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DETECTING CROP DISEASE AND CLASSIFICATION *VIA* CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE ON CASSAVA, PLANTAIN, AND COCOA LEAVES AND POD DATASET



BY

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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF PHILOSOPHY DEGREE IN AGRICULTURAL ENGINEERING.

DEPARTMENT OF AGRICULTURAL ENGINEERING

SCHOOL OF ENGINEERING SCIENCES

COLLEGE OF BASIC AND APPLIED SCIENCES

UNIVERSITY OF GHANA

LEGON

AUGUST, 2025

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DECLARATION

I, MENSAH STEPHEN ARDEY, author and conductor of this project do hereby declare that this work, DETECTING CROP DISEASE AND CLASSIFICATION *VIA* CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE ON CASSAVA, PLANTAIN, AND COCOA LEAVES AND POD DATASET, except for references cited, the work there in submitted was done entirely by me at the University of Ghana from AUGUST 2023 to AUGUST 2025, under the supervision of DR. EVANS ASENSO and DR. PEACE KORSHIWOR AMOATEY. This work has never been presented either in whole or in part for any degree of the University of Ghana or elsewhere.

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DEDICATION

This work is dedicated to the Lord Almighty, whose divine grace has made the completion of this research possible. In the face of challenges, I was reminded of the words: "*For they all made us afraid, saying, 'Their hands shall be weakened from the work, that it be not done.' Now therefore, O God, strengthen my hands.*" Indeed, God strengthened my hands and enabled me to achieve this feat. I also dedicate this work to my wonderful family, whose untiring support and encouragement have been a constant source of strength throughout this study and my postgraduate journey at the University of Ghana.



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ACKNOWLEGEMENTS

I express my deepest gratitude to my supervisor, Dr. Evans Asenso, whose exceptional guidance, and continuous encouragement have been instrumental in the success of this research. His optimism and enthusiasm pushed me to strive beyond expectations, ensuring the completion of this study.

I extend my sincere gratitude to my co-supervisor Dr.-Ing. Peace K. Amoatey, Head of Department and Senior Lecturer, Agricultural Engineering Department, for her invaluable guidance, support, and insightful advice through seminars and frequent engagements, which greatly contributed to the successful completion of this project.

I am also sincerely thankful to my good friend, Benjamin Setor Gbadago, Founder of African Cocoa Stories, who provided invaluable assistance in gaining access to cocoa farms in the Eastern Region and to farmers for disease identification. My heartfelt appreciation extends to Reindolf Rich Baah (Computer Engineering, University of Ghana), Noble Eselase Vulley, and Patrick Komla Dogbatse (Computer Science, University of Ghana) for their significant contributions to image pre-processing and database management.

I am eternally grateful to everyone who contributed, in various ways, towards the successful completion of this project.

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ABSTRACT

Detection of crop diseases is crucial to avert the losses in productivity and in yield. It is not obvious to monitor the crop diseases manually as the act of disease detection is very critical. It needs a huge effort, along with knowledge of crop diseases and extensive processing times, as early and accurate detection is critical for ensuring food security and improving agricultural productivity. This study evaluated the performance of five CNN architecture, AlexNet, DarkNet-53, DenseNet-201, GoogLeNet, and ResNet-101 in detecting and classifying diseases in cassava, plantain, and cocoa from leaf and pod images. The models were trained and tested under two T-T split ratios (80:20 and 90:10) to investigate the impact of dataset partitioning on performance. Key evaluation metrics used to assess model performance included accuracy, precision, recall, and F1-score. Across both split ratios, DenseNet-201 consistently outperformed other models, while DarkNet-53 and AlexNet recorded the weakest results. Under the 80:20 split, the multi-crop approach achieved its best performance with DenseNet-201 (Accuracy: 89.58%, Precision: 90.00%, Recall: 89.00%, F1-Score: 89.00%) compared to DarkNet-53 with the lowest scores across all metrics (Accuracy: 73.33%, Precision: 73.00%, Recall: 72.00%, F1-Score: 72.00%). For the individual crop datasets, DenseNet-201 again yielded superior results, attaining up to 97.61% accuracy and an F1-Score of 96.50% on plantain and cocoa, whereas AlexNet on cassava performed the least (Accuracy: 93.45%, F1-Score: 92.00%). Similar trends were observed under the 90:10 split, where DenseNet-201 reached peak performance in both approaches, achieving 92.90% accuracy in the multi-crop setting and 99.00% accuracy with an F1-Score of 98.20% in the plantain dataset. DarkNet-53 recorded the lowest multi-class performance (Accuracy: 78.80%, F1-Score: 77.50%), while AlexNet and DarkNet-53 also underperformed on the cassava classes, with accuracies of 94.80% and 95.80% and F1-scores of 94.70% and 95.90%, respectively. Results showed that DenseNet-201 consistently outperformed other models across all crops and metrics, achieving

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its highest performance at the 90:10 split. Findings indicate that, while both splits produced strong results, the 90:10 T-T ratio yields superior results, whereas the 80:20 split offered a more balanced evaluation, reflecting both training accuracy and generalizability of the model under diverse field conditions. The study highlights limitations such as dataset diversity, image quality variability, and lack of real-time testing. These results show the potential of CNN-based models in advancing precision agriculture and hence, recommendations for future integration into mobile and IoT-based disease monitoring systems made. In conclusion, DenseNet-201 is recommended for deployment under farm conditions, given its consistently superior performance across all crops and evaluation metrics observed in this study.



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List of Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Networks
BBTV	Banana Bunchy Top Virus
CAD	Cassava Anthracnose Disease
CBB	Cassava Bacterial Blight
CBSD	Cassava Brown Streak Disease
CMD	Cassava Mosaic Disease
CNN	Convolutional Neural Network
CRI	Crops Research Institute
CSSV	Cocoa Swollen Shoot Virus
DL	Deep Learning
FAO	Food and Agriculture Organization
FC	Fully Connected
GPU	Graphics Processing Unit
IoT	Internet of Things
KNN	K-Nearest Neighbours
ML	Machine Learning
ReLU	Rectified Linear Unit
SVM	Support Vector Machine
T-T	Train-Test

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CHAPTER ONE

INTRODUCTION

1.1 Background

Plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming. However, crop diseases are threatening the livelihood of this important source (Wallelign et al., 2018). According to (Hewitt, 2000; FAO, 2017), about 10 to 20% of staple foods and cash crops are destroyed by diseases. The study of plant diseases in general refers to the studies of visually observable patterns of a particular plant. Nowadays crops face many diseases. Crop diseases pose a serious threat to global food security and cost farmers in most agricultural countries a large amount of money each year. Notwithstanding, the trivial impact of crop diseases on production and thereby causing economic losses in agriculture. These diseases do not usually kill the plants, but they can cause severe production and quality losses.

Identifying types of plant disease is extremely important and is considered a crucial issue (Andrew et al., 2022). Early detection of crop disease is a critical step in ensuring food security. The symptoms of crop diseases can be rather striking. Wilting, mottling, streaking and discoloration of leaves and flowers, and abnormal growths are among them. Crop leaf diseases vary in shape, size, and color. Certain diseases have identical colors, but dissimilar shapes; while some have dissimilar colors but identical shapes (Vasavi et al., 2022). Detection is usually achievable at a stage when disease signs are obvious on the plant's aerial section. Disease detection entails numerous processes, including the evaluation of key site information and the examination of diseased tissue. However, after the disease has spread to various regions of the plant, there is little that can be done to save the condition (Owomugisha et al., 2020). Some diseases grow slowly; disease progression can be tracked over time and treatment options

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can be made. Other diseases spread quickly. When plant disease signs appear, it may be too late to manage it. It has been observed many times that plant leaf diseases are difficult to control as their population varies according to environmental conditions (Niharika & Sahana, 2021; Chandra et al., 2020). Disease identification methods that function well outside of the laboratory are needed to correctly identify diseases and prevent instances of incorrect chemical control (Craze et al., 2022).

