space)

SVM - Support Vector Machine

UNet - U-Net (a type of convolutional network used for image segmentation)

CRISP-DM - Cross Industry Standard Process for Data Mining

NLP - Natural Language Processing

IoT - Internet of Things

ASPP - Atrous Spatial Pyramid Pooling

Chapter 1: Introduction

1.1 General Overview

It is undeniably that agriculture has been the foundation of human civilization for centuries, serving as a driving force behind economic development, ensuring food security, and sustaining livelihoods across the globe (FAO, 2017). It is not merely an economic activity but a fundamental human enterprise that supports the social and cultural fabric of societies. However, the agricultural sector today faces unprecedented challenges that poses a threat to the growing need of a rapidly expanding global population. Among the most pressing of these challenges are climate change and the increasing incidence of crop diseases. These factors collectively exacerbate the vulnerability of global food systems, making the protection of crops from diseases more critical than ever before (Savary et al., 2019).

Crop diseases are a formidable threat, with the potential to devastate entire harvests, leading to significant yield losses and jeopardizing food security at local, national, and global levels. They also impose severe economic burdens on farmers, especially in developing regions, where agriculture serves as the primary source of income and sustenance for much of the population. Addressing crop diseases effectively is not just a matter of enhancing agricultural productivity but also a crucial step toward achieving broader goals such as poverty alleviation, sustainable development, and environmental conservation.

1.2 Research Problem

Historically, crop disease management has relied heavily on traditional methods, including manual inspections and the widespread use of chemical pesticides. While manual inspections are valuable, they are labour-intensive, often impractical for large scale farming, and prone to human error, leading to inconsistent and inaccurate diagnoses (Bock et al., 2020).

The extensive use of chemical pesticides, although effective in controlling pest and disease outbreaks, has led to environmental degradation, the emergence of resistant pest and pathogen strains, and serious health risks for humans, particularly those in direct contact with these chemicals (Aktar, Sengupta, & Chowdhury, 2009; Carvalho, 2017). The runoff of these chemicals into water bodies presents a serious threat to aquatic ecosystems, while their accumulation in the soil diminishes soil health and reduces biodiversity. Consequently, there is critical need for more advanced, accurate, and sustainable methods of crop disease management that can overcome the limitations of traditional approaches.

1.3 Motivation of Study

The drive behind this study grows from the zeal to contribute in the ever growing field smart agriculture within the scope the limitations of current crop disease management practices. The convergence of deep learning and agriculture presents a promising avenue to revolutionize how we diagnose and manage crop diseases. Despite the existence of AI models for disease detection, there are only few works on quantifying the severity of detected diseases. This study is motivated by the potential to develop models that not only diagnose but also measure the extent of disease impact, offering a more comprehensive and actionable approach to crop disease management.

1.4 Objectives

Holistically, this research aims to utilize deep learning techniques to magnify the efficiency of disease detection and severity estimation. Expansively, the specific objectives of this research includes:

1. **Development of a Deep Learning Classification Model:** Design a machine learning model equipped to accurately diagnosing a range of fungal and bacterial diseases across four key crops—Cashew, Cassava, Maize, and Tomato using

eight distinct convolutional neural networks (CNNs) for image-based feature detection.

2. **Advanced Image Segmentation Techniques:** Implement advanced segmentation methods to isolate diseased areas from natural backgrounds and further segment visible symptoms on affected leaves using HSV colour segmentation, Otsu's method, SegNet, and LinkNet models.
3. **Estimate Disease Severity:** Develop quantitative methods to evaluate the extent of disease impact by calculating the affected area ratio from segmentation outputs.
4. **Assess Model Performance and Robustness:** Test the models on unseen data to validate their accuracy and robustness in varying field conditions.
5. **Propose Improvements and Future Directions:** Identify limitations of current models and propose potential enhancements. Additionally, suggest future work on real-time deployment and further dataset expansion.

1.5 Research Questions

This dissertation is guided by the listed research questions, each addressing a critical aspect of the problem:

1. How can deep learning algorithms be enhanced to achieve accurate detection and diagnosis of crop diseases across multiple species using convolutional neural networks?
2. What are the most effective image segmentation techniques for isolating diseased areas from natural backgrounds and segmenting visible symptoms on affected crops?
3. How can the severity of crop diseases be quantified accurately, and what methods best calculate the affected area ratio from segmentation outputs?
4. What are the limitations and potential improvements for developed deep learning models, and how can these be addressed to amplify model performance and strength in varying field conditions?

1.6 Significance of the Study

The real value of this study lies in its ability to advance smart agriculture by addressing major gaps in current crop disease management. By creating deep learning models that can not only detect diseases but also assess their severity, this research provides a more holistic and effective way to manage crop health. The emphasis on developing reliable and resource-efficient models ensures that the solutions are accessible across various agricultural settings, including those with limited technological resources. Furthermore, the study's emphasis on future directions and potential improvements contributes to the ongoing development of AI-based tools in agriculture, paving paths for more sustainable and effective crop management practices.

1.7 Structure of the Dissertation

This dissertation is arranged into multiple chapters, each of which addressing a critical part of the research:

- **Chapter 1: Introduction** – Ushers the context, lays out the research problem, objectives, key questions, and the significance of the study.

- **Chapter 2: Background & Literature Review** – Reviews the current state of AI in agriculture, particularly focusing on disease management and identifying gaps in the existing literature.

- **Chapter 3: Methodology and Materials** – Details the methodologies and materials used in this research, encompassing data acquisition, model development, and evaluation methodologies.

- **Chapter 4: Data Preparation and Exploratory Analysis** – Describes the dataset used, problems encountered during data preparation, and the exploratory analysis performed to guide model development.

- **Chapter 5: Model Design and Implementation** – Discusses the design, training, and evaluation of deep learning models for detecting crop diseases and estimating their severity.

- **Chapter 6: Results and Discussion** – Presents the results of the models' performance, compares them against the research objectives, and discusses the implications of the findings.

- **Chapter 7: Limitations, Conclusion and Future Work** – Summarizes the research findings, discusses the study's limitations, and proposes areas for future research.

Chapter 2: Background & Literature Review

2.1 Introduction

In the ever-evolving landscape of agriculture, innovation is not just a necessity but the driving force behind overcoming long-standing challenges and unlocking new potentials. Among these challenges, crop diseases remain a persistent danger to global food security, necessitating more effective and sustainable solutions. The era of artificial intelligence (AI) has revolutionized how farmers tackle these threats, moving beyond traditional methods to embrace advanced AI tools that offer unprecedented precision, scalability, and sustainability in disease management. This chapter explores the transformative impact of AI in agriculture, with a specifically on the inspirations and innovations behind Agromedic AI.

Historically, disease management in agriculture relied on chemical treatments and manual inspections—methods that were effective but often labor-intensive and environmentally harmful. The introduction of AI marked a significant shift, beginning with basic machine learning techniques such as Support Vector Machines (SVMs) and Decision Trees. While these early models required extensive manual feature extraction and faced limitations due to the available computational power and datasets, they laid the groundwork for more advanced systems.

Early AI systems, such as expert systems and decision support tools, played crucial roles in aiding farmers with disease diagnosis and treatment recommendations (McCown, 2002). Although limited in capability, these early systems laid the groundwork for more advanced solutions like Agromedic AI, which hopes to continuously drive innovation in the field. As AI technology is advancing, its agricultural applications became increasingly sophisticated. Convolutional Neural Networks now enables automatic image feature extraction.

A significant advancement in AI-driven agriculture is the development of Agromedic AI. This system integrates techniques like image segmentation, transfer learning, and disease severity quantification to magnify the accuracy of disease detection while reducing dependance on chemical treatments, encouraging more sustainable farming practices (Kamilaris & Prenafeta-Boldú, 2018).

2.2 Fundamentals of Agricultural Disease Management

2.2.1 Plant Pathology and Disease Dynamics

Plant pathology, the study of plant diseases, is crucial for understanding the interactions between crops, pathogens, and the environment. Pathogens such as fungi, bacteria, viruses, nematodes, and oomycetes each have distinct life cycles and infection mechanisms, making disease management a multifaceted challenge. The dynamics of plant diseases are governed by the disease triangle, which involves the interaction of the pathogen, host plant, and environmental factors (Garrido, 2024). The disease triangle, as shown in Figure 2.1, highlights the interaction between the host plant, pathogen, and environmental factors necessary for disease to manifest (Tjosvold, 2018).

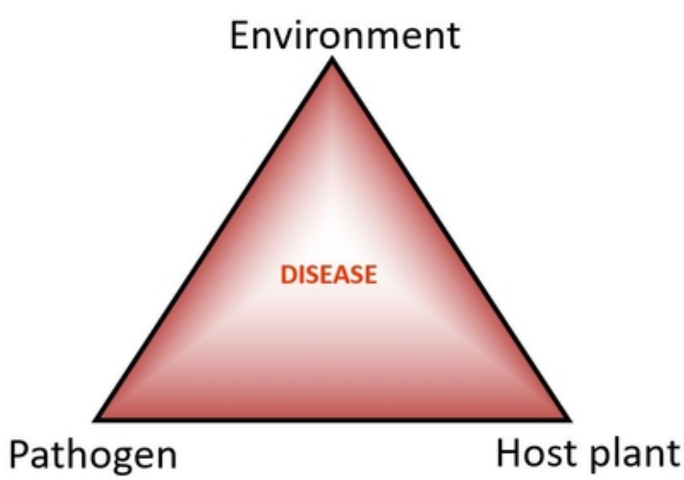

Figure 2.1: The Disease Triangle Illustrating the Interaction Between Pathogen, Host Plant, and Environmental Factors Required for Disease Development

The Disease Triangle Illustrating the Interaction Between Pathogen, Host Plant, and Environmental Conditions Required for Disease Development

Conditions like high humidity and temperature accelerate the spread of fungal pathogens, leading to reduced crop yields. Recent breakthroughs in molecular biology and genomics have profoundly improved our ability to identify pathogenic strains and understand the mechanisms behind these diseases. This knowledge is essential for developing effective strategies to manage crop diseases. Moreover, a multidisciplinary approach to plant pathology that integrates ecological principles and crop management practices is increasingly recognized as vital for addressing the complex challenges of plant diseases (CABI Agriculture and Bioscience, 2023).

2.2.2 Integrated Disease Management

Integrated Disease Management (IDM) is a holistic process that combines multiple strategies to sustainably manage plant diseases. IDM use of diverse tactics like cultural practices, biological controls, resistant crop varieties, and chemical treatments to reduce reliance on synthetic pesticides and minimize environmental impact (Santra et al., 2023).

Crop rotation and intercropping are crucial practices in IDM. Crop rotation prevents pathogens from establishing by alternating crop families, while intercropping enhances plant diversity, limiting pathogen spread by reducing available hosts and increasing competition, ultimately reducing disease incidence in crops.

Biological controls employ natural predators or beneficial microbes to suppress harmful pathogens, offering an eco-friendly alternative to chemicals. Resistant crop varieties, developed through breeding or genetic engineering, also reduce chemical dependency. However, the constant evolution of pathogens necessitates ongoing updates to these varieties (Gonzalez-Dominguez et al., 2023).

Chemical controls, while often necessary are applied judiciously in IDM to delay the development of pathogen and minimize environmental harm. Precision agriculture techniques can help in optimizing the application of these chemicals, to ensure that they are only used sparingly and effectively.

2.3 Precision Agriculture

Precision agriculture (PA), also known as Precision farming, is a contemporary farming management approach that uses technology and data to optimize agricultural practices. It involves gathering and analysing data on factors like soil conditions, weather patterns, crop health, and other variables to make strategic decisions about planting, irrigation, fertilization, and pest control. In disease management, PA utilizes technologies like remote sensing, GPS, and IoT devices to monitor crop health and recognize early signs of disease. Drones equipped with multispectral cameras, for example, can capture high-resolution images of crops, identifying stress patterns indicative of disease (Veroustraete, 2015).

The integration of precision agriculture with AI-driven tools is transforming disease management from a reactive to a proactive process. These tools process large datasets to deliver real-time insights, enabling farmers to make well-informed decisions and implement interventions precisely where and when needed, thereby reducing waste and environmental impact (Garrido, 2024; Leal Filho et al., 2022). This approach not only enhances disease management but also promotes the enduring sustainability of agricultural systems by reducing the reliance on broad-spectrum pesticides.

2.4 Artificial Intelligence in Agriculture

The integration of Artificial Intelligence (AI) into agriculture has transfigured the industry, promoting more efficient, precise, and sustainable farming techniques. AI technologies, which simulate human intelligence in decision-making, learning, and problem-solving, are particularly impactful in automating tasks, optimizing resource use, and enhancing crop management. AI in agriculture is thus paving way for smarter, more efficient, and environmentally friendly farming systems.

2.4.1 Artificial Intelligence (AI)

The term AI encompasses a holistic concept that includes various technologies designed to carry out tasks that usually demand human intelligence. In agriculture, AI applications are diverse and span from predictive analytics to robotic systems that carry out physical tasks such as planting, weeding, and harvesting. The ability of AI to process large volumes of data and generate actionable insights has transformed traditional farming into a more data-driven practice, allowing for increased productivity and sustainability.

For instance, AI-driven systems can access weather patterns, soil conditions, and crop health to predict potential pest outbreaks or the onset of diseases, allowing farmers to take preemptive action. Additionally, AI can optimize irrigation based on real-time data, ensuring crops are watered precisely with the right amount at the ideal time, thus conserving resources and improving yields.

2.4.2 Machine Learning

Machine Learning (ML) is a key subset of Artificial Intelligence that focuses on building algorithms which allow computers the ability to learn from data and make informed decisions without the need for explicit programming. ML systems enhance their accuracy over time as they process and learn from more data, refining their predictive capabilities and classification performance.

In the domain of agricultural disease management, ML algorithms are particularly effective. By training on datasets comprising images of crops at various diseased crops, these algorithms can detect patterns and features that hints specific plant diseases. Once trained, these models can accurately detect diseases in new, unseen data, providing farmers with and precise diagnostics. Common ML models used in these tasks include decision trees, support vector machines (SVM), and random forests (Kamilaris & Prenafeta-Boldú, 2018).

2.4.3 Deep Learning

Deep Learning (DL) is an advanced subset of Machine Learning, distinguished by its use of multi-layered neural networks that emulate the structure and functionality of the human brain (LeCun, Bengio, & Hinton, 2015). DL is particularly powerful in processing unstructured data, such as images and videos, which are prevalent in agricultural applications. The deep layers in DL models enable the instant extraction of complex features automatically from raw data, avoiding the necessity for hand-crafted feature engineering.

In agriculture, DL has become instrumental in advancing image-based analysis for various tasks, including crop disease detection, yield estimation, and plant phenotyping (Zhang et al., 2019). Convolutional Neural Networks (CNNs), a type of DL model, are widely utilized for image classification and segmentation tasks. CNNs are particularly effective in identifying and segmenting diseased areas on plant leaves, distinguishing between distinct types of diseases, and assessing the severity of infections (Mohanty, Hughes, & Salathé, 2016). The ability of DL models to process high-dimensional data and learn complex, non-linear patterns make them ideal for applications where precision and accuracy are critical.

Moreover, DL models can be combined with other AI technologies, such as computer vision and natural language processing (NLP), to develop comprehensive systems that aid decision-making in various agricultural operations (Kamilaris & Prenafeta-Boldú, 2018). For example, DL can be combined with drones equipped with multispectral cameras to monitor large fields, detect early signs of disease, and assess crop health in real-time, providing a powerful tool for precision agriculture (Liakos et al., 2018).

2.5 Key Concepts and Terminologies

Below, some of the primary concepts and methodologies relevant to this study are explored.

1. **Supervised Learning**: Supervised learning is central to this project, where models are trained on labeled datasets to detect and classify crop diseases. By using images labeled as healthy or diseased, the model learns to identify specific disease patterns.

2. **Unsupervised Learning**: Unsupervised learning operates without labeled data and is useful for exploring new patterns in crop images. It can help identify clusters of similar disease symptoms or discover new disease categories, providing insights that complement supervised models and support exploratory data analysis.