Manually monitoring plant diseases is quite tough. It takes a significant amount of effort and processing time as it is often done by eye inspection or laboratory investigation, which causes delays and yield loss by the time identification is complete (Patil et al., 2026). The naked eye observation gives poor accuracy, and it is subjective which will vary from person to person. Inconsistency and delays in the detection of plant diseases also reduce crop quantity and quality (Yan et al., 2025).

The automated identification of plant diseases using plant leaves is critical in the field of agricultural demand. Furthermore, early and accurate identification of plant diseases enhances agricultural productivity and quality (Sakkarvarthi et al., 2022). The objective behind the ensemble approach is to create a prediction model by combining numerous models. Ensemble approaches are well-known for their ability to improve prediction performance (Rokach, 2006). The ensemble method usually produces more accurate results than a single model.

1.2 Problem Statement

The detection of plant diseases most of the time is done only through the naked eye observation (Takti et al., 2022). This is a traditional way to deal with the detection of plant diseases (Singh & Misra, 2017). Local farmers are likely to consult experts who spend a lot of time trying to specify the type of disease that is affecting the plants' leaves either through laboratory analysis or in most cases historical trends of diseases affecting a particular crop in certain geographical

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context. These experts may base their analytics that includes categorizing and classifying the diseases, only on the visual symptoms that are usually shown on the leaves (Takti et al., 2022). Marginal effort has gone into automating the identification of disease in crops using photographs. The majority of agriculturists rely on the presence of visible disease signs on the plant's leaves or stem to predict the presence or prevalence of disease. A limited number of research have looked on disease detection before it becomes symptomatic on the plant (Pfordt & Paulus, 2025; Wu et al., 2019). Plant leaf disease has the potential to significantly reduce the number of agricultural products produced on each farm (Demilie, 2024).

Automatic detection of plant diseases is an important study issue as it is beneficial in monitoring large fields of crops and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves. Consequently, looking for fast, automatic, less expensive and accurate method to detect disease will be an added advantage for farmers to boost crop productivity.

Deep learning (DL) architecture such as Convolutional Neural Network (CNN) helps to distinguish diseased or non-diseased leaf (Harakannanavar et al., 2022). In DL, CNN or Convnet, is most commonly applied to analyze visual imagery, particularly for classification tasks, as it gives more accurate results (Kompalli et al., 2022). With the advancement of DL, CNN models are increasingly used for the precise and accurate identification of plant leaf diseases. CNN consumes less time in image recognition and classification task compared to any manual procedure, and they can be easy to process with sufficient dataset (Marathe et al., 2013).

Despite significant advances in CNN-based plant disease detection, existing studies remain largely focused on mainstream crops, lack model comparisons, underexplore variations in train-test (T-T) splits, and often rely on idealized datasets (Islam et al., 2023; Upadhyay et al., 2025; Lu et al., 2021). Therefore, this study employs selected CNN models, including ResNet-

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101, AlexNet, DenseNet-201, GoogLeNet, and DarkNet-53, which are renowned for their exceptional accuracy and efficiency in classification tasks. These models are utilized to detect crop diseases and classify the dataset of Cassava, Plantain, and Cocoa leaves and pods.

1.3 Research Objective

The aim of the study is detecting crop disease and classification via Convolutional Neural Network Architecture on Cassava, Plantain, and Cocoa Leaves and Pod Dataset.

1.4 Specific Objectives

To achieve the primary aim of this study, the following specific objectives were formulated to guide the experimental design and performance evaluation of the CNNs used in this study:

I. To evaluate the ability of the selected CNN models to accurately detect and classify leaf diseases in the selected test crops under investigation.

I. To conduct a comparative analysis of the neural networks used in this study, to ascertain the neural network that demonstrates superior performance and efficiency.

II. To investigate the effect of different T-T split ratios on the performance of CNN models for crop disease detection.

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CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The agricultural industry plays an important role in meeting global food demand and generating revenue. Countries with good agricultural land have a significant advantage in food security and economic growth through exports. However, agriculture faces severe strain due to rising food demand as the world's population grows (Memon et al., 2022). Crop diseases pose a serious threat to global food security. Plants are affected by various diseases causing mild to severe damage to plant tissues such as leaf, stem, seed, and fruit (Kompalli et al., 2022). Among these tissues, leaf diseases are particularly common and deadly to plants because the leaf is the most vulnerable and important photosynthetic source tissue. Early diagnosis and detection are essential for improving prognosis and preventing incorrect chemical control (Mustofa et al., 2023). Thus, disease identification methods that work in the field are useful for rapid action to prevent its spread (Craze et al., 2022).

Typically, plant disease detection occurs at a stage when symptoms are visibly apparent on the aerial parts of the plant. By this point, the disease has often progressed to the extent that effective intervention is severely limited (Owomugisha et al., 2020). In recent years, climate change has contributed to an increase in leaf diseases. Traditional intuitive diagnoses by farmers are unreliable and inefficient (Mustofa et al., 2023).

As a result, plant-leaf diseases are still one of the key problems in crop production with a significant impact on the global economy. The Food and Agriculture Organization of the United Nations (FAO) estimates that plant pests cause annual global harvest losses of 10–16% equivalent to $220 billion USD (Kumar & Kalita, 2017). Early detection of plant leaf diseases remains challenging due to the diversity of plant species and the regional features, varying

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symptoms between plant species and the number of pathogens and pests known to cause crop leaf diseases.

The signs of infection on infected leaves can differ from one plant to another or even from one leaf to another on the same plant. According to the International Society for Plant Pathology, plants are vulnerable to a variety of pathogens and pests, including bacteria, nematodes, viruses, and over 19,000 fungi (Vijayvergia et al., 2019) are known to cause diseases in crop plant leaves worldwide. Researchers continue to develop automated, practical solutions and effective methods for detecting plant diseases (Tugrul et al., 2022).

The main focus is on correctly identifying diseases affecting crops to improve global food security and agricultural productivity. Despite ongoing advancements in crop disease detection, current farm practices remain largely dependent on manual visual inspection by farmers and experts, which is time-consuming, subjective, and often unreliable (Khan et al., 2025).

While automated approaches using deep learning (DL), particularly convolutional neural networks (CNNs), have shown promising results, existing studies are largely limited to a narrow range of crops, depend on idealized datasets, and lack sufficient comparative analysis across multiple models, as shown in Fig. 2.1, which highlights the challenges of manual detection and the potential of CNN-based methods to address them. Consequently, there is a need for a comprehensive evaluation of diverse CNN architectures across a wide range of crop datasets to improve accuracy, generalizability, and practical applicability in real-world agricultural settings.

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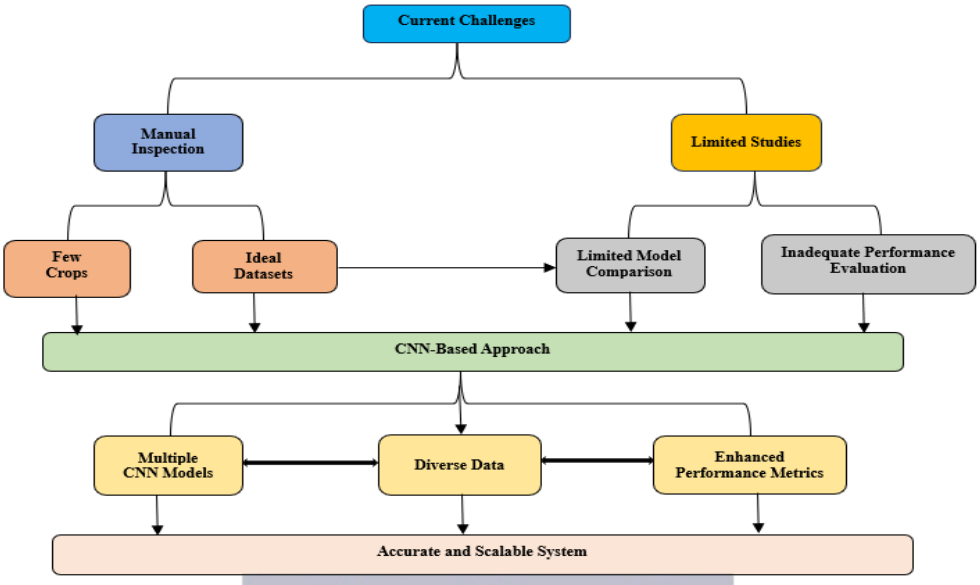


Figure 2. 1 Graphical framework illustrating the existing problem and CNN-based solutions for crop disease detection.