3. **Neural Networks**: Neural networks are the foundation of the AI-driven approaches utilized in this study. These models, inspired by the human brain, consist of layers that process input data to generate predictions. In this project, deep neural networks are used to model complex relationships in crop images, supporting accurate disease detection and severity estimation.

4. **Convolutional Neural Networks (CNNs)**: CNNs, specialized for image data, are crucial in detecting diseases in crops. They instantly extract features from images, enabling high accuracy in distinguishing between healthy and diseased plant tissues. The ability of CNNs to handle image data efficiently makes them ideal for disease classification tasks.

5. **Transfer Learning**: Transfer learning entails adapting pre-trained models to the specific dataset used in this study, greatly improving performance, even with limited agricultural data. By leveraging models pre-trained on large datasets like ImageNet, training time is reduced and model accuracy is enhanced.

6. **Image Processing Techniques in Agriculture**: Image processing techniques, such as segmentation and thresholding, are vital for preparing crop images for analysis. These techniques enhance the quality of the input data, ensuring that models can accurately detect diseased areas. They also aid in generating ground truth annotations necessary for training supervised models.

7. **Controlled vs. Uncontrolled Image Environments**: Controlled environments, such as laboratory settings, allow for consistent lighting, background, and image quality, making it easier to capture clear images for analysis. In contrast, uncontrolled environments, such as open fields, introduce variability in lighting, weather, and background, posing challenges for image consistency and model accuracy.

2.6 Related Works

Recent AI-driven advancements in disease classification have been revolutionized by deep learning, particularly CNNs. First and foremost, models like PD2SE-Net by Liang et al. (2019) and INC-VGGN by Chen et al. (2020) have set new standards. PD2SE-Net, with its integration of CNNs and residual learning, enabled real-time disease diagnosis, marking a significant leap from manual feature extraction methods. Likewise, INC-VGGN improved classification accuracy in complex environments by incorporating inception modules for better feature selection.

AI models have also evolved beyond simple binary classifications to offer nuanced evaluations of disease severity. Traditional methods, often limited by visual inspections and basic statistical models, have been outpaced by deep learning solutions. For example, Wang et al. (2017) used the PlantVillage dataset to train CNNs that accurately estimate disease severity in apple crops, while Esgario et al. (2020) developed a multi-task system combining deep learning and computer vision, enhancing both identification and severity assessment in coffee plants.

Several foundational works have directly influenced the present state of AI in agriculture. A pivotal moment came with the work of Mohanty et al. (2016), which demonstrated the superior performance of CNNs in plant disease classification, compared to traditional methods, was evident in this study. It emphasized the potential of deep learning to transform agricultural practices by offering more accurate and scalable solutions. Additionally, the multi-task frameworks developed by researchers like Esgario et al. (2020) have shown the importance of integrating various AI techniques to create comprehensive solutions for crop management. These foundational works have paved the way for the advanced AI systems being developed and implemented today, which are capable of not just identifying diseases but also assessing their severity and suggesting appropriate interventions.

Disease segmentation has also seen a substantial shift from traditional image processing techniques to sophisticated AI-driven methods. Early approaches, such as Otsu’s thresholding and watershed algorithms, were limited in precision and scalability. However, these were quite useful in this research, as they layered ground for a different method of image annotation. The introduction of deep learning models like U-Net and SegNet marked a turning point by enabling precise segmentation of diseased regions from complex backgrounds. A recent advancement is the lightweight dense-scale network model (LDSNet) proposed by Zeng et al. (2022). LDSNet is particularly notable for its application in mobile devices, successfully segmenting and identifying crop diseases in real-time with high compatibility and performance across various conditions. This progression illustrates the growing capability of AI models to handle the intricate task of disease segmentation, making them invaluable tools in modern agriculture.

Classical methods like K-means clustering and Support Vector Machines (SVM) have also played a significant role in disease segmentation and classification. For instance, Mandal et al. (2023) applied K-means clustering to segment affected areas due to Phoma blight on potato leaflets, while Behera et al. (2018) used a fusion of K-means clustering, multi-class SVM, and fuzzy logic to classify citrus diseases and estimate severity. Additionally, colour thresholding techniques, such as those employed by Hu et al. (2023) and Zhang Jingyao et al. (2021), have been instrumental in segmenting diseased areas based on HSV colour features, enabling more accurate disease detection and monitoring.

The evolution of AI-driven models in agriculture, particularly for disease classification, segmentation, and severity estimation, has been marked by significant advancements in deep learning. Foundational works and traditional methods have laid the groundwork for these innovations, which now offer more accurate, scalable, and comprehensive solutions for crop disease management. As AI continues to evolve, its application in agriculture is poised to further enhance precision farming, leading to better crop yields and sustainable agricultural practices.

2.7 Severity Estimation

Traditional methods for estimating disease severity relied on manual observation and image processing techniques. These methods included visual scoring systems, such as the Disease Severity Scale developed by ICAR for maize diseases like TLB and rust. While simple, these methods were highly subjective and prone to human error, leading to inconsistent results.

Quantifying crop disease severity is crucial for effective management. Manual assessment, though common, is time-intensive and lacks objectivity. Recent breakthroughs in machine learning (ML) have led to the development of automated methods for severity assessment.

Studies by Pal and Kumar (2023) and Hu et al. (2023) introduced custom methods for evaluating segmented leaves, focusing on the ratio of healthy pixel area to the total leaf area. Pal and Kumar (2023) further classified disease severity into five categories: Normal, Mild, Moderate, Severe, and Critical. This approach was replicated in the current study with slight adjustments to the severity classification.

These advancements in ML offer a more consistent, objective, and efficient approach to disease severity assessment, addressing the limitations of traditional methods.

2.8 Gaps in the Literature and Future Directions

Despite the significant advancements in AI-driven agricultural practices, several critical gaps in the literature remain. Many deep learning models are trained and tested in controlled environments with specific datasets, raising concerns about their performance in real-world agricultural settings. There is a pressing need for models that can generalize across diverse environmental conditions, crop varieties, and disease types. Developing models that are adaptable to variations in lighting, weather conditions, and other environmental factors is essential for their practical deployment in diverse agricultural environments.

While supervised learning has been extensively explored in crop disease detection, the potential of unsupervised learning techniques remains under-researched. Unsupervised learning could reduce the dependency on large, labeled datasets, which are often difficult and expensive to obtain in agricultural settings. By leveraging unsupervised methods, future research could explore new patterns and anomalies in crop health, leading to the discovery of novel disease indicators and improving the adaptability of AI models to new disease types.

Moreover, although there has been progress in automating disease severity assessment, most studies focus on specific diseases and crops. This narrow focus limits the applicability of these models across the broader agricultural landscape. There is a gap in developing models that can assess the severity of a wide range of diseases across various crops, providing a more universal solution for farmers.

Finally, while AI technologies promise to reduce reliance on chemical treatments and promote sustainable farming practices, their long-term economic and environmental impacts are not yet fully understood. Future research should aim to quantify these impacts, ensuring that AI-driven approaches are not only practically efficient but also economically viable and environmentally sustainable.

By addressing these gaps, Agromedic AI aims to contribute to smart agriculture, offering more comprehensive, robust, and accessible solutions for crop disease management. Future directions should focus on expanding datasets, exploring unsupervised learning, broadening the scope of disease severity models, and assessing the economic and environmental impacts of AI technologies in agriculture.

Chapter 3: Methodology and Materials

3.1 Introduction

This chapter presents a detailed overview of the methodologies and materials employed in this research. This approach combines traditional image processing techniques with advanced deep learning frameworks, resulting in robust models designed to handle a wide range of agricultural data. This chapter is structured to detail the processes involved in data acquisition, model development, segmentation, and severity estimation, laying the groundwork for the technical implementation discussed in Chapter 5.

3.2 Proposed Research Design

The research design, as illustrated in Figure 3.1, follows a systematic and structured approach, encompassing seven key phases. Initially, a diverse dataset of crop disease images was acquired, ensuring a robust foundation for model development. This data underwent thorough preprocessing and exploratory analysis to uncover critical patterns essential for model training. Advanced deep learning models were then developed and optimized for accurate disease classification. Image and colour segmentation techniques were employed to isolate and differentiate diseased regions from healthy tissue, enhancing detection accuracy. Disease severity was quantified using percentage-based metrics, providing objective measures. Finally, rigorous model evaluation confirmed the effectiveness and generalizability of the models for practical application.

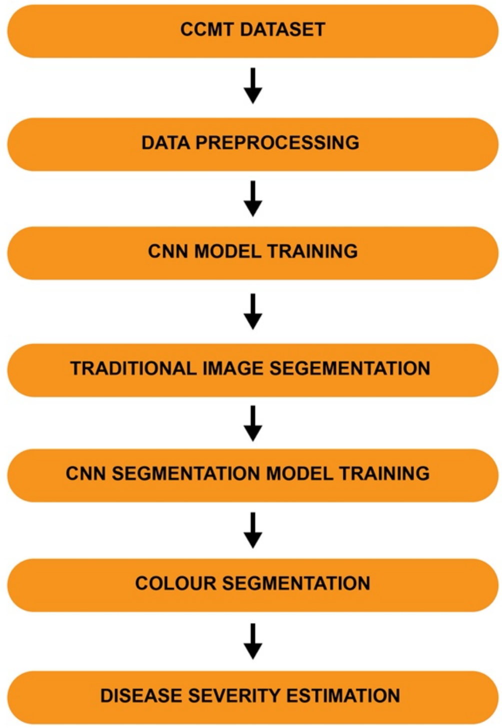

Figure 3.1: Structured Research Design Phases for Agromedic AI

3.3 Dataset

The data selection process for this project was carefully planned, involving an extensive review and careful curation of a dataset that comprehensively captures a diverse range of crop diseases. The chosen dataset includes images from various environmental conditions, both controlled (laboratory) and uncontrolled (field), ensuring a robust foundation for developing and training both classification and segmentation models.

The dataset's diversity in disease types and environmental factors is critical for enhancing model generalizability and accuracy. Additionally, the substantial number of images included allows for thorough training and validation, addressing potential challenges such as class imbalances and varying image quality. The dataset was structured to include various categories, each representing different crops and disease conditions, which are elaborated in detail in Chapter 4. The steps taken to prepare this dataset included rigorous preprocessing, such as resizing, normalization, and augmentation, to enhance the models' performance during training.

3.4 Libraries and Tools

3.4.1 Overview

This section outlines the key libraries and tools used in this project, each selected for its specific role in data processing, model development, and evaluation.

LIBRARY/TOOL	PURPOSE
TensorFlow	Core framework for deep learning.
Keras	High-level API for neural network design.
NumPy	Numerical computations.
Pandas	Data manipulation and analysis.
Matplotlib/Seaborn	Data visualization.
PIL/OpenCV	Image processing and video analysis.
ImageDataGenerator	Real-time data augmentation for images.
Scikit-learn	Dataset splitting and model evaluation.
Logging/OS/Zipfile	Error tracking, file management, and data handling.

Table 3.1: Libraries and Tools Used

3.4.2 Justification for Library Selection

- **TensorFlow and Keras:** Tensorflow paired with Keras, provides a powerful yet flexible platform for creating and deploying deep learning models. The high-level API in Keras simplifies the design of complex neural networks, allowing for rapid prototyping and fine-tuning. TensorFlow's scalability and extensive community support made it the preferred choice for implementing deep learning architectures.

- **NumPy and Pandas:** These libraries were indispensable for processing numerical data and managing datasets. NumPy facilitated fast mathematical operations on large arrays and matrices, which was critical for high-dimensional data processing. Pandas provided high-performance, easy-to-use data structures essential for data analysis and preprocessing, enabling efficient data manipulation and preparation.

- **Matplotlib and Seaborn:** These libraries were widely utilized to visualize data distributions, model performance metrics, and outcomes. Effective visualization is crucial for gaining insights into data patterns and understanding model behaviour, particularly during the EDA and evaluation phases.

- **OpenCV and PIL:** Employed for image processing operations such as resizing, cropping, and format conversion, ensuring that the images were standardized for model training. OpenCV's advanced functionalities, such as edge detection and thresholding, were particularly useful for traditional image processing tasks, while PIL handled basic image manipulation tasks.

- **ImageDataGenerator:** This tool facilitated on-the-fly data augmentation during model training, which was critical for enhancing model generalization and reducing overfitting. It allowed for real-time transformations of the training data, including rotation, shifting, zooming, and flipping, which expanded the diversity of the dataset without increasing the number of images.

3.5 Software and Hardware Utilized

3.5.1 Hardware Specifications

The primary local development was conducted on a MacBook Pro with the following specifications:

- Processor: 2.9 GHz Quad-Core Intel Core i7
- Memory: 16 GB 2133 MHz LPDDR3
- Graphics: Radeon Pro 560 with 4 GB and Intel HD Graphics 630 with 1536 MB

This setup supported initial data preprocessing, exploratory data analysis (EDA), and preliminary model development. However, given the high computational demands of deep learning, especially with large datasets, additional cloud-based resources were necessary.

3.5.2 Software Environment

For intensive model training, Google Colab was utilized, leveraging cloud computing and access to powerful hardware accelerators. The primary programming environment was Python 3, with libraries detailed in Chapter 3.4. Training predominantly used NVIDIA A100 GPUs**,** which drastically reduced training times and enhanced model accuracy, this makes it an ideal choice for managing large datasets and complex neural networks.

3.6 Models and Technique(s) Selection

3.6.1 Classification Model

The primary purpose of this study is to build a robust classification model for accurately diagnosing various fungal and bacterial diseases across four key crops: Cashew, Cassava, Maize, and Tomato. Given the complexity and diversity of these plant diseases, selecting an optimal deep learning architecture is critical for attaining high accuracy and reliability. To achieve this, eight convolutional neural networks (CNNs) were selected, utilizing using transfer learning from pre-trained models on large datasets such as ImageNet. This method shortens training time and improves model performance, even with limited data.

The models were selected from the Keras Applications API, a high-level neural networks API built in Python and running on top of TensorFlow. Keras offers a diverse range of pre-trained models, extensively tested and validated on large-scale image classification tasks (Chollet, 2015). The selection procedure required a thorough review of models available on the Keras platform, accessed via their official website, and evaluated based on the Top-1 Accuracy metric.

Table 3.2 presents the selected models for this project, which were subsequently fine-tuned to align with the specific characteristics of the dataset. This adaptive process ensures that the models can accurately classify the various diseases affecting the target crops.

S/N	MODEL	TOP-1 ACCURACY	PARAMETERS
1	**Xception**	79.0%	22.9M
2	**VGG16**	71.3%	138.4M
3	**ResNet152V2**	78.0%	60.4M
4	**InceptionResNetV2**	80.3%	55.9M
5	**EfficientNetB6**	84.0%	43.3M
6	**DenseNet201**	77.3%	20.2M
7	**NASNetLarge**	82.5%	88.9M
8	**ConvNeXtXLarge**	86.7%	350.1M

Table 3.2: Selected CNN Models for Crop Disease Classification

3.6.2 Traditional Segmentation and Edge Detection Techniques

For effective image segmentation, especially in creating ground truth annotations required to train CNN models, traditional image processing methods were employed. These methods automate the annotation process, reducing the need for manual annotation of each image. The selected techniques were based on previous research that successfully applied these methods in segmentation tasks.

Techniques such as Watershed (Meyer, 1994), Otsu's method (Otsu, 1979), and GraphCut (Kwatara et al., 2003), along with recent work by Gensheng Hu et al. (2023), provided the foundation for using these methods to annotate the dataset. These classical techniques have not been extensively explored in combination with deep learning approaches, highlighting the novelty and potential impact of this research. The specific methods used include Otsu's thresholding, adaptive thresholding, Sobel edge detection, and contour detection techniques.