2.2 Review Methodology

This review was conducted through a systematic search of relevant literature across major academic databases, including Scopus, Web of Science, ScienceDirect, PubMed, ResearchGate, and Google Scholar. The search targeted studies published between 2013 and 2026, focusing on recent advancements in the application of CNNs for crop disease detection and classification. To ensure the quality and relevance of the included studies, the following inclusion criteria were applied: publications must be peer-reviewed journal articles; the language of publication must be English; the studies must directly address the application and effectiveness of CNNs in the detection and classification of diseases affecting cocoa, plantain, and cassava; and studies must fall within the specified publication window of 2013 to 2026. Articles were initially screened based on their titles and keywords to assess their relevance to the research objectives. The first round of selection included papers that aimed to solve the problem of crop disease detection using CNN and DL techniques, particularly for early disease identification in the aforementioned crops. Studies that did not employ CNN or DL-based methods for plant disease detection were excluded from further consideration. This method

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ensured that the review concentrated on the most pertinent and methodologically consistent contributions in the field.

This study uniquely evaluates multiple CNN architectures—ResNet-101, AlexNet, DenseNet-201, GoogLeNet, and DarkNet-53—across diverse crop datasets, including cassava, plantain, and cocoa leaves and pods. Unlike prior research that focuses on a single crop, a single model, or idealized datasets, this work offers a comprehensive assessment of model performance, effectiveness, and practical applicability within real-world agricultural contexts. The selected CNN architectures are widely adopted and have demonstrated high performance in image classification tasks. Cassava, plantain, and cocoa were chosen due to their economic importance in tropical regions and their prominence in recent studies, enabling meaningful comparative analysis. Consistent evaluation criteria, including train-test splits and performance metrics such as accuracy, precision, recall, and F1-score, were employed to ensure comparability of results across studies.

2.3 Research Strategy

Recent progress in CNN-based crop disease detection has largely been confined to single-crop scenarios or controlled datasets. Critical gaps remain, as few studies systematically compare multiple CNN architectures under different train-test splits or assess performance across diverse crops in real-world conditions, motivating the need for broader experimental validation. To ensure a comprehensive and structured literature search, the search terms were systematically selected and categorized into three thematic domains. The first domain encompassed terms related to plant and crop diseases, specifically focusing on cocoa diseases, cassava diseases, plantain diseases, and general plant disease detection. The second domain covered the use of CNNs and DL within the context of agriculture and plant health monitoring. The third domain included terms associated with technological applications for disease detection in agriculture, such as remote sensing, smart farming, sensor technologies, and

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computer vision. The keywords used in the search queries are presented in Table 2.1. These keywords were combined using Boolean operators such as AND, OR, and NOT to construct precise and inclusive queries that maximized the retrieval of relevant literature across the selected databases. The search was conducted within each database by applying the defined search queries, and the results were refined based on several inclusion parameters. Specifically, the search was limited to studies published between 2013 and 2026, and included review articles, original research papers, and conference proceedings.

Five CNN architectures—ResNet-101, AlexNet, DenseNet-201, GoogLeNet, and DarkNet-53—were rigorously evaluated on cassava, plantain, and cocoa leaf and pod datasets across varying train-test splits. Model reliability and efficacy were comprehensively assessed using accuracy, precision, recall, and F1-score. Furthermore, the scope of the search was narrowed by selecting specific subject areas relevant to the study, including Engineering, Computer Science, Agricultural and Biological Sciences, Artificial Intelligence (AI) in Agriculture, Sensors, Smart Agriculture Technologies, and Computers and Electronics in Agriculture. To further enhance the relevance of the retrieved studies, subdisciplines such as AI and Computer Intelligence were emphasized within the second domain, thereby ensuring a focused exploration of CNN and DL applications in plant disease detection.

Table 2. 1 Keywords Groups Used for the Search Query

Group	**Keywords**
Group 1	Agriculture plant disease detection, crop disease detection, leaf disease detection, cocoa plant disease, cassava disease detection, plantain disease detection, cocoa disease detection, and cocoa pod.

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Group 2	Artificial intelligence, Deep Learning, computer vision, image classification, Convolutional Neural Networks, and technology digital agriculture.

2.4 State-of-the-Art CNN Architectures

The work of Andrew et al. (Wlodarczak, 2019), which addresses the recognition of foliar diseases in crops using DL models, especially pre-trained CNN models like Inception V4, ResNet50, VGG-16 and DenseNet-121 stands out among the several studies reviewed in the introduction section that deal with the usage of DL in crop disease detection. The utilized dataset was PlantVillage (Wlodarczak, 2019), comprising 38 classes and 54,305 pictures. They used hyperparameter optimization and standardization methods to enhance accuracy and mitigate overfitting. DenseNet121 attained the best accuracy (99.81%) in the multiclass classification of agricultural crop diseases, emerging as the most appropriate model for this particular task. Sanga, Mero, and Machuve (Ramcharan et al., 2024) also concentrated on binary classification models, but they did not compare DL models or do a multiclass analysis.

However, relevant studies on the use of DL in other crops have been found and are detailed here. A deep meta-architecture that tackles class imbalances and false positives was presented by Blanc-Talon et al. (Blanc-Talon et al., 2020), who concentrated on using DL approaches in real-world field settings. Improvements in disease diagnosis in actual field circumstances were attained when the team tested their approach on a dataset of tomato diseases. Jadhav et al. (Jadhav et al., 2020) employed pre-trained CNN models, namely GoogleNet and AlexNet, with the help of transfer learning to identify three prevalent diseases in 649 photos of soybean leaves. AlexNet and GoogleNet achieved accuracy of 98.75% and 96.25%, respectively. Using the PlantVillage dataset, Atila et al. (Atila et al., 2020) also applied the EfficientNet model to categorize a number of diseases in the leaves of potato, orange, raspberry, strawberry, pumpkin,

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soybean, maize, peach, tomato, and grape. They trained several EfficientNet versions (B0 to B7) and evaluated how well they performed in comparison to advanced models like Inception V3, VGG16 and ResNet50. The EfficientNetB4 and B5 models outperformed the others, with mean accuracy of 99.97% and 99.91%, respectively. The effectiveness of EfficientNet for the multiclass classification of crop diseases and the probability for early detection was addressed. These state-of-the-art CNN architectures demonstrate significant advancements in feature extraction, accuracy, and scalability, positioning them as highly effective tools for automated crop disease detection in modern precision agriculture.

2.5 The Need for Advanced Detection Methods

During pandemic situations like COVID-19, nations depended on the advanced technologies to prevent and address the issues to reduce the transmission of the diseases (Harakannanavar et al., 2022). Most current methods of plant leaf diagnosis rely on visual inspection of the plants by agricultural experts. Once symptoms have manifested, efforts can be taken to mitigate the spread of the diseases (Owomugisha et al., 2020). In certain instances, the indicators can solely be discerned in segments of the electromagnetic spectrum that are imperceptible to humans (Min, 2024). Most diseases, however, produce some form of expression within the visible range (Kompalli et al., 2022). Some diseases may exhibit the same color yet possess different shapes, whilst others may display different colors but share identical shapes (Vasavi et al., 2022). Farmers may face increased costs due to the need for more extensive and aggressive control measures when diseases are identified late, impacting their income stability.