3.6.3 Segmentation Model Selection

The third objective of this research is to develop a method for distinguishing between healthy and diseased regions on crop leaves. This segmentation task is crucial for accurately diagnosing plant health, which is essential for managing crop diseases and improving agricultural productivity. By segmenting the healthy (green) parts from the diseased areas, this method enables the visualization of disease extent, aiding in timely intervention and treatment.

To achieve this, the method employs HSV (Hue, Saturation, Value) colour thresholding, effectively isolating specific colour ranges, such as the green of healthy leaf tissue. The segmentation process involves creating a mask that separates the healthy regions from the diseased ones based on their colour characteristics. Specifically, green areas, indicative of healthy tissue, are segmented using predefined HSV thresholds, while diseased areas, exhibiting colour changes due to infection, are identified by inverting this mask.

This approach builds on prior studies that have successfully used HSV-based colour segmentation in agricultural applications. For instance, Zhang, T. et al. (2021) employed similar techniques for segmenting cucumber leaf images, enabling further disease detection and growth monitoring. The application of colour thresholding in leaf disease segmentation is particularly advantageous because it allows for a more nuanced and accurate distinction between healthy and affected areas, which is crucial for subsequent disease severity estimation.

3.6.4 Colour-Based Segmentation Technique

The third objective of this research is to develop a method for distinguishing between healthy and diseased regions on crop leaves. This segmentation task is crucial for accurately diagnosing plant health, which is essential for managing crop diseases and improving agricultural productivity. By segmenting the healthy (green) parts from the diseased areas, this method enables the visualization of disease extent, aiding in timely intervention and treatment.

To achieve this, the method employs HSV (Hue, Saturation, Value) colour thresholding, effectively isolating specific colour ranges, such as the green of healthy leaf tissue. The segmentation process involves creating a mask that separates the healthy regions from the diseased ones based on their colour characteristics. Specifically, green areas, indicative of healthy tissue, are segmented using predefined HSV thresholds, while diseased areas, exhibiting colour changes due to infection, are identified by inverting this mask.

This approach builds on prior studies that have successfully used HSV-based colour segmentation in agricultural applications. Zhang Jingyao et al. (2021) employed similar techniques for segmenting cucumber leaf images, enabling further disease detection and growth monitoring. The application of colour thresholding in leaf disease segmentation is particularly advantageous because it allows for a more nuanced and accurate distinction between healthy and affected areas, which is crucial for subsequent disease severity estimation.

3.7 Model Evaluation Metrics

To accurately evaluate the performance of the classification models, segmentation models, and other techniques employed in this research, specific metrics were carefully selected. These metrics provided a comprehensive evaluation of the models' performance, allowing for an in-depth analysis of their strengths and weaknesses across different tasks. The chosen metrics include:

1. **Accuracy:** Represents the ratio of correctly classified images to the total number of images, whether they are images or individual pixels, out of the total number of instances. It serves as a fundamental indicator of the model's general performance, providing a straightforward assessment of how often the model makes correct predictions.

2. **Precision, Recall, and F1-Score:** Accuracy can sometimes be misleading in the presence of class imbalances, which is where Precision, Recall, and F1-Score. These metrics were used to evaluate the model's ability to accurately identify diseases while minimizing false positives and false negatives.

$$Precision = \frac{\text{True Positive}}{True\ Positive\ +\ False\ Positive} \qquad (3.1)$$

$$\frac{\text{True Positive}}{True\ Positive\ +\ False\ Negative} \qquad 3.2)$$

$$F1\,Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{T\text{Precision} + \text{Recall}} \qquad 3.3)$$

3. **Intersection over Union (IoU):** IoU is a standard metric for segmentation tasks, measuring the overlap between the predicted and actual masks relative to their total combined area. A higher IoU indicates better segmentation performance. It is defined as:

$$IoU = \frac{|A \cap B|}{|A \cup B|} \qquad 3.4)$$

Where:

- A is the set of predicted pixels (predicted mask).
- B is the set of actual pixels (ground truth mask).

3.8 Severity Estimation Metrics

In this research, disease severity is quantified using the Percentage of Disease Severity (PDS), calculated as the ratio of the diseased area to the total leaf area, expressed as a percentage. This method provides a clear, objective measure of infection extent directly from segmented images. By using binary masks to count the pixels corresponding to diseased and healthy regions, the PDS offers an accurate assessment of disease impact.

The PDS is then used to classify disease severity into five categories: Normal, Mild, Moderate, Severe, and Critical. These categories, based on thresholds from existing literature, such as those by Pal and Kumar (2023), allow for nuanced feedback that can guide targeted interventions. This method is justified for its ability to provide precise, actionable insights into disease severity, helping to prioritize management actions based on the extent of infection.

Chapter 4: Data Preparation and Exploratory Analysis

4.1 Dataset Overview

The dataset used in this research is the "Dataset for Crop Pest and Disease Detection" (CCMT Plant Diseases), consisting of 25,220 images categorized into 22 classes. These images represent various fungal, bacterial, and pest-induced diseases across four major crops: Cashew, Cassava, Maize, and Tomato. The dataset includes images captured under both controlled (laboratory) and uncontrolled (field) conditions, providing a realistic basis for developing robust detection models.

4.2 Data Source

The dataset was sourced from the Mendeley Data repository, curated by Kwabena et al. (2023), and is available under the CC BY 4.0 license. The images were captured using high-resolution cameras on local farms in Ghana, with validation provided by plant virologists from KNUST, ensuring their reliability for machine learning tasks.

4.3 Dataset Description

The dataset is categorized into four crops with associated diseases. Table 4.1 provides a breakdown of the dataset by crop, disease, and the number of images per category.

CROP	DISEASE	IMAGE COUNT
MAIZE	Leaf Spot	1,239

	Streak Virus	965
	Leaf Blight	1,288
	Grasshopper	673
	Leaf Beetle	933
	Healthy	1,193
	Fall Armyworm	285
TOMATO	Leaf Curl	511
	Septoria Leaf Spot	2,743
	Verticillium Wilt	772
CASHEW	Leaf Miner	1,378
	Gumosis	392
	Red Rust	1,682
	Anthracnose	1,729
CASSAVA	Green Mite	1,015
	Mosaic	1,205
	Bacterial Blight	2,614
	Brown Spot	1,481
TOTAL		**25,126**

Table 4.1: Breakdown of Dataset Structure and Image Count

4.3.1 Data Structure

Originally, the dataset was organized into a complex folder structure, complicating the preprocessing workflow. To streamline the process, the dataset was reorganized, focusing on 15 relevant classes of fungal and bacterial diseases. This restructuring facilitated easier access and processing of images.

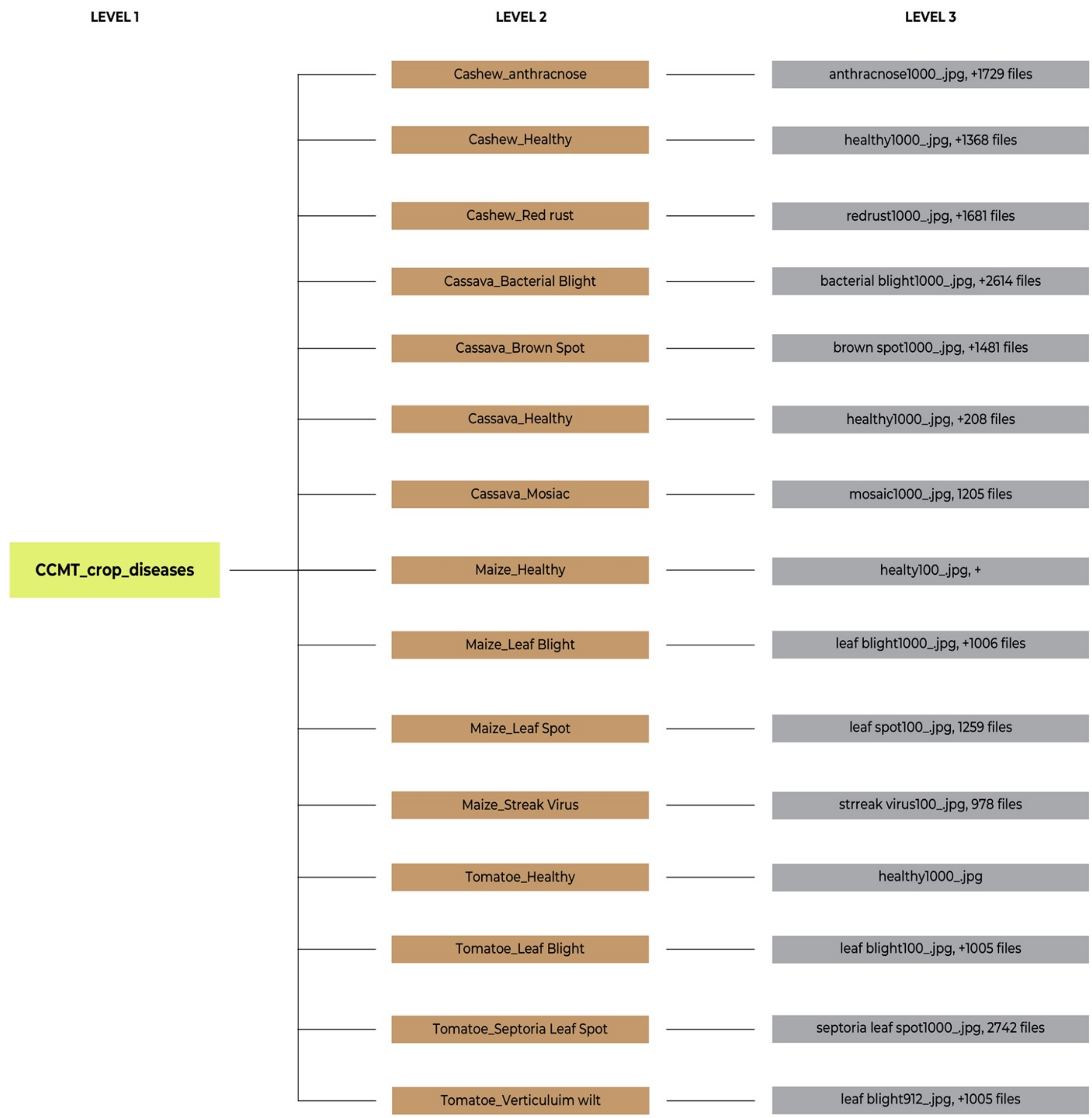

Figure 4.1: Reorganized Dataset Structure

4.3.2 Data Challenges

Throughout the research, several challenges were encountered that affected the dataset's suitability for model training and testing. These challenges included:

- **Class Imbalances:** The dataset exhibited significant class imbalances, with some diseases underrepresented. This was addressed through data augmentation techniques, such as oversampling the minority classes and undersampling majority classes, to achieve a more balanced representation of diseases during model training.
- **Image Quality Variations:** Variations in image quality, caused by environmental factors, camera quality, and lighting conditions, posed a challenge. These issues were mitigated by applying preprocessing steps such as image resizing and normalization, which enhanced the consistency of the dataset.
- **Noisy Data:** The dataset contained noisy data, including images that were out of focus, poorly lit, or irrelevant to the disease categories. Careful cleaning and preprocessing were necessary to remove these images, ensuring the dataset's suitability for developing robust and accurate models. These efforts were crucial for improving model performance and reducing the risk of overfitting.
- **Corrupt images:** some of the images were corrupt and contained formats that could not be read by OS in a python environment.

4.4 Data Preprocessing

4.4.1 Cleaning Data

As is often seen with image datasets, some files may be corrupted or saved in an unknown format. To avoid potential issues during model training, this process was deemed crucial. Each image file was tested by attempting to open and convert it to the RGB format, ensuring that the image fully loads. Files that could not be opened were assumed to be corrupted and were deleted from the directory. After this process, a total of 95 corrupted images were removed from the dataset. This step ensured that the dataset always remained readable and only contained usable images.

4.4.2 Reorganizing the Dataset

Due to the complex folder structure of the dataset and the fact that not all classes were needed for this study, the dataset was reorganized to simplify the folder structure and remove unnecessary classes. The focus was on crop diseases caused by fungal and bacterial attacks, resulting in a final dataset structure that included 15 classes across 19,939 images. Figure 4.1 illustrates the new dataset classes.

4.4.3 Image Resizing

To ensure consistency in model training, all images were adjusted to a uniform dimension of 224x224 pixels. This standardization was essential because convolutional neural networks (CNNs) require consistent input sizes to process data effectively.

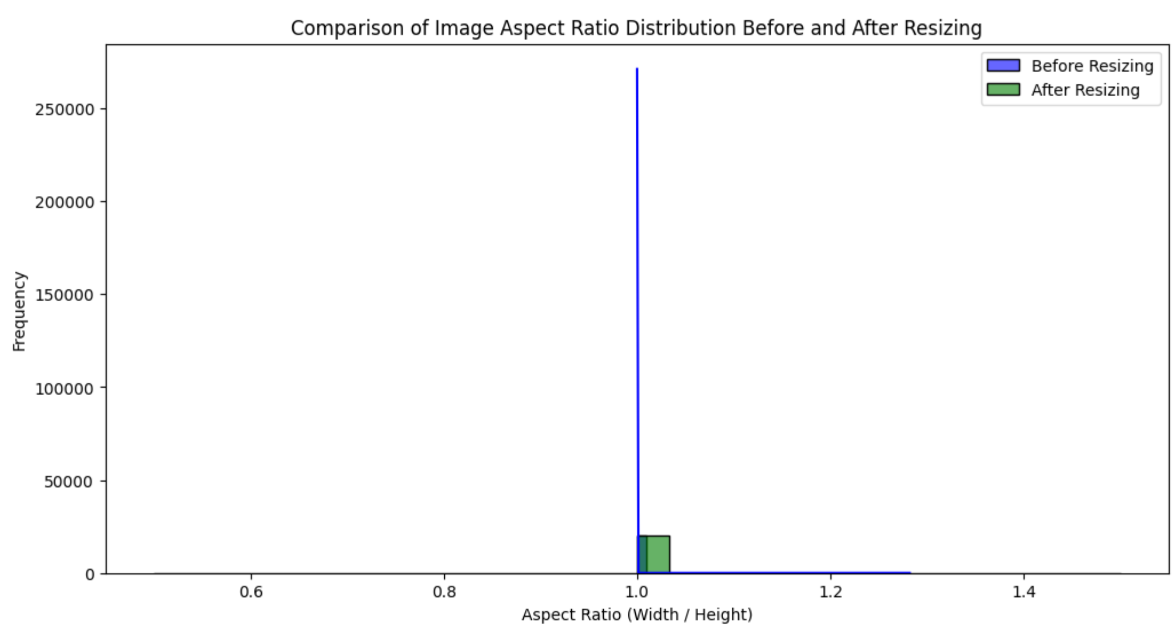

Figure 4.2: Image Size Distribution Before and After Resizing

4.5 Exploratory Data Analysis (EDA)

4.5.1 Image Quality Assessment

Random samples of images were inspected to assess variations in lighting, focus, and background conditions. This assessment was crucial for identifying potential sources of noise that could impact model performance.