Some plant diseases persist in the soil or plant debris, posing long-term risks to future crops if not managed timely (Abokyi et al., 2020). The integration of automated methodologies into agriculture aims to improve the precision and efficiency of diseases recognition processes through advanced techniques. Significant advancements in DL algorithms have enabled the detection and recognition of objects within photos. DL methodologies have lately been

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investigated in many agriculture and farming practices following their successful application in multiple domains (Tugrul et al., 2022). A survey of research initiatives that use CNN, a type of DL, to address various plant disease detection concerns are highlighted in this study (Shoaib et al., 2023). DL has demonstrated significant potential and success across multiple domains of application (Ahmed et al., 2023). Automated detection options for plant diseases are faster, inexpensive and less time-consuming method compared with the traditional methods such as naked-eye observation. Recent advancements in DL indicates that hybrid CNN–Transformer models and multimodal learning frameworks enhance plant disease detection by integrating localized feature extraction, global contextual modeling, and complementary data sources, leading to a more accurate, robust, and timely identification of complex disease patterns (Assudani & Krishna, 2025).

2.5.1 Early Methods of Disease Detection

The detection of plant diseases has a long history, dating back to ancient agricultural practices (He et al., 2021). Traditionally, farmers relied on their own observations and experiences to identify and manage plant diseases as shown in Fig. 2.2. This method was largely based on visual inspection of plants for symptoms such as discoloration, spots, wilting, and other visible signs of distress (John et al., 2023). Farmers used their knowledge of local conditions and plant behaviors to diagnose disease problems and implement remedies, which often included manual removal of diseased plants, crop rotation, and the use of natural pesticides (Imoro et al., 2019). Even before the formal establishment of plant pathology, there were significant early scientific observations that contributed to the understanding of plant diseases (Moral et al., 2023). Early farmers also recognized the importance of environmental factors in the occurrence and spread of plant diseases. They observed that certain weather conditions, such as prolonged wet periods or unusually dry seasons, could influence disease outbreaks (Pokhrel, 2021). This knowledge

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helped them develop and adopt agronomic strategies such as adjusting planting times or choosing resistant crop varieties to mitigate risks of disease outbreak.

While early conventional methods of disease detection and management were innovative and practical, they had significant limitations. Visual inspection was highly subjective and relied on the individual farmer's knowledge and experience, leading to potential inaccuracies. Without advanced tools, it was difficult to accurately diagnose the specific pathogen causing a specific plant disease (Caliendo et al., 2013). Many traditional practices were reactive which involved addressing symptoms after they appeared rather than preventing disease onset. Traditional knowledge was often localized, limiting its applicability to different regions with varying climates and plant species (John et al., 2023). The development of microscopes allowed scientists to observe pathogens directly, and the discovery of microorganisms as causative agents of disease revolutionized plant disease diagnostics. This period marked the beginning of a more systematic and scientific approach to understanding and managing plant diseases, setting the stage for the advanced techniques used today (Mehetre et al., 2021)



Figure 2. 2 Traditional visual inspection of plant disease detection by farmers. (Author's original photograph)

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2.6 Comparison of Traditional Methods and Convolutional Neural Networks

Traditional crop disease detection methods, such as visual inspection and laboratory testing, have been the cornerstone of agricultural practices for decades. However, these methods come with limitations that can hinder timely and accurate diagnosis (John et al., 2023). Visual inspection relies heavily on the expertise and experience of the observer, which can lead to inconsistencies and human error. Additionally, this method is labour-intensive and time-consuming, particularly in large-scale farming operations (Neethirajan, 2023). Laboratory testing, while more accurate, often involves costly and complex procedures, requiring specialized equipment and trained personnel. This process can be slow, delaying the implementation of necessary interventions to prevent the spread of disease (Regan & Forsman, 2006). In contrast, CNNs offer a modern, technology-driven approach to crop disease detection that addresses many of the shortcomings of traditional methods. CNNs automatically identify and extract relevant features from images, providing consistent and objective analysis without the biases associated with human inspection. This automation allows for rapid processing of large volumes of data, enabling real-time disease detection and immediate response. CNNs are also highly scalable, making them suitable for both smallholder farmers and large agricultural enterprises (Bagga & Goyal, 2024).

CNN-based approaches are robust to variations in scale, rotation, and translation of images, which is particularly useful in agricultural contexts where plants may exhibit different symptoms and orientations. This robustness ensures that CNNs can accurately identify diseases under varying environmental conditions, something that is challenging for traditional methods. Additionally, CNNs have demonstrated superior accuracy in disease detection, often outperforming traditional techniques, especially in early-stage disease identification where symptoms may not be visually apparent (Ahmad et al., 2020). While traditional methods have been valuable, they are increasingly being outpaced by the efficiency, accuracy, and scalability

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offered by CNN-based approaches (Chen & Tsou, 2022). The adoption of CNNs in crop disease detection not only enhances the precision of diagnosis but also empowers farmers with timely information, leading to better crop management and higher yields.

2.6.1 Comparative Analysis of Machine Learning Techniques

ML has revolutionized various fields, including agriculture, by providing powerful tools for advanced applications such as plant disease detection (Ngugi et al., 2024). Different ML techniques offer distinct advantages and drawbacks, making it crucial to understand and compare them for effective application (Patil et al., 2024). This section provides an in-depth comparative analysis of the most prominent ML techniques used in plant leaf disease detection: Traditional ML, DL, and CNNs as shown in Table 2.2. The interconnected framework of artificial intelligence, machine learning, neural networks, and deep learning is also visualized in Fig 2.3 (Li et al., 2021). The predominant Traditional ML Techniques include: Support Vector Machines (SVMs), Decision Trees (DT) and Random Forests (RF), and K-Nearest Neighbours (KNN). SVMs are supervised learning models that analyze data for classification and regression analysis. They work by finding the hyperplane that best separates the classes of data points. They are effective in high-dimensional spaces and works well with clear margin of separation. They are mostly versatile with different kernel functions for decision boundaries. Despite the ability to perform these functions, they are computationally intensive for large datasets and less effective with noisy data or overlapping classes (Gillet & Leach, 2007).

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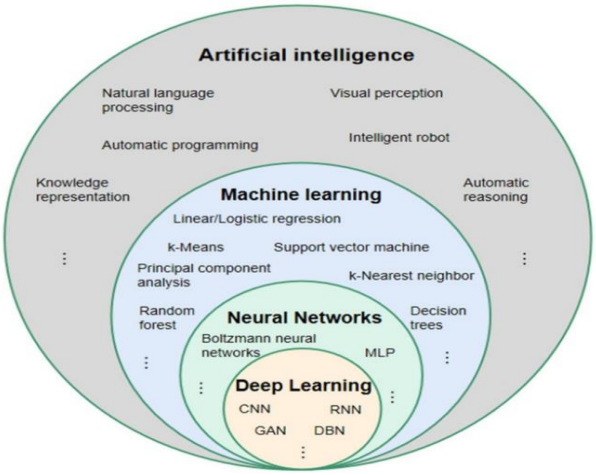


Figure 2. 3 Relationship between artificial intelligence, machine learning, neural network, and deep learning. MLP: multilayer perception; CNN: convolutional neural network; RNN: recurrent neural network; DBN: deep belief network; GAN: generative adversative network.

Decision trees on the other hand split data into subsets based on feature values, creating a tree-like model. Random forests are ensembles of decision trees that improve accuracy and reduce overfitting. Decision trees are easy to interpret and visualize. They have the ability to handle both numerical and categorical data. Generally robust against overfitting with ensemble methods like random forests. While good at all these, they are prone to overfitting if not pruned properly. Random forests can become complex and less interpretable with many trees (Srihith et al., 2023). KNNs are mostly non-parametric method used for classification and regression. They classify data points based on the majority class among its K nearest neighbours. KNNs are simple and easy to implement. They make no assumptions about data distribution and are effective for small datasets with clear clusters. Nonetheless, they are computationally expensive for large datasets and sensitive to irrelevant features and the choice of K (Nadkarni, 2016). Conversely, DL approaches, especially CNNs, represent the most promising method for autonomously acquiring critical and distinguishing characteristics (Kattenborn et al., 2021).

CNNs are specialized Artificial Neural Networks (ANNs) designed for processing structured grid data, such as images. ANNs are computer frameworks modelled after the human brain, comprising layers of interconnected neurones. They are used for various tasks, including

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classification and regression. They are capable of learning complex patterns and have good performance with large datasets. However, they require extensive computational resources and large amounts of labelled data for training (Jaiswal, 2024). On the other hand, CNNs use convolutional layers to automatically and adaptively learn spatial hierarchies of features. They are highly effective for image recognition and classification and reduces the need for manual feature extraction (Yamashita et al., 2018).

Table 2. 2 The comparative analysis between Traditional ML techniques and DL techniques

Aspect	Traditional ML Techniques	DL Techniques
Performance	Generally, performs well with small to medium-sized datasets. Struggles with complex and high-dimensional data.	Excels with large datasets and complex problems. CNNs outperform traditional methods in image-based tasks.
Ease of Use	Easier to implement and interpret. Techniques like decision trees provide clear insights into the decision-making process.	Requires more expertise to design, train, and tune. Models often seen as black boxes, making them harder to interpret.
Computational Requirements	Less demanding in terms of computational resources, suitable for environments with limited processing power.	Requires significant computational power and specialized hardware (e.g., GPUs) for training, especially for large and complex models like CNNs.
Data Requirements	Performs adequately with smaller datasets and less labelled data.	Requires large amounts of labelled data to achieve high accuracy, which can be a limitation in data-scarce environments.
Techniques Covered	SVMs, DT, RF, KNN	ANN, CNN
Feature Extraction	Often requires manual feature extraction and selection.	Automatically learns and extracts features from raw data, especially in CNNs for image data.
Interpretability	Generally, more interpretable and easier to understand.	Often less interpretable, making it harder to understand the decision-making process.

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To further elucidate the effectiveness of CNNs in crop disease detection, Table 3 presents a comparative analysis contrasting CNNs with conventional classification methods and traditional image processing combined with machine learning. This comparison evaluates their advantages, limitations, and applicability within agricultural contexts.

2.6.2 Comparative Analysis of Model Performance Across Studies

To garner deeper knowledge of the global landscape of crop disease detection, Table 2.4 presents a comparative examination of selected research to assess the effectiveness and use of various models in plant disease detection. The analysis focusses on accuracy, a critical performance parameter, as well as the geographical context in which each study was done, providing information about both methodological efficacy and regional research emphasis.

Table 2. 3 Comparative Study of CNN and Existing Classification Techniques for Crop Disease Detection

Technique	Advantages	Disadvantages	Limitations
CNN	High accuracy in image-based classification	Requires large labelled datasets	Performance is sensitive to data imbalance
	Automatic feature extraction	Computationally intensive	Limited interpretability
	Scalable for large datasets	Needs high-performance hardware	
	Robust to variations in image size, orientation, and lighting		
SVM	Effective in high-dimensional spaces	Requires manual feature extraction	Limited ability to capture complex patterns in image data
	Good generalization in small datasets	Slow training on large datasets	
	Works well with clear margin of separation	Not well-suited for multi-class classification without modification	

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KNN	Simple to implement No training phase	Computationally expensive during inference	Not suitable for real-time applications with large datasets
	Good for low-dimensional data	Sensitive to noisy and irrelevant features	
		Poor scalability	
DT	Easy to interpret Requires less data preprocessing	Prone to overfitting Unstable to small variations in data	Poor performance on high-dimensional data like images
	Handles categorical and numerical data		
RF	Reduces overfitting compared to DT	Less interpretable than single trees	Still relies on manual feature engineering
	Handles large datasets well	Can be slower with many trees	
	Can manage missing data		
Traditional Image Processing + ML (Colour, Texture + SVM/ANN)	Useful in specific environments	Limited adaptability Performance drops in complex backgrounds Requires expert-designed features	Not scalable for diverse field conditions Poor generalization in real-world scenarios
	Requires low computational power		
	Human interpretable features		

Table 2. 4 Studies focused on the recognition and analysis of crop diseases

Authors	**Crop(s) & Diseases**	**Location in Africa**	**AI Algorithm and Architecture**	**Accuracy**
Aduwo et. al. (Aduwo et al., 2010)	Cassava (CMD)	Uganda	ML (NB, MLPN, SVM, KNN, DBLVQ)	Classifier accuracies (HSV (74% - 87%), SURF (91% to 98%), SIFT (94% - 98%))
Ramcharan et. al. (Ramcharan et al., 2017)	Cassava (BLS, RMD, GMD, CBSD, CMD)	Tanzania	DL (CNN)	96% (RMD), 95% (GMD), 98% (CBSD), and 96%
Owomugisha et. al. (Owomugisha et al., 2018)	Cassava (CBSD, CMD)	Uganda	ML (KNN, SVM, DT)	70% - 100%

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Selvaraj et al. (Selvaraj et al., 2019)	Banana diseases (8) and pest	Congo, Central Uganda, Burundi, Benin Republic	DL (CNN) – ResNet50, InceptionV2, MobileNetV1	Between 70 and 99%
Sweetwilliams et al. (Sweetwilliams et al., 2019)	Banana (BS)	South Africa	ML (Multilayer Perceptron ANN)	98%
Selvaraj et al. (Gomez Selvaraj et al., 2020)	Banana (BBTD; BXW; HBC and IBP)	DR Congo, Benin	ML (RF and SVM)	99.4% (BBTD); 92.8% (BXW); 93.3% (HBC); 90.8% (IBP); overall 97%
Sanga et al. (Sanga et al., 2020)	Banana (FWB, BS)	Tanzania	CNN (VGG16, Resnet18, Resnet50, Resnet152, InceptionV3)	99%
Sambasivam & Opiyo (Sambasivam & Opiyo, 2021)	Cassava (CGM, CBB, CMD, CBB)	Uganda	CNN	93% (CMD, CBSD, CBB, CGM)
Mankal et al. (Mankal et al., 2021)	Cassava (CMD, CGM, CBSD, CBB)	Uganda	CNN (Inceptionresnetv2, Inceptionv3, Resnet50), OpenCV	83.01% (InceptionV3), 84.77% (InceptionResNetV2), 78.29% (ResNet50)
Sibiya & Sumbwanyambe (Sibiya & Sumbwanyambe, 2019a)	Maize (NCLB, CR, GLS)	South Africa	K Means Clustering, Fuzzy logic	45.21% (Healthy), 54.79% (Diseased)
Sibiya & Sumbwanyambe (Sibiya & Sumbwanyambe, 2019b)	Maize (NCLB, CR, GLS)	South Africa	CNN	99.9% (NCLB), 91% (GLS), 87% (CR), 93.5% (Healthy)
Adedoja et al. (Adedoja et al., 2019)	Apple (Apple scab), Grape (black rot)	South Africa	CNN, NASNet	93.82%

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Adekunle (Adekunle, 2020)	Corn (LRD, LSD, Healthy leaf)	Nigeria	SVM, RF, Neural Networks	93.6% (SVM), 96.7% (RF), 95.3% (NN)
Mohamed (Kulkarni et al., 2020)	Potato (LB, EB, Healthy)	Egypt	CNN	98%

2.6.3 Comparative and Statistical Analysis of CNN Models

A structured comparative analysis is essential for critically evaluating the effectiveness of CNNs in crop disease detection for cassava, cocoa, and plantain. Existing research indicates that model performance varies not only by architecture (Alzubaidi et al., 2021) including AlexNet, ResNet-101, DenseNet-201, GoogLeNet, and DarkNet-53—but also by crop type and dataset characteristics (Wang et al., 2021). Deeper architectures such as ResNet-101 and DenseNet-201 consistently achieve higher classification accuracy due to their capacity to capture complex feature representations (Zhang, 2021), whereas lighter models like AlexNet deliver comparatively lower yet still competitive performance (Zhang, 2025). Among the three crops, studies focused on plantain tend to report the highest accuracies, often exceeding 99% under controlled conditions, as shown in Table 2.5. In contrast, cassava studies exhibit greater variability, reflecting the challenges posed by real-world field data, including background noise and visual similarity among diseases.