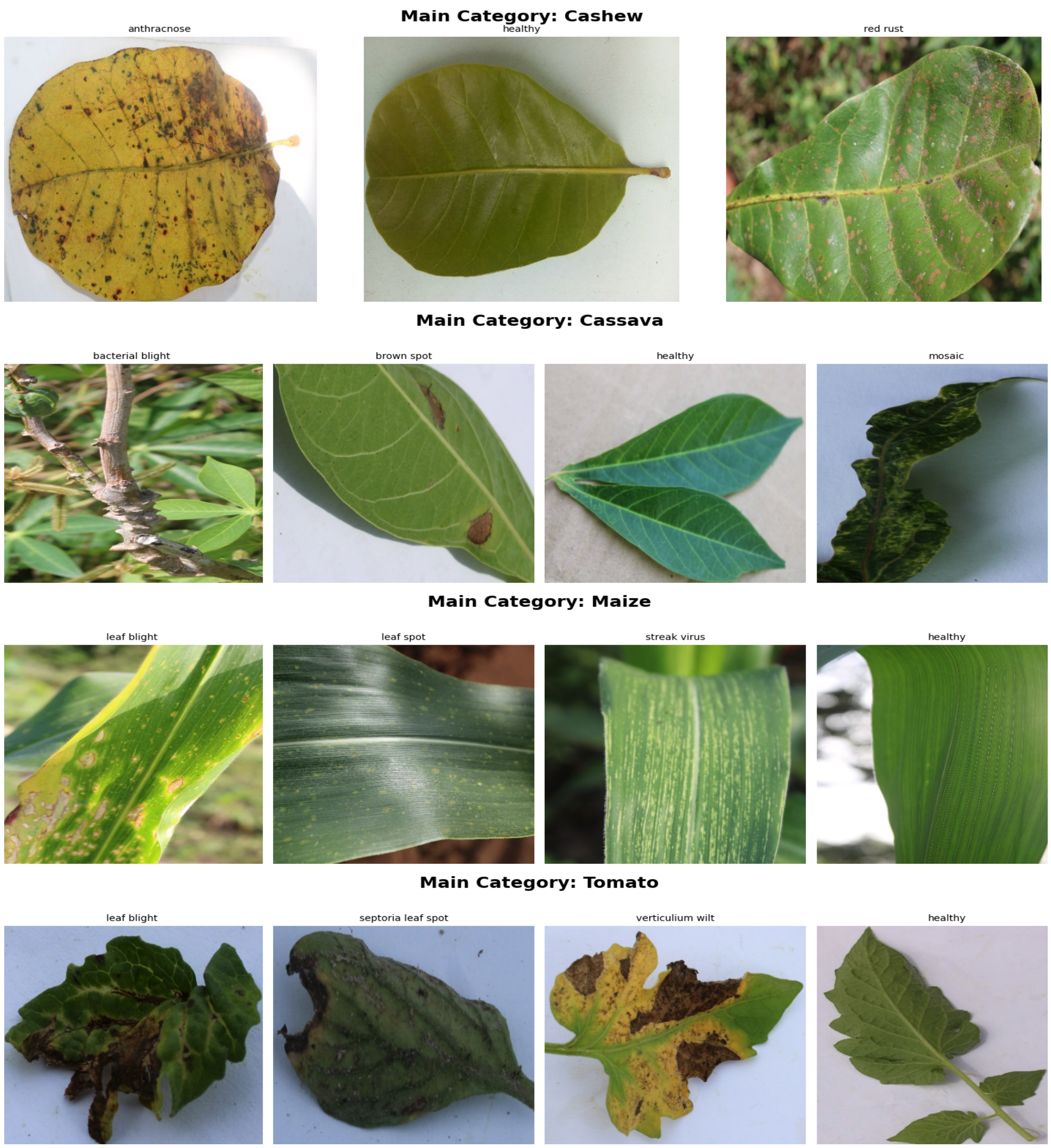

Figure 4.3: Visual Representation of all Crop Class

4.5.2 Class Distribution Analysis

A bar plot was generated to visualize the distribution of images across the 15 classes. This analysis highlighted class imbalances, which were addressed during model training using techniques such as oversampling, undersampling, and data augmentation.

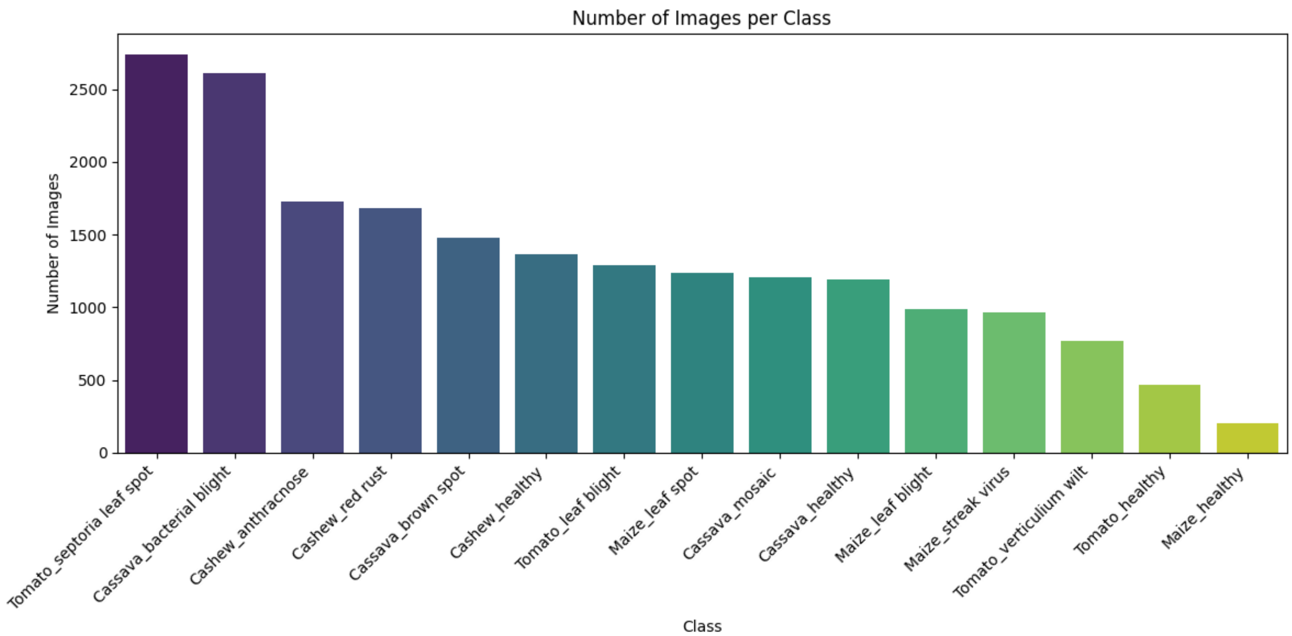

Figure 4.4: Class Distribution of Images Across 15 Disease Categories, Highlighting Imbalances Addressed During Model Training

Chapter 5: Model Design and Implementation

5.1 Introduction

This chapter offers a thorough details of the development, and implementation of deep learning models specifically tailored for detecting crop diseases and estimating their severity. Building on the methodologies discussed in Chapter 3, this chapter delves into the technical aspects of model configuration, training, and evaluation. It covers the setup and customization of convolutional neural networks (CNNs), the application of image segmentation techniques, and the fine-tuning of pre-trained models.

5.2 Classification Models

5.2.1 Understanding Model Architecture

This section provides an overview of the convolutional neural network (CNN) architectures evaluated for crop disease classification in this research. Each architecture was assessed for its efficiency, accuracy, and computational requirements to determine the most appropriate models for the study's first research objective. Below are the distinct features and suitability of each model:

- **Xception:** Improves upon the Inception architecture by using depthwise separable convolutions, which split spatial filtering from channel-wise filtering for greater efficiency.This design is parameter-efficient and computationally less demanding. Xception employs linear residual connections to maintain gradient flow during training, enhancing efficiency. This model was selected for its ability to capture fine-grained details, crucial for differentiating similar crop diseases, and its suitability for deployment in resource-constrained environments.

- **VGG16:** Characterized by its simplicity and depth, with 16 layers arranged in a uniform architecture, making it easy to implement and understand. Despite its simplicity, VGG16 demonstrated robustness in crop disease classification and served as a useful baseline for comparison with more advanced architectures.
- **ResNet152V2:** Extends the original ResNet architecture to 152 layers, using identity mappings within residual blocks to address the degradation problem in deep networks. Batch normalization after each convolution stabilizes and accelerates training. ResNet152V2 was chosen for its depth and ability to learn complex patterns, making it effective in identifying intricate disease patterns in crops.
- **InceptionResNetV2:** Combines the strengths of Inception modules and ResNet's residual connections. Inception modules capture multi-scale features through parallel convolutions with varied kernel sizes, beneficial for detecting diverse crop disease patterns. Residual connections mitigate the vanishing gradient problem, enabling efficient learning in deep neural networks. InceptionResNetV2 was fine-tuned on the crop disease dataset to leverage its capability to discern subtle visual differences between diseases.
- **EfficientNetB6:** Optimizes the network's depth, width, and input resolution through compound scaling, achieving state-of-the-art accuracy while preserving computational efficiency. It incorporates squeeze-and-excitation blocks to enhance focus on important features. This model was selected for its ability to deliver high accuracy with fewer resources, making it appropriate for agricultural applications with limited computational power.
- **DenseNet201:** Introduces dense connections in which each layer receives input from all previous layers, encouraging feature reuse and enhancing gradient flow. Despite its depth, DenseNet201 uses fewer parameters than traditional deep networks. This model was particularly effective in capturing significant features related to crop diseases, distinguishing diseases with subtle differences.

- **NASNetLarge:** Discovered through Neural Architecture Search (NAS), NASNetLarge optimizes model structure for performance, balancing accuracy and computational efficiency. It was valuable in achieving high classification accuracy for crop disease detection.

- **ConvNeXtXLarge:** Integrates insights from transformer models, emphasizing simplicity and efficiency with design choices like larger kernel sizes and fewer normalization layers. Its advanced design and balanced performance make it effective for complex image classification tasks like crop disease detection.

Figure 5. provides a generalized architecture of the classification models used in this research, illustrating the common structure shared by these diverse CNN models.

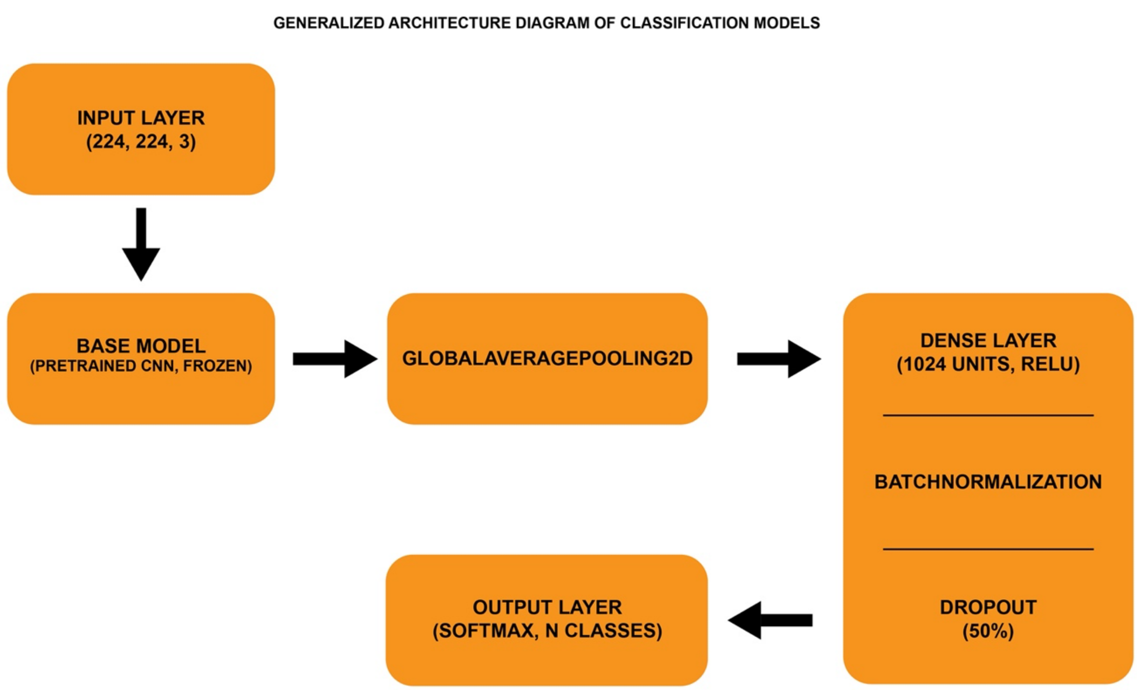

Figure 5.1: Generalized Architecture Diagram of Classification Models

5.2.2 Model Setup and Configuration

5.2.2.1 Dataset Preparation and Splitting

The dataset was divided into training (60%), validation (20%), and testing (20%) subsets using balanced sampling to maintain consistent class distribution across all subsets. This approach ensures a balanced representation of each crop disease category, crucial for model training and evaluation.

5.2.2.2 Data Augmentation

To improve model generalization and reduce overfitting, data augmentation techniques were implemented on the training dataset. Techniques such as random rotations, shifts, shears, and flips were utilized to artificially expand the dataset. The Keras "ImageDataGenerator" class facilitated real-time augmentation during model training, exposing the model to various set of inputs and thereby improving its robustness.

5.2.2.3 Model Customization and Optimization

The models were implemented in Keras with TensorFlow as the backend. Transfer learning was employed by initializing models with pre-trained weights from the ImageNet dataset, leveraging the extensive feature extraction capabilities developed from large-scale image data. The training process for these models followed a structured approach designed to optimize performance while preventing overfitting. Key steps included:

- **Input Layer Modification:** The input layer was configured to accept images resized to 224x224x3, aligning with the input dimensions required by the pre-trained networks.

- **Custom Fully Connected Layers:** After the final convolutional block of the pre-trained models, custom fully connected layers were added, designed specifically for crop disease classification. The final layer was a softmax-activated output layer to generate class probabilities.

- **Loss Function:** The Cross-Entropy Loss function is utilized as the loss function for this multi-class classification task. This function is appropriate for categorical data and is defined as follows:

$$\text{Loss} = -\sum_{i=1}^{N} y_i log"(p_i) \tag{5.1}$$

  Where:

  - y_i is the true label.
  - p_i is the predicted probability for class i.

  The cross-entropy loss penalizes the model more heavily for incorrect predictions, driving the optimization process towards minimizing prediction errors.

- **Optimizer:** The Adam optimizer was applied with the following parameters:

  $Learning\ rate = 0.001 \qquad \beta_1 = 0.9 \qquad \beta_2 = 0.999 \qquad \epsilon = 1 \times 10^{-7}$

  Adam was selected for its ability to adapt the learning rate during training, improving convergence speed and stability.

- **Learning Rate Scheduler:** A dynamic learning rate scheduler was implemented to alter the learning rate based on the validation loss. The learning rate was decreased by a factor of 0.1 after 5 consecutive epochs without improvement in validation loss.

- **Early Stopping**: To help prevent overfitting, early stopping was implemented. Training was halted if the validation loss did not improve after 5 consecutive epochs.
- **Batch Size:** A batch size of 32 was chosen, offering a balanced trade-off between training speed and memory usage.
- **Epochs:** The models were trained over 30 epochs, with early stopping implemented to prevent overfitting. Early stopping monitored the validation loss and stopped training if there was no improvement after 5 consecutive epochs.
- **Dynamic Learning Rate Adjustment**: The learning rate scheduler dynamically adjusted the learning rate when improvements in validation loss plateaued, optimizing model performance.

5.2.3 Implementation of Models

The models were implemented by first compiling them with the appropriate optimizer, loss function, and evaluation metrics. For hyperparameter tuning, pre-trained models initially had their convolutional layers frozen to retain the powerful feature extraction capabilities developed during pre-training on the ImageNet dataset. The newly added fully connected layers were trained specifically on the crop disease dataset, adapting the model to the task at hand. A selective unfreezing strategy was then employed, gradually unfreezing layers to fine-tune the feature extraction process. This method improved accuracy by allowing the network to learn more detailed and crop-specific features, enhancing overall performance.

5.2.4 Model Evaluation

5.2.4.1 Performance Metrics

Following training, the models were rigorously evaluated on the test dataset to assess their classification capabilities. Accuracy served as the primary metric, providing a straightforward measure of the models' overall performance. Additionally, Loss, Precision, Recall, and F1 Score were monitored to offer a more comprehensive understanding of each model's strengths and weaknesses. These metrics, discussed in detail in Chapter 3, allowed for a nuanced evaluation, particularly in distinguishing between correctly and incorrectly classified instances. By analysing these metrics, comparisons were drawn between the various architectures to ascertain the most effective model for crop disease classification.