In contrast, cocoa-focused studies remain relatively scarce and often report only accuracy, with less attention given to comprehensive metrics such as precision, recall, and F1-score—limiting the scope for robust statistical comparison. This inconsistency in reporting underscores a critical gap in the literature and highlights the need for standardized evaluation frameworks. To address this, Table 2.5 provides a comparative summary of selected studies, synthesizing the reported performance metrics to facilitate clearer identification of model effectiveness, methodological variations, and research gaps across the three crops.

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Table 2. 5 Comparative analysis of CNN-based crop disease detection studies across cassava, cocoa, and plantain

Study/Year	Crop	CNN Model	Performance Metric	Key Findings
(Chilakalapudi & Jayachandran, 2024) in 2024	Cassava	AlexNet	Accuracy 92.80%, Precision 93.40%, Recall 92.20%, F1-Score 94.30%	Moderate performance; struggles with complex patterns
(M & K, 2025) in 2025	Cassava	ResNet-based hybrid	Accuracy 98.15%, Precision 96.02%, Recall 97.96%, F1-Score 97.22%	Hybrid CNN significantly improves performance
(Thanjaivadivel et al., 2024) in 2024	Cassava	AlexNet	Precision 91.00%, Recall 91.00%, F1-Score 91.00%	Balanced performance but limited robustness
(O. et al., 2026) in 2026	Cassava	ResNet hybrid	Accuracy 95.25%, Precision 97.98%, Recall 93.65%, F1-Score 85.71%	High precision but uneven recall across classes
(Alvarado et al., 2025) in 2025	Cocoa	GoogLeNet	Accuracy 95.00%	Effective feature extraction for cocoa pod diseases
(Kumar et al., 2025) in 2025	Cocoa	ResNet-101	Accuracy 97.00%	Deep residual networks improve classification accuracy
(Palkar & Deshpande, 2026) in 2026	Cocoa	DenseNet-201	Accuracy 97.00%	Handles complex cocoa textures effectively
(Rajkumar et al., 2024) in 2024	Cocoa	DarkNet-53	Accuracy 95.00%	Suitable for real-time detection tasks
(Syihad et al., 2023) in 2023	Plantain / Banana	ResNet	Accuracy 99.00%	Very high accuracy under controlled datasets
(Toda & Okura, 2019) in 2019	Plantain / Banana	AlexNet, GoogLeNet	Accuracy 99.35%	Classic CNNs remain competitive
(Santoso et al., 2024) in 2024	Plantain / Banana	DenseNet	Accuracy 99.75%	Highest performance among evaluated models
(Chong et al., 2025) in 2025	Plantain / Banana	AlexNet	Accuracy 88.70%, Precision 89.00%, Recall 89.00%, F1-Score 89.00%	Lower performance compared to deeper CNNs

The findings reveal that while advanced architectures such as ResNet and DenseNet outperform others across most crops, the lack of consistency in evaluation metrics—

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particularly in cocoa research, limits effective cross-study comparisons. This highlights the urgent need for standardized evaluation practices in crop disease detection.

2.7 Architecture of Convolutional Neural Networks

The architecture of CNNs is inspired by the visual cortex's organization in the human brain. It typically consists of multiple layers, each serving a distinct purpose in feature extraction and learning. Fig. 2.4 (Maraaba et al., 2020) provides a visual representation of the CNN architecture, highlighting key layers and processes. The main layers of a CNN are explored in the following section. The input layer receives the raw pixel values of the image. For instance, a color image is typically represented as a three-dimensional array with dimensions corresponding to height, width, and color channels (RGB) (Montesinos-López et al., 2022). Convolutional layers apply a set of filters (or kernels) to the input image to extract features. Each filter is a diminutive matrix that traverses the input image, executing element-wise multiplication and aggregating the results to generate a feature map (Namatēvs, 2017).

This layer is crucial for capturing spatial hierarchies and patterns in the image, such as edges, textures, and shapes. The next layer is the Activation Function. In this layer, the Rectified Linear Unit (ReLU) is widely used due to its simplicity and efficiency. Other functions like Sigmoid and Tanh are also used in specific scenarios. The Activation Function incorporates non-linearity into the network, allowing it to discern intricate patterns unattainable by linear models (Brownlee, 2019). The Pooling Layers function to diminish the dimensionality of each feature map while preserving the most critical information.

Prevalent pooling operations encompass Max Pooling and Average Pooling. Max Pooling identifies the largest value from a collection of values, whereas Average Pooling computes the mean value. This process helps in reducing computational load and overfitting (Zafar et al., 2022). The Fully Connected (FC) Layers connect all neurons in one layer to all neurons in the

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next layer, allowing the network to make final predictions based on the features extracted by previous layers. The output from the last pooling layer is flattened into a one-dimensional vector and passed through one or more fully connected layers (Yamashita et al., 2018). The Output Layer produces the final output of the network, such as class scores in a classification task. For binary classification, a single neuron with a sigmoid activation function is used, while SoftMax activation is used for multi-class classification (Solovyeva & Abdullah, 2021).

2.8 Key Components of CNNs

CNNs consist of several key components that work together to process image data. The input layer receives the image data, which is then passed to convolutional layers that apply filters to detect local patterns. Following this, activation layers introduce non-linearity using functions such as ReLU. Pooling layers are used to down-sample the data, reducing spatial dimensions while preserving important features. Next, fully connected layers flatten and process these features for classification. Finally, the output layer produces the predicted results based on the processed information (Yamashita et al., 2018).

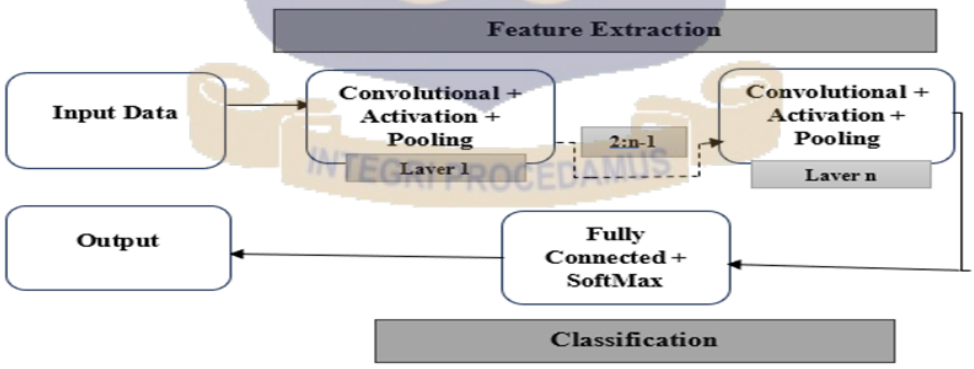


Figure 2. 4 Block diagram of a visual representation of a typical CNN architecture.