5.2.4.2 Comparative Analysis

A comparative analysis was carried out to evaluate the performance of the models, highlighting the specific strengths and weaknesses of each architecture. This analysis provided insights into which models performed best under different conditions and will be discussed in detail in Chapter 6, where the results of these evaluations are presented and interpreted.

5.3 Masking Technique and Data Annotation

This study employed advanced image segmentation techniques to effectively isolate crop leaves from various environments and segment diseased areas from healthy regions. Traditionally, manual annotation is used to create ground truth masks for CNN model training, but this process is time-consuming and prone to errors, especially with large datasets. Instead, an innovative approach combining texture analysis, gradient magnitude, contour detection, and pixel intensity analysis was used to accurately detect edges and fine details in 19,939 images. Techniques such as Otsu Thresholding, Adaptive Thresholding, Sobel Edge Detection, and Contour Detection were employed to generate precise masks, with their comparative performance detailed in Chapter 6.

5.3.1 Understanding Techniques utilized.

Traditional image segmentation techniques served as a foundational step in this study. These methods were essential for isolating crop leaves from their backgrounds, which was crucial given the time constraints and the infeasibility of manual image annotation for over 20,000 images. The following techniques were employed:

1. **Otsu Thresholding**: This medium automatically determines an optimal threshold by reducing intra-class variance, effectively separating the foreground (leaves) from the background in grayscale images (Otsu, 1979). This method computes the histogram of pixel intensities and finds a threshold that reduces the variance within classes (foreground and background).

2. **Adaptive Thresholding**: Unlike Otsu’s method, which applies a global threshold, adaptive thresholding dynamically adjusts the threshold for each pixel based on its local neighbourhood, making it particularly useful for images with uneven lighting conditions (Bradley & Roth, 2007). This technique calculates the threshold for smaller regions of the image, allowing different thresholds to be applied across various parts of the image.

3. **Sobel Edge Detection**: This technique calculates the gradient of the image intensity at each pixel, emphasizing areas with significant intensity changes—typically corresponding to edges (Sobel, 1968). Sobel filters apply convolutional kernels to the image to detect horizontal and vertical edges, combining them to produce a gradient magnitude image.

4. **Contour Detection**: Contour detection is used to identify and outline the edges of objects in the image. In this study, contours were particularly useful for delineating leaf boundaries (Canny, 1986). The technique applies edge detection (Canny edge detector) and then traces the detected edges to form contours around the objects.

These methods produced initial masks that isolated the leaves, laying the groundwork for the subsequent CNN-based segmentation.

5.3.2 Refined Masking: Fusion of Techniques

To enhance segmentation accuracy, Adaptive Thresholding and Contour Edge Detection were combined in a refined masking approach. Adaptive Thresholding dynamically adjusted thresholds based on local pixel intensities, effectively separating leaves from varying backgrounds, while Contour Edge Detection precisely mapped leaf edges, ensuring accurate boundaries. This robust strategy was applied to the entire dataset, producing consistent and precise semi-automated annotations that served as high-quality ground truth for training CNN models. This automated method not only saved significant time but also delivered reliable results, highlighting the effectiveness of traditional image processing techniques in large-scale dataset annotation.

5.3.3 Annotation of Dataset

The integration of Adaptive Thresholding and Contour Edge Detection was the most effective strategy for annotating the dataset, as discussed in Chapter 4.7.2. The resulting masks, distinguishing foreground leaves from the background, were systematically applied across the dataset. This automated process ensured efficient generation of a high-quality annotated dataset, crucial for the success of this project.

5.3.4 Step by Step procedure for refined Mask generation and data annotation

A detailed step-by-step approach was applied in this study to create masks and annotate the dataset for segmentation model training:

1. **Loading Image:** The input image was loaded in grayscale mode, simplifying the data to a single intensity channel.
2. **Apply Gaussian Blur:** A Gaussian blur was applied to reduce noise and smooth the image, improving subsequent thresholding effectiveness.
3. **Adaptive Thresholding:** The smoothed image was transformed into a binary mask using adaptive thresholding.
4. **Invert the Threshold:** The binary mask was inverted so that the foreground (leaves) became white and the background black.
5. **Morphological Operations:** Morphological operations (e.g., closing) were applied to close small gaps in the binary mask.
6. **Contour Detection:** Contours were detected in the binary mask, and the largest contour was selected.
7. **Generate Refined Mask:** If the largest contour exceeded a predefined area threshold, the contour was filled to create a solid mask.
8. **Process the Dataset:** A function iterated through all images, generating refined masks and saving them in a new directory.
9. **Pair Images with Masks:** A function paired each image with its corresponding mask, ensuring the dataset was ready for CNN model training.

5.3.5 Evaluation and Comparative Analysis

The five techniques were visually inspected alongside their original images, focusing on each method's ability to differentiate pixel intensity, accurately detect contour patterns, and produce fine, continuous edges. Particular attention was given to how well each technique recognized these details. The results from this evaluation, along with the justification for selecting the final methods, are thoroughly discussed in Chapter 6. This assessment ensured that the chosen techniques were optimal for the specific needs of the study.

5.3 Segmentation Models

The models selected in Chapter 3 were crucial for the image segmentation process, utilizing deep learning to automatically segment images based on an annotated dataset. These CNN-based models effectively detected and isolated leaves from their backgrounds, enhancing the precision and efficiency of segmenting healthy and diseased areas.

5.3.1 Understanding Model Architecture

These CNN-based architectures were specifically chosen for their ability to overcome the limitations of traditional segmentation methods. Each model was selected for its distinct advantages and proven effectiveness in managing large-scale datasets, particularly for isolating crop leaves and distinguishing between healthy and diseased areas with high accuracy and efficiency.

1. **U-Net Architecture:** U-Net, a CNN-based model with a symmetric encoder-decoder structure, is central to the image segmentation process in this research. Initially designed for biomedical image segmentation, U-Net has shown great effectiveness in tasks requiring accurate localization of objects within images. Its architecture consists of a contracting path (encoder) and an expansive path

(decoder), connected by skip connections between corresponding layers. These connections allow the model to merge low-level spatial details with high-level contextual information, resulting in more precise segmentation results.

In the context of this research, U-Net's ability to express both the spatial context and fine details is particularly advantageous. The model is trained to segment leaves from their backgrounds, a task that requires distinguishing subtle differences in shape, colour, and texture. The U-Net architecture excels in this task by preserving the resolution of the input image while effectively delineating leaf boundaries. This is crucial for accurately identifying the edges of leaves, especially when dealing with complex backgrounds or overlapping objects. During the training process, U-Net is fed with a manually annotated dataset, where the leaves have been carefully marked. The model iteratively learns to recognize the key features of leaves, refining its ability to segment them with each training cycle. Once trained, U-Net is applied to the entire dataset, producing segmented images where the leaves are clearly isolated against a black background. This automation not only improves the accuracy of the segmentation but also significantly reduces the time required compared to manual methods.

2. **SegNet Architecture:** While U-Net focuses on precise localization, SegNet is optimized for efficiency, particularly when handling large-scale datasets. SegNet's architecture is built for memory efficiency, making it an excellent choice for scenarios with limited computational resources or when processing large volumes of images.
   SegNet features an encoder-decoder structure similar to U-Net, but with a key difference is the streamlined nature of the decoder in SegNet model, It reuses the pooling indices from the encoder's max-pooling layers, avoiding the need for complex upsampling methods. This design choice reduces the memory footprint of the model, enabling it to process large volumes of data more efficiently. In the context of this research, where the dataset comprises tens of thousands of

images, SegNet's efficiency becomes a critical factor. During training, SegNet is similarly fed with the annotated dataset, where it learns to identify the distinguishing features of leaves. Despite its emphasis on efficiency, SegNet maintains a high level of accuracy, ensuring that the leaves are accurately segmented from the background. Once trained, SegNet can rapidly process large batches of images, generating segmented outputs that are consistent and reliable.

3. **DeepLabV3+ for Enhanced Image Segmentation** DeepLabV3+ is another CNN-based architecture incorporated into this research to enhance the image segmentation process. Unlike U-Net and SegNet, DeepLabV3+ employs atrous convolution (also known as dilated convolution) to gather multi-scale contextual information while preserving spatial resolution. This feature allows the model to effectively handle varying object sizes within an image, making it particularly suitable for segmenting leaves that might vary significantly in scale.
   The DeepLabV3+ architecture builds upon the original DeepLabV3 by introducing a decoder module that improves segmentation accuracy, particularly around object boundaries. Its atrous spatial pyramid pooling (ASPP) module utilizes atrous convolution at multiple scales, enabling the model to capture both fine details and broader contextual information simultaneously. This is crucial when dealing with complex backgrounds where leaf edges need to be clearly delineated. In this research, DeepLabV3+ is trained using the same manually annotated dataset, where its ability to capture both small and large-scale features allows it to excel in segmenting leaves with unique varrying shapes and sizes. The model’s robust performance, even in the presence of occlusions and overlapping objects, makes it a valuable addition to the segmentation process. Once trained, DeepLabV3+ produces highly accurate segmentation maps that are particularly effective in challenging scenarios, such as densely packed foliage or intricate leaf structures.

4. **LinkNet Architecture:** LinkNet is included in this research to address the need for real-time image segmentation without compromising on accuracy. LinkNet is designed as a lightweight and efficient architecture, making it ideal for scenarios where processing speed is critical. It combines elements of both U-Net and ResNet architectures, incorporating skip connections that link the encoder and decoder layers directly, which helps in preserving spatial information while keeping the network shallow and fast.
   LinkNet's streamlined structure is especially beneficial when handling large datasets or when segmentation tasks need to be executed on devices with limited computational resources. Despite its efficiency, LinkNet does not sacrifice accuracy; the skip connections ensure that high-level features are effectively combined with lower-level details, allowing for precise segmentation. In this research, LinkNet is trained on the annotated dataset to segment leaves from various backgrounds. Its ability to quickly and accurately produce segmentation outputs makes it an excellent choice for applications requiring rapid processing of large image datasets. LinkNet's performance in maintaining a balance between speed and accuracy contributes significantly to the overall efficiency of the image segmentation process in this study.

5.3.2 Model Setup and Configuration

5.3.2.1 Dataset Preparation and Splitting

The dataset preparation for segmentation models was critical to ensure effective training, validation, and testing. Unlike classification models, the segmentation dataset was divided into 80% for training, 10% for validation, and 10% for testing. This 80:10:10 split prioritized a larger training set, essential for accurate segmentation. The splitting was conducted in a temporary global folder to conserve disk space, prevent overfitting, and to ensure an unbiased assessment of the model's performance across different data subsets.

5.3.2.2 Data Augmentation and Data Generator

To improve model generalization and reduce overfitting, data augmentation was applied to the training dataset. Techniques such as random rotations, shifts, flips, and scaling were used to artificially increase the dataset by introducing diverse variations. These augmentations are crucial for segmentation tasks to ensure that the model learns to segment images under various conditions.

A custom data generator was developed to optimize the handling of image and mask pairs during training. This generator processes data in small, manageable batches, thus avoiding the need to load the entire dataset into memory at once. Upon initialization, the generator receives a list of file paths for images and masks, along with the desired batch size and target image dimensions. The generator then calculates the number of batches per epoch based on the total dataset size.

During training, the generator efficiently processes each batch by loading the corresponding images and masks from disk. The images are resized to the specified dimensions and normalized, with pixel values scaled between 0 and 1. The images are processed in RGB format, while the masks are converted to grayscale to ensure suitability for the segmentation model's input requirements. To further enhance the model's generalization capabilities, the generator shuffles the order of the data at the end of each epoch, disrupting any potential memorization of data sequences by the model and promoting the learning of much stronger and generalized features.

5.3.2.3 Model Customization and Optimization

To ensure effective convergence and avoid overfitting, the segmentation models were customized and optimized using strategies similar to those employed in the classification models, both of which were implemented using Keras and TensorFlow. However, the segmentation tasks required additional adjustments, particularly in learning rate management and loss function design, to address the specific challenges inherent in image segmentation. All other customizations were consistent with those discussed in Chapter 5.2.

1. **Learning Rate Adjustment:** A dynamic learning rate scheduler was implemented to calibrate the model's learning rate based on validation loss. When the validation loss plateaued, indicating that the model's improvement had stagnated, the learning rate was automatically reduced by a factor of 0.5. This adjustment allowed the model to make finer, more precise updates as it approached an optimal solution, preventing it from getting stuck in suboptimal minima. The new learning rate was calculated as:

$$New\ Learning\ Rate\ =\ Current\ Learning\ Rate\ x\ 0.5 \tag{5.2}$$

   This dynamic approach ensured that the learning process remained stable and continued to improve, even as the model reached the later stages of training.

2. **Epochs and Early Stopping**: The models were trained over a span of 30 epochs. To avoid overfitting, early stopping was employed by observing the validation loss throughout the training process. Training was halted if the validation loss did not improve after 5 consecutive epochs. This strategy helped prevent the models from overfitting to the training data, ensuring improved generalization to new, unseen data. Early stopping is essential in segmentation tasks, as overfitting can cause models to perform exceptionally on the training data but falter when applied to new unseen data.

5.3.2.4 Loss Functions in Image Segmentation

Selecting an appropriate loss function is crucial in image segmentation tasks, as it directly influences the model’s ability to distinguish between different regions within an image. The loss functions employed in this research; Dice Loss, Binary Cross-Entropy (BCE) Loss, and a combined BCE-Dice Loss play complementary roles in achieving accurate segmentation, particularly when addressing challenges such as class imbalance, a common issue in segmentation tasks.

1. **Dice Loss:** Dice Loss is particularly effective in scenarios where there is a significant disparity between the foreground (object) and background pixels in an image. In many segmentation tasks, the background pixels significantly outnumber those of the object of interest. This imbalance can skew traditional loss functions, causing the model to favour predicting the majority class, which is usually the background. Dice Loss mitigates this issue by focusing on the overlap between the predicted segmentation and the ground truth, thereby reducing the bias towards the majority class.

$$\text{Dice Loss} = 1 - \frac{2 \times |A \cap B|}{|A| + |B|} \tag{5.3}$$

Where:

- A is the set of predicted pixels (predicted mask).
- B is the set of actual pixels (ground truth mask).

In a more general form, using tensors:

$$\text{Dice Loss} = 1 - \frac{2 \times \sum_{\iota=1}^{n} (\mathcal{Y}_{true,\iota} \times \mathcal{Y}_{pred,\iota})}{| \sum_{\iota=1}^{n} \mathcal{Y}_{true,\iota} + \mathcal{Y}_{pred,\iota}} \tag{5.4}$$

Where:

- $\mathcal{Y}_{true,\iota}$ is the ground truth binary label for the ι pixel.
- $\mathcal{Y}_{pred,\iota}$ is the predicted probability for the ι pixel.

Dice Loss gauges the similarity between the predicted and actual segmentation, with a Dice Loss of zero indicating perfect overlap. By emphasizing the intersection between the prediction and the ground truth relative to their combined sizes, Dice Loss ensures that even small objects, which might be overshadowed by the background, are correctly segmented. This makes Dice Loss particularly valuable in applications where accurately segmenting the object, despite its size, is critical.

2. **Binary Cross-Entropy (BCE) Loss:** While Dice Loss is effective for handling imbalanced datasets, it may not always guarantee pixel-level accuracy, which is crucial for detailed segmentation tasks. Binary Cross-Entropy (BCE) Loss directly addresses this need for precise pixel-level classification. In the context of segmentation, BCE Loss treats the task as a pixel-wise binary classification problem, where each pixel is classified as belonging to the object (foreground) or the background. The BCE loss is given by:

$$\text{BCE Loss} = -\frac{1}{N}\sum_{\iota=1}^{N}[\mathcal{Y}_{true,\iota} \cdot log(\mathcal{Y}_{pred,\iota}) + (1 - \mathcal{Y}_{true,\iota}) \cdot log(1 - \mathcal{Y}_{pred,\iota})] \quad (5.5)$$

Where:

- N is the total number of pixels.
- $\mathcal{Y}_{true,\iota}$ is the ground truth label (0 or 1) for the ι pixel.
- $\mathcal{Y}_{pred,\iota}$ is the predicted probability for the ι pixel.