These components work together to enable CNNs to automatically identify and extract relevant features from image data, making them highly effective for image classification, object detection, and image segmentation. Fig. 2.5 provides an in-depth visualization of the CNN's layered architecture (Smeda, 2019). In CNNs, small matrices known as filters slide over the

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input image to extract various features. The number and size of these filters are crucial factors that can significantly impact the network's performance (Krichen, 2023). The step size, or stride, with which the filter moves across the input image also plays a vital role. A stride of one result in a dense feature map, capturing more details, while a larger stride reduces the spatial dimensions, leading to a more compressed representation (Dertat, 2017). Additionally, padding techniques are used to control the spatial dimensions of the output feature map by adding extra pixels around the input image. Common padding techniques include 'valid' padding, which means no padding is applied, and 'same' padding, which pads the input to ensure the output dimensions remain the same as the input dimensions (Alrasheedi et al., 2023). Deeper networks can capture more complex features but require more computational resources. Also, deeper networks, which include more layers, can capture more complex features but come with the trade-off of requiring more computational resources. As a result, careful consideration of filter size, stride, padding, and network depth is essential to optimize the performance of CNNs in feature extraction and image analysis tasks (Zhao et al., 2024).

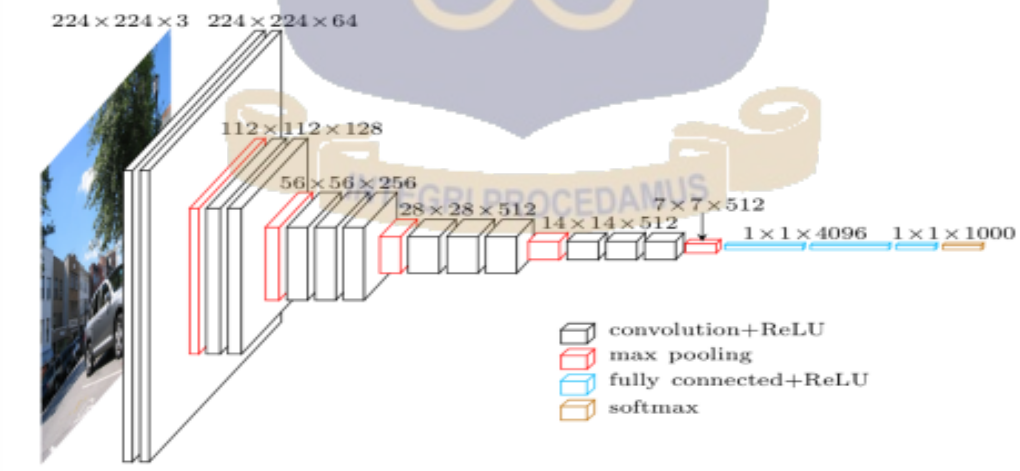


Figure 2. 5 Understanding the visualization of the CNN's layered architecture.

2.9 Advantages of CNNs in Plant Leaf Disease Detection

CNNs can automatically learn and extract relevant features from images without manual intervention, reducing the time and effort required for feature extraction (Yamashita et al.,

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2018). CNNs are robust to variations in scale, rotation, and translation of images. This makes them ideal for detecting diseases in plant leaves, which may exhibit different symptoms and orientations (Bagga & Goyal, 2024). CNNs have achieved remarkable accuracy in various image recognition tasks, outperforming traditional machine learning techniques in plant disease detection. Their ability to capture complex patterns and relationships in data enhances diagnostic precision (Guo, 2023). CNN architectures can be easily scaled and adapted to different tasks and datasets. As these technologies continue to evolve, they hold the potential to revolutionize agricultural practices, particularly in regions where timely and accurate disease detection is crucial for crop yield and food security (Abiri et al., 2023). The prompt detection and accurate identification capabilities of AI significantly contribute to reducing crop losses. This enables farmers to quickly identify and address diseases and pests, thereby curtailing their spread and minimizing damage.

The preservation of crops leads to increased yields and, therefore, more steady income for farmers. In a nation where a significant segment of the populace depends on agriculture for their sustenance, this can greatly influence communal welfare and economic stability (Qange et al., 2025). The guarantee of a more reliable and secure yield enables farmers to strategize for the future, invest in their operations, and enhance their overall quality of life. AI-powered detection systems allow farmers to utilize resources like pesticides and fertilizers more effectively. By focusing exclusively on the impacted regions, rather than administering treatments indiscriminately, farmers can markedly diminish waste and enhance resource utilization. This precision agriculture approach not only conserves vital inputs but also lowers production costs, leading to more sustainable farming practices (Pandey & Mishra, 2024). For farmers, who often face resource constraints, such efficiency can translate into better crop management, improved yields, and enhanced profitability, all while reducing the environmental impact of their farming activities.

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2.10 Cassava, Plantain, and Cocoa Leaf and Pod Image Datasets

The availability and quality of image datasets are crucial in advancing the detection of diseases in economically significant crops like cassava, plantain, and cocoa (Ahmad et al., 2023). These datasets often include a wide array of images depicting leaves and pods affected by various diseases, serving as a foundation for training CNNs. The image quality within these datasets is a significant factor, as high-resolution images allow for the precise identification of disease symptoms. For instance, (Ramcharan et al., 2017) used Inception v3 CNN model CNN to detect Cassava Mosaic Disease and Cassava Brown Streak Disease, achieving accuracy rates over 90% even in complex field environments (Ramcharan et al., 2017). The study by Nandhini et al. (Nandhini et al., 2021) investigated and compared different data augmentation and feature selection techniques that improve the accuracy of classifying and detecting diseases in plantain trees. Harvyanti, et al. (Harvyanti et al., 2023) Compared four CNN architectures: DarkNet, SqueezeNet, AlexNet, and a customized CNN to detect cocoa plants infected with VSD.

Similarly, datasets for plantain and cocoa often include images of both healthy and diseased leaves and pods, annotated to reflect various stages and types of infections. Annotations in these datasets are typically detailed, providing information on the type of disease, severity, and sometimes the stage of infection (Maguire & Hochberg, 2017). These annotations are essential for the accurate training of CNN models, allowing the algorithms to distinguish between subtle differences in disease symptoms. However, challenges persist, such as the need for standardized data collection methods to ensure consistency across datasets. Variability in image quality, differences in annotation detail, and the need for more comprehensive datasets that cover a broader range of diseases and environmental conditions are ongoing concerns in this field (Luca et al., 2022).

The use of such datasets presents challenges, particularly in ensuring that the images represent the diversity of real-world conditions, such as varying lighting, angles, and occlusions. The

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development of these datasets often requires collaboration between agronomists, data scientists, and local farmers, ensuring that the images collected are representative of the actual challenges faced in the field (Macedo et al., 2024). Despite these challenges, the continued refinement and expansion of cassava, plantain, and cocoa leaf and pod image datasets remain critical to improving disease detection accuracy in diverse agricultural settings (Mora et al., 2024).

2.11 CNN–Transformer and Multimodal Models for Disease Detection

Recent improvements in computer vision for plant disease detection increasingly highlight hybrid CNN–Transformer architectures and transformer-based multimodal frameworks, as these methodologies mitigate significant limitations of conventional DL models (Upadhyay et al., 2025). Hybrid CNN–Transformer models integrate the superior local feature extraction abilities of CNNs with the global attention and long-range dependency modeling of Transformers, facilitating enhanced accuracy and robustness in image classification and disease detection in complicated environments (Lucas et al., 2025). For instance, the study conducted by (Jain et al., 2025) illustrates that a CNN-Transformer based automated disease detection system can classify crop diseases from leaf images with an accuracy of 88–90% and facilitate quick inference, hence ensuring timely and reliable diagnosis.

The findings indicated significant possibilities for enhancing sustainable agricultural practices through informed decision-making and less reliance on manual (Fig. 2.1) inspections and excessive chemical applications. (Jia & Wang, 2025) proposed ConvTransNet-S model achieves high-accuracy crop disease recognition while maintaining low computational complexity, demonstrating 98.85% accuracy on the PlantVillage dataset and strong performance in complex field environments. The results confirm that the hybrid CNN–Transformer design effectively improves robustness, efficiency, and discrimination of disease features, making it well suited for real-world intelligent agricultural applications.