BCE Loss penalizes deviations from the true label for each pixel, making it particularly effective in ensuring pixel-level accuracy across the entire image.

This pixel-wise focus allows the model to learn fine details in the segmentation, which is especially important when precise boundaries are needed. However, when used alone, BCE Loss can struggle with imbalanced datasets, as it might disproportionately favour the majority class (often the background). This limitation can lead to suboptimal segmentation performance, particularly in scenarios where the object of interest is small or occupies a minor portion of the image.

3. **BCE-Dice Loss:** To leverage the strengths of both Dice Loss and BCE Loss, a combined BCE-Dice Loss was employed in this research. The BCE-Dice Loss is formulated to enhance image segmentation by addressing both class imbalance and the need for pixel-level accuracy. Dice Loss ensures segmentation coherence by focusing on the overlap between predicted and true masks, while BCE Loss offers precise pixel-level classification. The combined loss function is expressed as:

$$BCE - DIce\ Loss\ =\ BCE\ Loss\ +\ DIce\ Loss \tag{5.6}$$

This combination allows the models to accurately classify individual pixels while maintaining the structural integrity of the segmented objects. The BCE-Dice Loss is particularly effective in complex tasks where both precise boundary delineation and robust segmentation are critical, such as in medical imaging and autonomous driving.

In the context of this research, the BCE-Dice Loss was highly effective for segmenting crop leaves and distinguishing between healthy and diseased regions, even in challenging datasets that included noise, varying lighting conditions, and overlapping objects. The synergy between BCE and Dice Loss provided a balanced approach, ensuring that the segmentation was both accurate and coherent across the entire dataset.

5.3.2.5 Implementation of Models

The CNN models were implemented using the Adam optimizer and a combined BCE-Dice loss function, with accuracy and Intersection over Union (IoU) as evaluation metrics. Starting with U-Net, its symmetrical encoder-decoder architecture excelled at capturing fine details, particularly in delineating leaf boundaries. SegNet, based on the VGG16 encoder-decoder structure, was optimized for computational efficiency, enabling faster training and segmentation for large-scale datasets. DeepLabV3+ utilized the Xception backbone with atrous convolution, enhancing multi-scale context capture to accurately segment varying object sizes. LinkNet, built on ResNet50, focused on efficient feature extraction and spatial reconstruction, balancing computational demands with high accuracy. All models underwent iterative learning, with continuous parameter adjustments to minimize segmentation errors, closely monitored by accuracy and IoU metrics.

5.3.3 Model Evaluation

Once the training of the segmentation models was concluded, the models were evaluated on the test dataset to assess and evaluate their capabilities. IoU was the primary metric used for evaluation, while still monitoring the Loss and accuracy score. The metrics with comparisons made across different architectures to identify the most effective model for crop disease classification. Details on the performance of the segmentation models will be further discussed in chapter 5.

The performance of various models was compared, highlighting the strengths and weaknesses of each architecture. This analysis will be detailed in Chapter 5, where the results of these evaluations are presented and discussed.

5.4 Colour-Based Segmentation Technique

The final stage of segmentation in this research involves distinguishing between healthy and diseased regions of crop leaves using colour-based segmentation techniques. This approach leverages the distinct colour variations typically observed between healthy and diseased plant tissues. Diseases often manifest through changes in colour, such as yellowing, browning, or spotting, making colour an effective feature for segmentation.

5.4.1 Principles and Implementation of Colour-Based Segmentation

Colour-based segmentation operates within the HSV (Hue, Saturation, Value) colour space, which aligns more closely with human perception of colour than the RGB model. The HSV model facilitates the isolation of specific colour ranges, enabling the effective differentiation between the healthy green areas of the leaf and the various colours associated with diseased tissue.

Step-by-Step Segmentation Procedure:

1. **Image Preprocessing:** After the leaves are isolated from the background using CNN-based models, the cropped images are converted from the RGB colour space to HSV. This conversion allows for more intuitive thresholding based on the tissue's colour properties, where hues can be more precisely identified and categorized.

2. **Colour Thresholding:** Specific thresholds are set in the HSV space to correspond to the colours of healthy tissue. For instance, green hues indicative of healthy leaf tissue are isolated by defining appropriate ranges for hue, saturation, and value. These thresholds are based on exploratory data analysis (EDA) of the dataset, ensuring that the green hues are accurately captured.

3. **Segmentation Process:** With the HSV thresholds defined, the algorithm generates a binary mask. Pixels within the specified range are marked as healthy

(green), and those outside the range are marked as diseased (red). In cases where diseases manifest in multiple colours (e.g., yellowing and browning), additional threshold sets or clustering techniques like k-means are employed to capture the full spectrum of colour variations.

4. **Post-Processing:** After the initial segmentation, morphological operations such as dilation and erosion are applied to refine the segmented regions. These operations help remove small artifacts and ensure that boundaries between healthy and diseased areas are continuous and accurate. This step enhances the precision of the disease boundary delineation.

5. **Final Segmentation Output:** The final output is a segmented image where diseased areas are highlighted in red and healthy areas in green, clearly differentiating the two. This color-coding provides an intuitive visual representation, making it easier to identify and assess the extent of disease within the leaf.

5.4.2 Evaluation of Colour-Based Segmentation Technique

The colour-based segmentation technique was evaluated using the IoU metric, similar to the evaluation approach applied to other segmentation models. IoU was calculated by comparing the segmented regions of diseased and healthy crop areas against manually annotated ground truth masks. The detailed results of the evaluation are presented in Chapter 6.

5.5 Severity Estimation

5.5.1 Severity Quantification

Severity estimation in this research is achieved through the calculation of the Percentage of Disease Severity (PDS). This is determined by computing the ratio of the diseased area to the total leaf area, expressed as a percentage. The process begins with the segmented images where binary masks produced during the final segmentation phase are utilized to classify and count the pixels belong to the diseased regions and the entire leaf area.

Calculation of PDS:

$$PDS = \left(\frac{Area\ of\ diseased\ Region}{Total\ Leaf\ \ Area}\right) \times\ 100\% \qquad (5.7)$$

By accurately calculating the number of pixels representing diseased and healthy areas, the PDS provides a quantitative measure of the extent of infection, which serves as the foundation for further analysis and classification.

5.5.2 Classification of Disease Severity

Following the calculation of PDS, the severity of the disease is classified into five predefined categories: Normal, Mild, Moderate, Severe, and Critical. These categories are determined by applying specific PDS thresholds to the segmented images, allowing for a structured and detailed assessment of disease severity.

Severity Categories:

- **Normal:** PDS = 0%
- **Mild:** 0% < PDS < 20%
- **Moderate:** 20% ≤ PDS < 30%
- **Severe:** 30% ≤ PDS < 50%
- **Critical:** PDS ≥ 50%

The classification process involves evaluating the PDS against these thresholds to categorize the severity level of each leaf. This classification not only quantifies the severity but also provides a practical framework for understanding the impact of the disease, aiding in targeted management and treatment strategies. By leveraging this detailed analysis, the research effectively translates the segmented data into actionable insights on crop health.

Chapter 6: Result Evaluation & Discussion

6.1 Introduction

This chapter critically evaluates and discusses the methodologies and techniques used in this research, analysing the results of various models developed for crop disease detection and severity estimation. It details the evaluation strategies and justifies the choice of specific metrics. The chapter then provides a comparative analysis of model performance, identifies limitations, and contextualizes the findings within existing research, offering a comprehensive understanding of the study's contributions and implications.

6.2 Evaluation Strategy

6.2.1 Recap of Evaluation Metrics

To analyse model performance, several evaluation metrics were utilized, including Accuracy, Precision, Recall, F1-Score, IoU, and Percentage of Disease Severity (PDS). These metrics, detailed in Chapter 3, provided a comprehensive framework for robust and reliable model and technique evaluation, ensuring accurate assessments of both classification, segmentation and disease severity outcomes.

6.3 Results Analysis

6.3.1 Classification Model Results

6.3.1.1 Training Performance

To gain insights into how the models learned and generalized from the data, the training and validation accuracy and loss trends were tracked over the course of 30 epochs. These trends help to illustrate the learning behaviour of each model.

Figure 6.1 shows accuracy progression, with models like ResNet152V2 and DenseNet201 steadily improving and maintaining consistent validation accuracy, indicating effective pattern recognition without overfitting. Figure 6.2 highlights loss reduction, where Xception and DenseNet201 demonstrate smooth, continuous declines, reflecting robust learning and strong convergence.

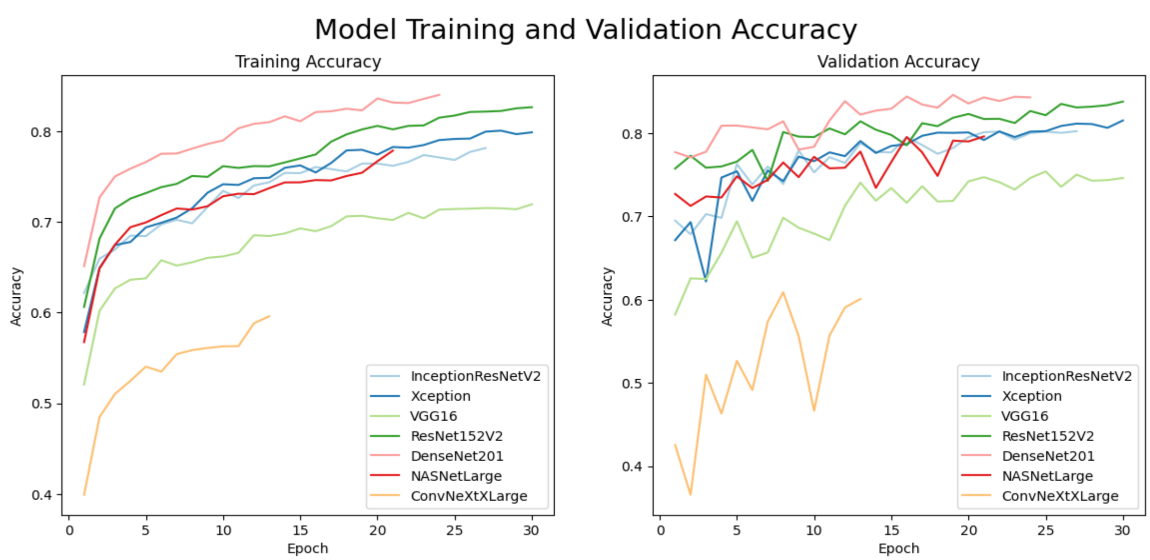

Figure 6.1: Accuracy Trends During Training and Validation

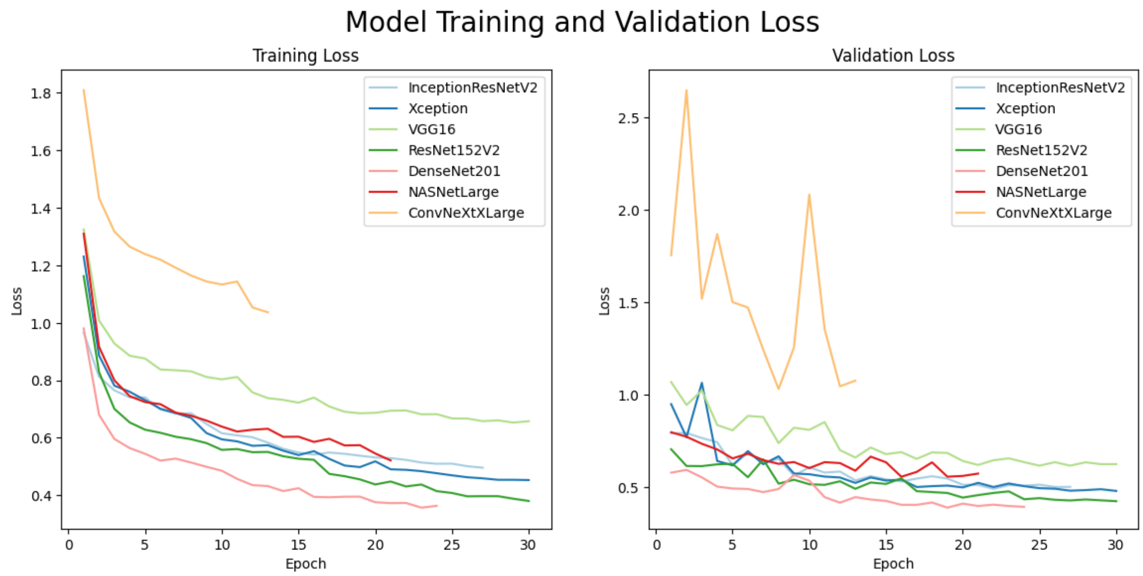

Figure 6.2: Loss Trends During Training and Validation

These patterns suggest that these models not only effectively captured the complexity of crop disease data but also generalized well to unseen data, ensuring reliability in practical applications.

6.3.1.2 Test Performance

The performance of the seven convolutional neural networks (CNNs) selected for crop disease classification was evaluated on unseen data (test data) using accuracy, precision, recall, and F1 score. Table 6.1 summarizes the performance metrics for each model.

MODEL	TEST LOSS	TEST ACCURACY	TEST PRECISION	TEST RECALL	TEST F1 SCORE
XCEPTION	0.491549	81.05%	83.44%	77.44%	80.33%
VGG16	0.637444	74.67%	79.74%	68.72%	73.82%

ResNet152V2	**0.435543**	**83.69%**	**85.98%**	**81.58%**	**83.72%**
InceptionResNetV2	0.495338	80.54%	84.44%	75.48%	79.71%
DenseNet201	**0.418530**	**83.09%**	**85.56%**	**81.65%**	**83.56%**
NASNetLarge	0.564713	78.20%	82.14%	72.43%	76.98%
ConvNeXtXLarge	1.049925	60.89%	68.93%	52.85%	59.83%

Table 6.1: Test Performance Metrics of Classification Models on Test Data

ResNet152V2 and DenseNet201 demonstrated strong performance, with ResNet152V2 achieving the highest Test Accuracy at 83.69%. These models excel in balancing depth and parameter efficiency, making them highly effective for agricultural classification tasks. Xception and InceptionResNetV2 also performed well, particularly in Test Precision, highlighting their ability to reduce false positives, which is critical for minimizing unnecessary interventions in practical agricultural scenarios.

Conversely, ConvNeXtXLarge underperformed, exhibiting the lowest Test Accuracy and highest Test Loss, potentially due to overfitting or an inability to generalize effectively to the test data. This may be attributed to the model's complexity or insufficient tuning for the specific dataset.

6.3.2 Masking Techniques Results

In Chapter 5, various traditional image preprocessing and segmentation methodologies were employed to create masks that were used to train CNN segmentation models. The techniques implemented included Otsu Thresholding, Adaptive Thresholding, Sobel Edge Detection, and Contour Detection. Each of these methods was applied to a representative set of images from the dataset, and their outputs were evaluated to determine their effectiveness in accurately recognizing textures, edges, background differences, and intensity variations.

The comparative results of these techniques are presented in Figure 6.3, which juxtaposes the original images with the processed outputs from each of the four methods. This visual comparison is an essential tool for assessing the strengths and weaknesses of each method in the context of crop disease detection.

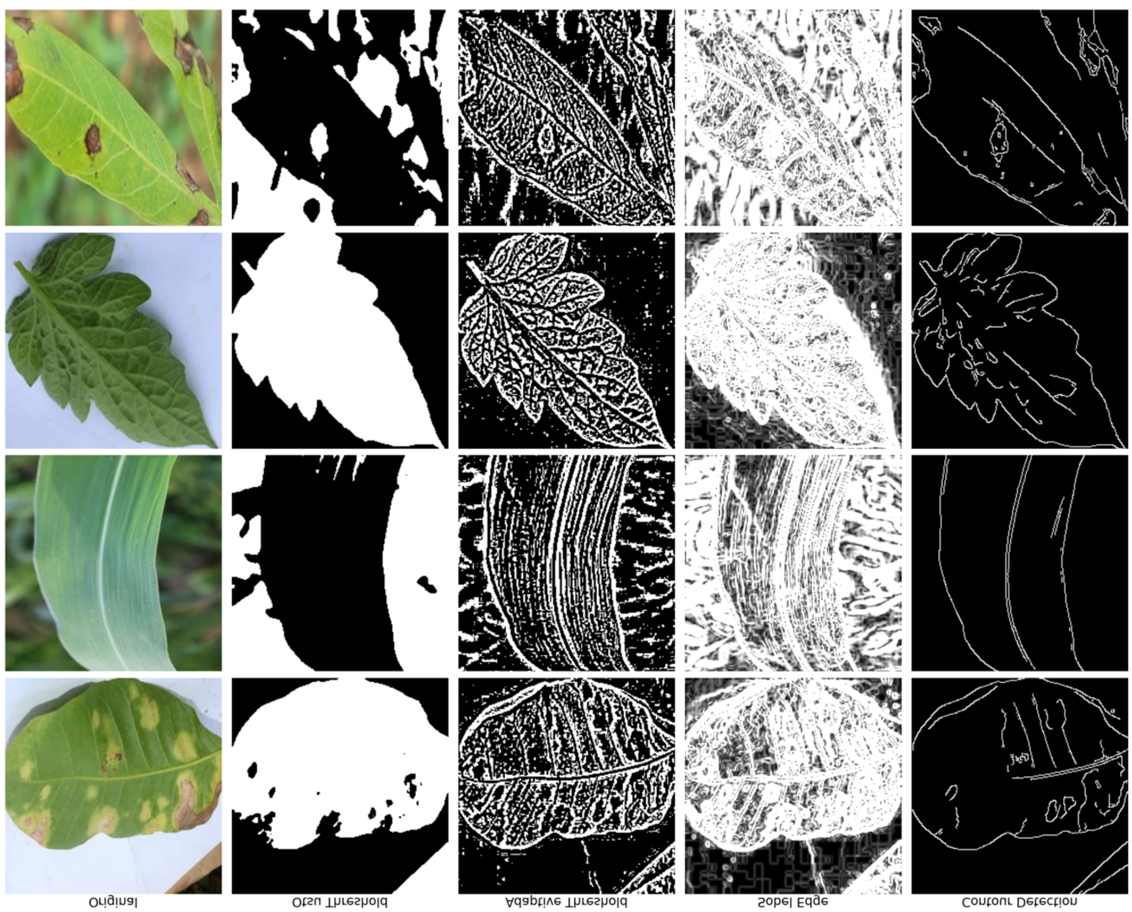

Figure 6.3: Comparison of Masking Techniques on Sample Crop Images

Upon close examination of the visual outputs, it was evident that Adaptive Thresholding and Contour Detection showed considerable promise. These methods effectively captured the relevant features of the diseased areas, particularly in terms of edge clarity and background differentiation, which are crucial for accurate segmentation.

Building on these observations, the strengths of Adaptive Thresholding and Contour Detection were fused and further refined to enhance contour and mask prediction. This fusion resulted in a more robust masking technique, as demonstrated in Figure 6.4, which produced superior results in terms of accurately delineating the diseased regions on the leaves.

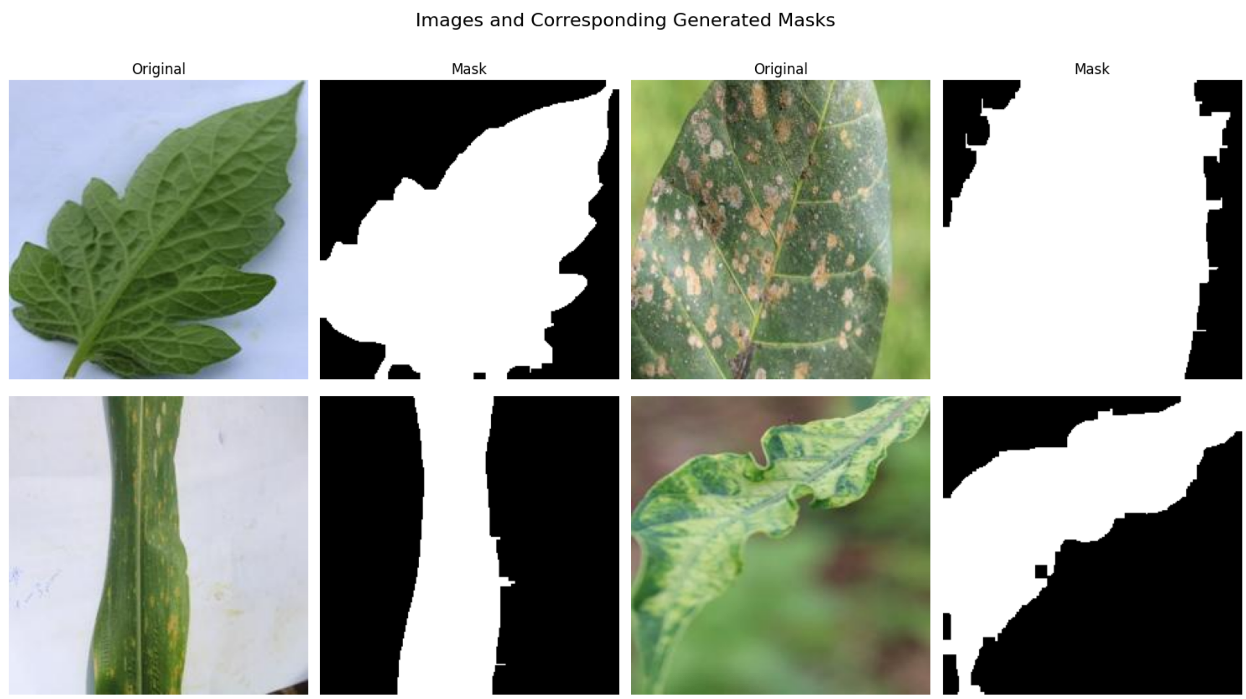

Figure 6.4: Enhanced Masking Technique Result

This improved methodology provided a solid foundation for creating annotations across the entire CCMT dataset. The refined masks were instrumental in training the segmentation models to accurately detect and segment leaves, irrespective of the environmental conditions in which the images were captured. The success of this approach underscores its potential applicability in a wide range of agricultural settings, where diverse and unpredictable environments pose significant challenges to traditional image segmentation techniques.

6.3.3 Segmentation Model Results

6.3.3.1 Model Performance

The segmentation models were trained and validated over 30 epochs, with accuracy and loss metrics closely monitored. Notably, due to the early stopping callbacks implemented, not all models completed the full 30 epochs. Figure 6.5 illustrates the training and validation accuracy curves, showing how quickly each model converged. SegNet and LinkNet exhibited rapid improvement in the early epochs, stabilizing at high accuracy levels. U-Net also performed consistently, starting with a slightly higher initial accuracy, while DeepLabV3+ showed a more gradual increase in accuracy.

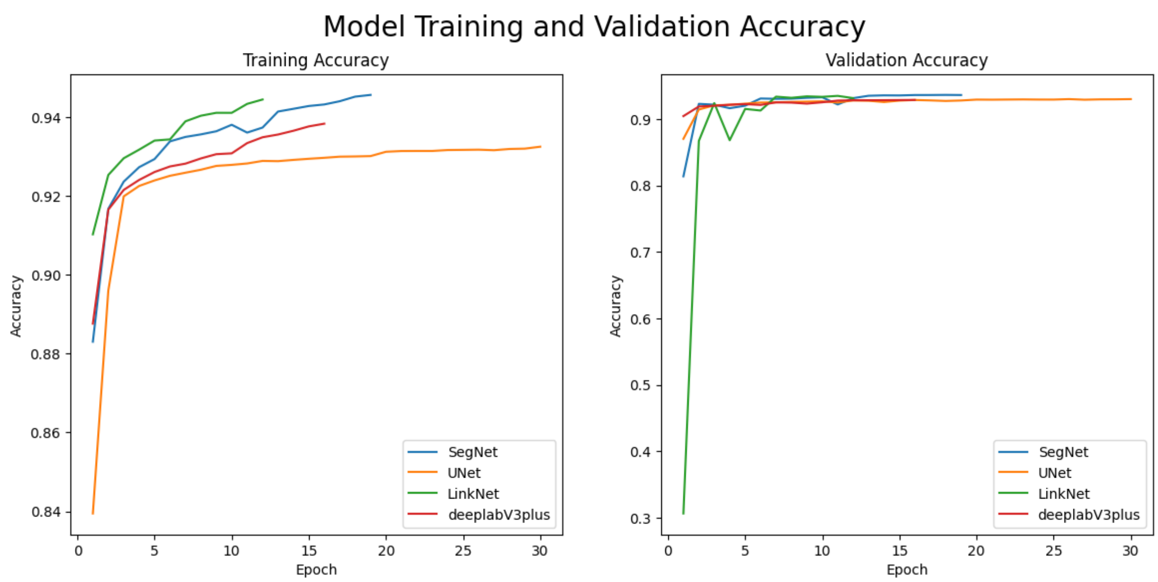

Figure 6.5: Model Training and Validation Accuracy

Figure 6.6 highlights the loss curves, offering deeper insights into the models' training dynamics. SegNet and LinkNet not only achieved lower final training loss values but also demonstrated smooth and stable convergence, indicative of robust learning. Although DeepLabV3+ started with a higher initial loss, it showed significant improvement by the fifth epoch. However, its validation loss remained slightly higher than the other models throughout the training process.

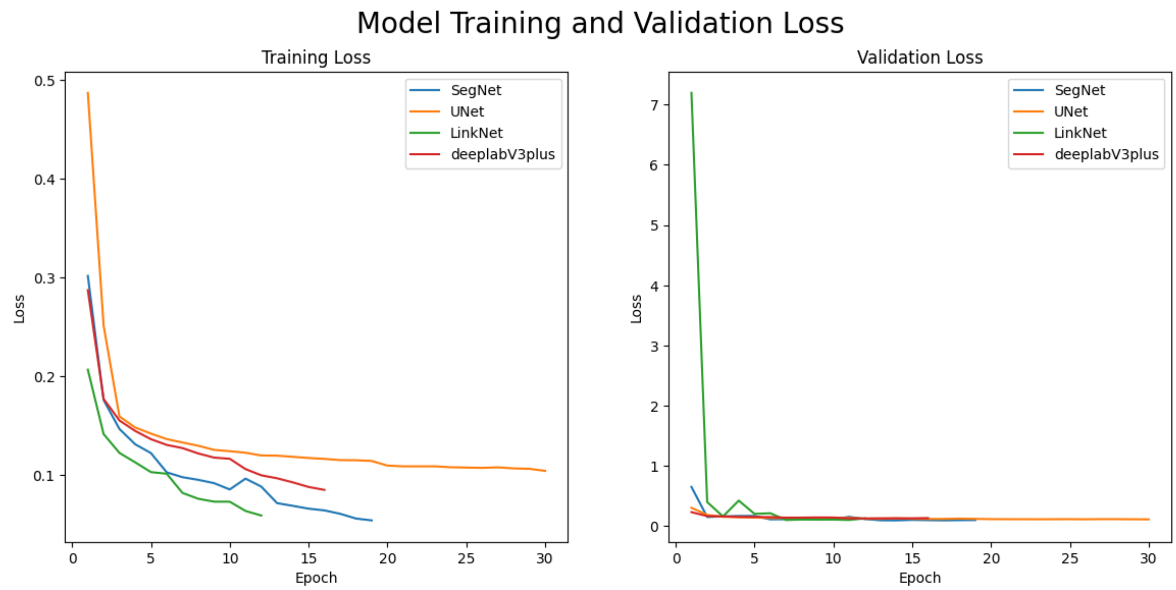

Figure 6.6: Model Training and Validation Loss

6.4.2 Comparative Analysis of Model Test Performance

Table 6.2 provides a comparative analysis of the test performance metrics across the four models, focusing on Test Loss, Test Accuracy, and Test IoU. These metrics are essential for assessing the practical effectiveness of the models in accurately segmenting crop diseases.

MODEL	TEST LOSS	TEST ACCURACY (%)	TEST IOU (%)
SegNet	0.087838	93.67	95.28
U-Net	0.105181	93.16	94.36
LinkNet	0.096856	93.44	94.74
DeeplabV3plus	0.123567	92.85	93.20

Table 6.2: Test Performance Metrics of Segmentation Models on Test Data

The heatmap highlights SegNet's superior performance, achieving the lowest test loss (0.088), the highest test accuracy (0.937), and the highest IoU (0.953). U-Net, while slightly behind SegNet, still delivers commendable results, particularly in maintaining a consistent balance between accuracy (0.932) and IoU (0.944).

LinkNet also performs competitively, with test metrics closely trailing those of U-Net, making it a viable option depending on specific application needs. DeeplabV3plus, although it lags slightly behind the other models, still shows strong performance with a test accuracy of 92.8% and IoU of 93.2%.

6.3.4 Colour-Based Segmentation Results

In the previous chapters, we detailed the implementation of colour-based segmentation techniques designed to distinguish between healthy and diseased areas on crop leaves. This method utilizes the distinct colour variations commonly seen between healthy and diseased regions to effectively differentiate them. The colour-based segmentation was executed after the initial segmentation step performed has taken place using the trained SegNet model which provided to be the best model to first crop the leaf out their environment as shown in figure 6.7. this step allowed the isolation of the leaf ensuring that no noise of external factors would influence the colour segmentation.

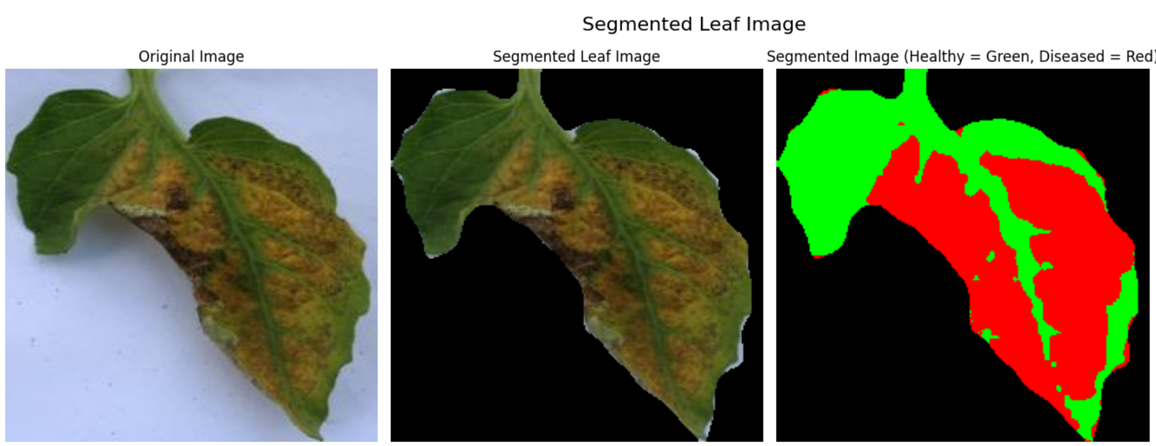

Figure 6.7: Segmented Image (Healthy = Green, Diseased = Red)

As seen in Figure 6.7, the left panel displays the leaf as isolated by the SegNet model, while the right panel highlights the healthy (green) and diseased (red) regions. This segmentation effectively separates the infected portions of the leaf, providing a clear visual representation of the disease spread.

To quantitatively evaluate the accuracy of the colour-based segmentation, a subset of images was manually annotated to serve as ground truth. The IoU metric was then computed to evaluate the performance of the method against these annotated masks. Figure 6.4.3 illustrates a sample comparison between the predicted diseased mask and the ground truth mask, with an IoU score displayed.

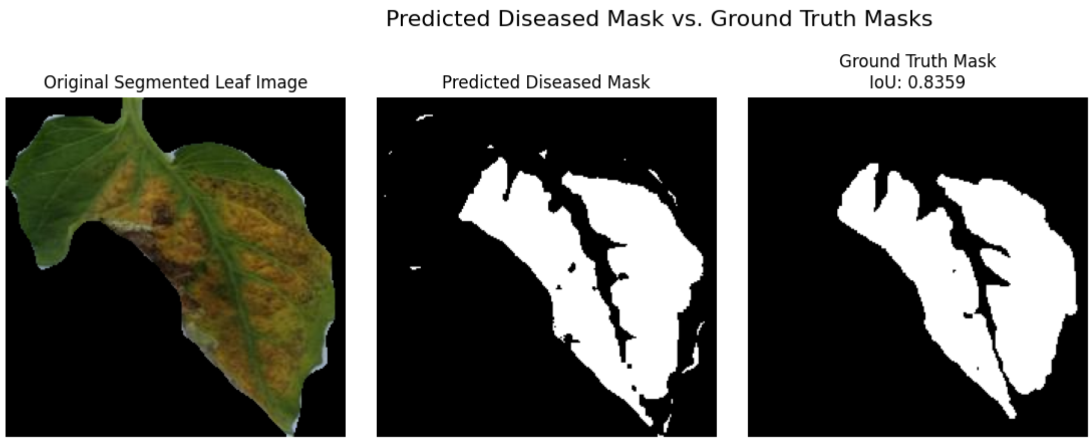

Figure 6.8: Comparison of Predicted and Ground Truth Masks

The IoU score achieved in this instance was 83.60%, indicating a high degree of overlap between the predicted and actual diseased regions. This demonstrates the efficacy of the color-based segmentation technique when applied to isolated leaf images.

6.2.4 Disease Severity Estimation Results

Following the segmentation process, disease severity on the segmented leaves was estimated using the Percentage of Disease Severity (PDS), quantifying the infected area relative to the total leaf area. Figure 6.9 illustrates the severity estimation process, showcasing a series of leaf images alongside their corresponding Segmentation results. The figure includes the original segmented leaf images, the segmented results, and the color-based segmentation outputs used to estimate the PDS.

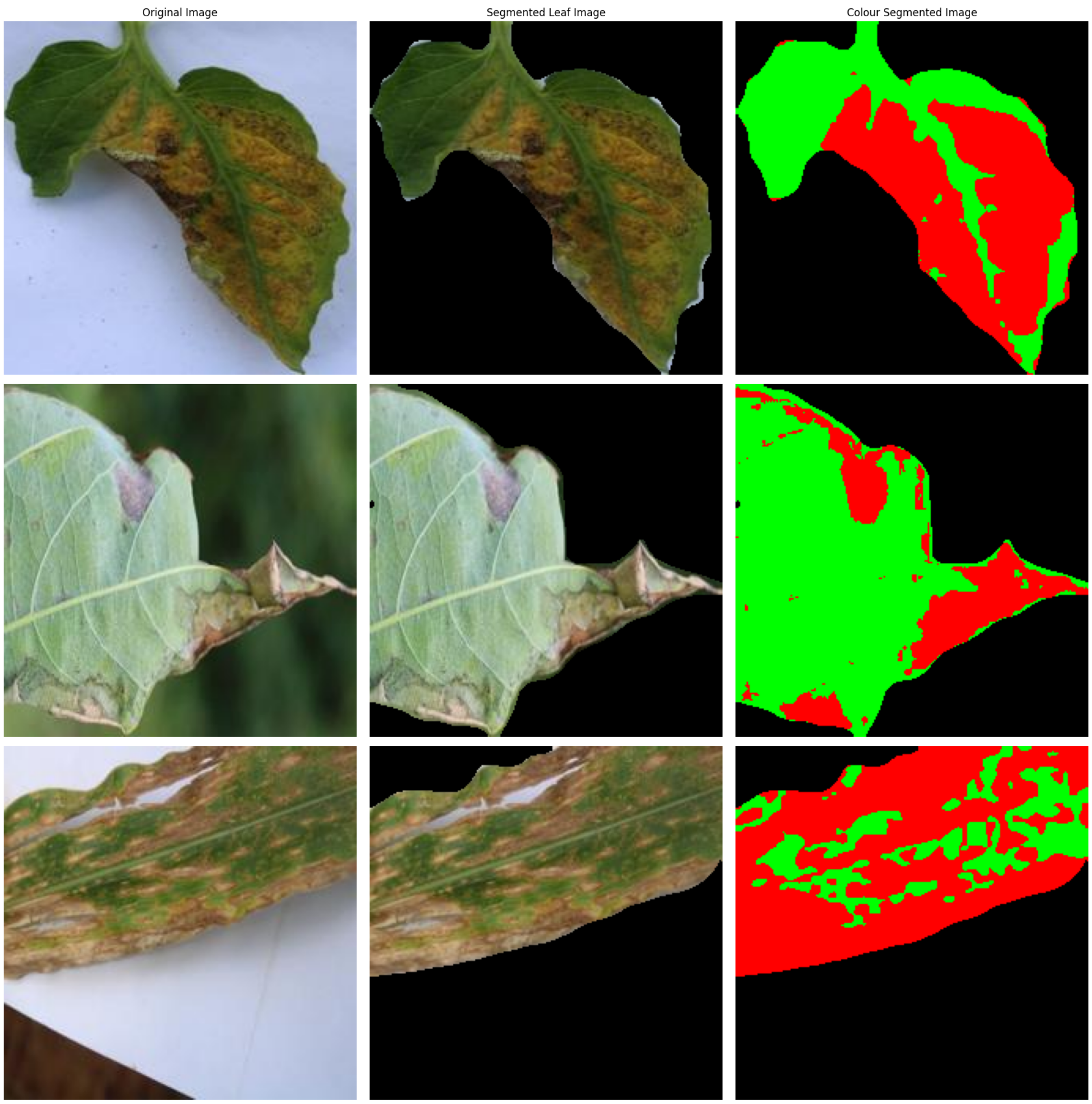

Figure 6.9: Sample results of disease severity estimation, displaying segmented leaf images and corresponding severity classifications.

The results are summarized in Table 6.3, which details the PDS values and severity classifications for selected leaf images. These findings highlight the model's ability to accurately distinguish between varying levels of disease severity. The color-based segmentation method effectively localized diseased areas, directly informing the PDS calculation and subsequent severity classification. Notably, leaves with higher PDS percentages, such as Leaf 1, Leaf 3, and Leaf 5, were accurately classified as "Critical," as illustrated in Table 6.3 and Figure 6.9, demonstrating the method's effectiveness.

LEAF IMAGE	PDS (%)	SEVERITY CLASSIFICATION
Leaf 1	55.75	Critical
Leaf 2	22.22	Moderate
Leaf 3	74.97	Critical

Table 6.3: Percentage of Disease Severity (PDS) and Severity Classifications for Selected Leaf Images

6.4 Discussion

The Agromedic Ai research has demonstrated the powerful potential of deep learning techniques, particularly CNNs, in advancing crop disease management. Notably, the ResNet152V2 and DenseNet201 models demonstrated high accuracy rates, exceeding 83% in classifying and segmenting diseased regions on crop leaves. This success underscores the models' ability to capture complex patterns associated with various plant diseases, providing a reliable alternative to traditional manual diagnosis, which can be labor-intensive and prone to errors.

Integrating traditional image processing techniques, such as color-based segmentation, with advanced CNNs provided a robust framework for disease detection. This combination not only fulfilled the initial objectives of enhancing precision and efficiency in crop disease management but also highlighted the versatility of these methods in adapting to diverse agricultural challenges. However, the study also revealed limitations. While color-based segmentation effectively isolated diseased areas in a controlled environment, its reliance on color changes alone may lead to inaccuracies in real-world scenarios, where factors like nutrient deficiencies or environmental stress can also alter plant coloration. This finding suggests that while the models show great promise, further refinement is needed to ensure their robustness across varied agricultural contexts.

Compared to existing research, this study marks a significant advancement in applying AI to agricultural disease management. While previous studies have primarily focused on detection, this research goes further by incorporating severity estimation, offering a more comprehensive tool for crop health management. The innovative use of CNNs not only confirms the efficacy of deep learning in image classification but also pioneers their application in estimating disease severity, a relatively underexplored area in the literature.

Chapter 7: Limitations, Future Works and Conclusion

7.1 Limitations

The study faced several limitations that affected its outcomes. One significant limitation was the variability in image quality across the dataset, which impacted the models' ability to generalize effectively. Diverse lighting conditions, resolutions, and angles introduced inconsistencies that complicated the segmentation and classification processes. Moreover, the study's limited hardware capacity restricted the number of epochs over which models could be trained, potentially preventing them from achieving their optimal performance.

Another limitation was the lack of time for comprehensive manual annotation of the dataset. While the segmentation methods applied in this study were effective, having a fully annotated dataset would have allowed for more rigorous validation and comparison of different techniques. The reliance on colour-based segmentation, while successful in this context, might not be the most reliable method in real-world applications due to the possibility of false positives from non-disease-related colour changes in plants.

7.2 Future Works

Future research should overcome these limitations by broadening the dataset to include a wider variety of images, thereby improving the models' generalizability. Additionally, integrating supervised learning with colour extraction techniques could enhance the accuracy of disease detection by allowing models to learn from annotated data about the specific forms and appearances of diseases. There is also a need to involve agricultural experts in determining the appropriate Percentage of Disease Severity

(PDS) classification ratios for different crops, ensuring that the models' outputs are both accurate and practical.

The long-term goal of this research is to develop a mobile and web-accessible platform, branded as “Agromedic AI,” which could revolutionize crop disease management. By integrating these models with Internet of Things (IoT) devices for real-time monitoring and analysis, the platform could significantly reduce the resources required for manual disease detection, leading to more efficient and scalable agricultural practices.

7.3 Conclusion

This dissertation has successfully demonstrated the application of deep learning models, particularly CNNs, in advancing the detection and management of crop diseases. The study not only achieved high accuracy in disease classification but also introduced a novel approach to estimating disease severity through a combination of image segmentation and color analysis. By integrating traditional image processing techniques with advanced AI models, the research presents a robust and improved framework over existing methods.

This work significantly contributes to the field of agricultural disease management by addressing a critical gap: the ability to quantify disease severity alongside detection. The broader implications are profound, offering potential reductions in crop losses and pesticide use while promoting sustainable farming practices. These advancements lay the groundwork for the development of "Agromedic AI," a platform poised to revolutionize global agriculture by enhancing food security and sustainability. As agriculture increasingly embraces digital transformation, the tools and methodologies developed here are likely to play a pivotal role in advancing smart farming and contributing to global efforts toward environmental sustainability.

References

Aktar, M. W., Sengupta, D., & Chowdhury, A. (2009). Impact of pesticides use in agriculture: Their benefits and hazards. *Interdisciplinary Toxicology*, 2(1), 1-12. https://doi.org/10.2478/v10102-009-0001-7

Bock, C. H., Poole, G. H., Parker, P. E., & Gottwald, T. R. (2020). Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. *Critical Reviews in Plant Sciences*, 29(2), 59-107. https://doi.org/10.1080/07352680903535527

Bradley, D., & Roth, G. (2007). Adaptive thresholding using the integral image. *Journal of Graphics Tools*, 12(2), 13-21. https://doi.org/10.1080/2151237X.2007.10129236

Canny, J. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8(6), 679-698. https://doi.org/10.1109/TPAMI.1986.4767851

Carvalho, F. P. (2017). Pesticides, environment, and food safety. *Food and Energy Security*, 6(2), 48-60. https://doi.org/10.1002/fes3.108

Chollet, F. (2015). *Keras*. https://keras.io

Food and Agriculture Organization of the United Nations. (2017). The future of food and agriculture – Trends and challenges. Rome: FAO. Available at: FAO Website

CABI Agriculture and Bioscience. (2023). Global challenges facing plant pathology: Multidisciplinary approaches to meet the food security and environmental challenges in the mid-twenty-first century. *CABI Agriculture and Bioscience*. https://doi.org/10.1186/s43170-023-00048-1

Garrido, C. (2024). Artificial intelligence: A promising tool for application in phytopathology. *Horticulturae*, 10(3), 197. https://doi.org/10.3390/horticulturae10030197

Hu, G., Wan, M., Wei, K., & Ye, R. (2023). Automated annotation techniques for training CNN models in agricultural image segmentation. *European Journal of Agronomy*, 144, 126756. https://doi.org/10.1016/j.eja.2023.126756

Gonzalez-Dominguez, E., Zarco-Tejada, P. J., & Martin, C. (2023). Process-based models in integrated disease management. *Precision Agriculture*. https://doi.org/10.1007/s11119-022-09907-5

Haridasan, P., Bhargava, S., & Misra, A. (2023). Automated identification and management of paddy diseases using deep learning techniques. *Frontiers in Plant Science*.

Hussein, E. (2021). Segmentation of plant leaves and disease detection using DeepLabV3+. *Agricultural Informatics Journal*.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70-90. https://doi.org/10.1016/j.compag.2018.02.016

Kwabena, P. M., Akoto-Adjepong, V., Adu, K., Ayidzoe, M. A., Bediako, E. A., Nyarko-Boateng, O., Boateng, S., Donkor, E. F., Bawah, F. U., Awarayi, N. S., Nimbe, P., Nti, I. K., Abdulai, M., Adjei, R. A., & Opoku, M. (2023). Dataset for Crop Pest and Disease Detection. Mendeley Data. https://doi.org/10.17632/bwh3zbpkpv.1

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444. https://doi.org/10.1038/nature14539

Leal Filho, W., Barbir, J., Lange Salvia, A., & Tozanli, S. (2022). AI in climate change adaptation: Implications for agriculture. *Climate and Agriculture Journal*. https://doi.org/10.1016/j.clim.2022.104876

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.

Mandal, S. N., Mukherjee, K., & Dan, S. (2023). Image-based potato Phoma blight severity analysis through deep learning. *Journal of the Institution of Engineers (India): Series B*, 104(1), 181-192. https://doi.org/10.1007/s40031-022-00820-9

Martins Crispi, G., Valente, D. S. M., Queiroz, D. M. de, Momin, A., Fernandes-Filho, E. I., & Picanço, M. C. (2023). Using deep neural networks to evaluate leafminer fly attacks on tomato plants. *AgriEngineering*, 5(1), 273-286.

McCown, R. L. (2002). Locating agricultural decision support systems in the troubled past and socio-technical complexity of 'models for management'. *Agricultural Systems*, 74(1), 11-25. https://doi.org/10.1016/S0308-521X(02)00020-3

Meyer, F. (1994). Topographic distance and watershed lines. *Signal Processing*, 38(1), 113-125. https://doi.org/10.1016/0165-1684(94)90060-4

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1419. https://doi.org/10.3389/fpls.2016.01419

Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1), 62-66.

Pal, A., & Kumar, V. (2023). AgriDet: Plant leaf disease severity classification using agriculture detection framework. *Engineering Applications of Artificial Intelligence*, 119, 105754. https://doi.org/10.1016/j.engappai.2023.105754

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, 3(3), 430-439.

Sarker, I. H. (2021). Deep learning: A comprehensive overview on techniques, taxonomy, applications, and research directions. *SN Computer Science*, 2(6), 1-20.

Sobel, I. (1968). A 3x3 isotropic gradient operator for image processing. Stanford Artificial Intelligence Project (SAIL).

Tjosvold, S. A. (2018). The disease triangle: Fundamental concept for disease management. *University of California Agriculture and Natural Resources*. Retrieved from https://ucanr.edu/repositoryfiles/disease-146227.pdf

Veroustraete, F. (2015). Drones in precision agriculture. *Precision Agriculture Journal*.

Zhang, T., Rao, Y., & Li, S. (2021). Segmentation of cucumber leaf images for disease detection and growth monitoring using the SegNet model. *Agricultural Engineering International: CIGR Journal*.

Zhang, X., Liu, Y., Luo, J., & Liu, G. (2019). A review on deep learning applications in agriculture. *Computers and Electronics in Agriculture*, 166, 105843. https://doi.org/10.1016/j.compag.2019.105843