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Simultaneously, transformer-based multimodal frameworks integrate visual information with supplementary data sources, including spectral, environmental, or contextual inputs, enabling models to discern hidden physiological and environmental signals that are not apparent in RGB images alone (Fareed et al., 2025). In the study by (Padshetty & Umashetty, 2024), it was discovered that the hybrid CNN–Transformer model achieves high crop disease classification performance by effectively combining local feature extraction and global contextual modeling, resulting in an accuracy of 98.92% across multiple datasets. These results demonstrate that the integrated attention and feature fusion mechanisms significantly enhance classification reliability, supporting the model's effectiveness for practical disease diagnosis.

Similarly, (Zhang et al., 2025) proposed multimodal DL model achieves robust and accurate jujube disease detection in challenging desert environments by effectively fusing image and sensor data, outperforming state-of-the-art detection methods across multiple performance metrics. The results demonstrate strong accuracy, robustness, and practical applicability for large-scale agricultural disease monitoring under complex environmental conditions. Collectively, these methodologies augment detection precision, enhance generalization across diverse situations, and provide earlier and more dependable plant disease diagnosis in practical agricultural environments.

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2.12 Challenges and Limitations in Crop Disease Detection

Crop disease detection using CNNs is a promising approach but confronts numerous obstacles and limitations that can impact the precision and efficacy of the models. One of the primary challenges is image quality (Iftikhar et al., 2024). High-resolution images are crucial for accurately capturing the subtle visual differences between healthy and diseased plants. Poor image quality, caused by factors like inconsistent lighting, low resolution, and background noise, can lead to misclassification and reduce the reliability of the CNN model (Guerri et al., 2024). To mitigate this issue, pre-processing techniques such as image enhancement, noise

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reduction, and data augmentation can be employed to improve the quality of images used for training the models (Maharana et al., 2022).

Another significant challenge is dataset size. Large and diverse datasets are essential for training CNNs to recognize various disease patterns across different crops and environmental conditions. However, creating such datasets can be time-consuming and resource-intensive, often leading to the use of smaller, less representative datasets that may not capture the full range of possible disease symptoms. This limitation can be addressed through data augmentation techniques, which artificially augment the dataset by generating altered versions of existing images, such as rotations, flips, and color adjustments. Additionally, transfer learning, in which models are pre-trained on extensive datasets, generic image datasets are meticulously refined for specific purposes in agricultural datasets, this can help overcome the limitations of smaller datasets (Ngugi et al., 2024). Class imbalance is another challenge that frequently arises in crop disease detection datasets. In many cases, images of healthy plants are far more abundant than those of diseased plants, leading to a skewed dataset where the model may become biased toward predicting the majority class. This imbalance can result in poor detection rates for rarer diseases, which are often the most critical to identify. Methods such as oversampling the minority class, under sampling the majority class, or employing weighted loss functions can effectively mitigate class imbalance, ensuring that the CNN model is better equipped to recognize diseases in real-world scenarios (Sambasivam & Opiyo, 2021).

Beyond these technical challenges, key limitations stem from the limited applicability of CNN models in real-world agricultural environments. Much of the existing research—especially studies involving cassava and plantain—relies on controlled or semi-controlled datasets, where images are captured under ideal conditions (Atanbori et al., 2019). In practical farm settings, however, factors such as variable illumination, occlusion from other leaves, the presence of multiple diseases on a single plant, and complex backgrounds significantly reduce model

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performance (Arora & Gautam, 2026). This gap between experimental and real-world conditions undermines the direct deployability of CNN models in the field.

Additionally, the computational demands and resource requirements of advanced CNN architectures pose a major constraint, particularly in developing regions where cassava, cocoa, and plantain are widely grown and access to high-performance computing infrastructure is limited. Despite the high accuracy achieved by these models, a divide persists between their real-world agricultural deployment and practical model development—especially for smallholder farmers who may rely on mobile or low-power devices. CNNs offer powerful tools for crop disease detection, but these challenges must be carefully managed to ensure a more accurate and reliable disease detection models that can be effectively applied on agricultural farms.

2.13 Future Directions and Opportunities in Crop Disease Detection

The future of crop disease detection lies in the integration CNNs with other advanced technologies, such as drones and Internet of Things (IoT) sensors, which together could revolutionize the agricultural industry. One of the promising avenues is the use of drones equipped with high-resolution cameras for aerial surveillance of large agricultural fields. By combining CNNs with drone technology, it is possible to quickly and accurately identify disease outbreaks over vast areas that would be time-consuming and labour-intensive to monitor manually. Drones can capture images from multiple angles and heights, providing a comprehensive view of the crop's health. These images can then be processed in real-time by CNN models to detect diseases, allowing for timely interventions (Slimani et al., 2024).

Another key area of future research is the integration of CNNs with IoT sensors. IoT devices, such as soil moisture sensors, temperature sensors, and humidity sensors, can provide crucial environmental data that, when combined with visual data from CNNs, can offer a more holistic

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view of crop health. For example, changes in soil moisture levels might correlate with certain diseases, and by integrating this data, CNNs can improve their predictive accuracy. This multi-modal approach would enable farmers to not only detect diseases but also understand the environmental conditions that contribute to their spread, leading to more targeted and effective disease management strategies (Rajak et al., 2023). Real-time processing and cloud-based platforms are likely to play a significant role in the future. By leveraging cloud computing, data collected from drones and IoT sensors can be processed and analyzed in real-time, allowing farmers to receive immediate feedback on the health of their crops. This could lead to the development of smart farming applications that provide farmers with actionable insights and recommendations, thus enhancing decision-making and productivity (Alazzai et al., 2024).

Again, collaborative research and open-source platforms could further advance the field by enabling the sharing of data, models, and insights across the agricultural community. This collaborative approach would accelerate innovation, improve the robustness of CNN models, and ensure that even smallholder farmers have access to cutting-edge technologies for crop disease detection (Tantalaki et al., 2019). CNNs' integration with pioneering technologies presents a transformative opportunity to enhance crop disease detection, making it more precise, efficient, and accessible to farmers, ultimately contributing to global agricultural sustainability.

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CHAPTER THREE

MATERIALS AND METHODS

3.1 Introduction

This chapter outlines the methodology employed in this study to evaluate the efficacy of CNNs for crop disease detection, specifically in cassava, plantain, and cocoa. The research methodology consists of several key components, including the selection and preparation of datasets, the implementation of CNN architecture, and the evaluation of model performance using various performance metrics. Building upon the insights gained from the literature review, this chapter provides a detailed approach to training and validating the CNN models. The methodologies discussed herein aim to address the challenges in accurately identifying diseases in crop leaves and pods, which is crucial for enhancing agricultural productivity. The following sections delve into the data collection process, the image pre-processing steps, the CNN model configurations, and the performance evaluation criteria used to assess model effectiveness.

3.2 Study Area

The experimental site for this study covers parts of three regions in Ghana, namely Eastern, Greater Accra, and Central. Data collection was conducted within specific agricultural clusters to ensure a diverse dataset of leaf and pod images. These sites include: The communities of Budu (West Akim Municipal) and New Tafo (Abuakwa North), specifically centered around latitude 6° 13' 21.873" N and longitude 0° 21' 46.064" W. The vicinities of Osu and Labadi, located at latitude 5° 33' 36.837" N and longitude 0° 9' 27.508" W and the communities of Bawjiase within the Awutu Senya district, positioned at latitude 5° 24' 13.646" N and longitude 0° 31' 5.367" W. These communities were selected due to the high density of the target test crops and the high natural prevalence of the leaf diseases under investigation. These locations

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span three distinct agro-ecological zones, providing the necessary environmental diversity to evaluate the CNN models' efficacy against varying background complexities and lighting conditions. This geographical spread ultimately facilitates a comprehensive comparative analysis of model performance across diverse geographic and climatic variables. The map below in Fig. 3.1 highlights the research sites selected for this study, showcasing the specific regions and communities involved in data collection as well as varying environmental conditions that may influence crop disease manifestations.

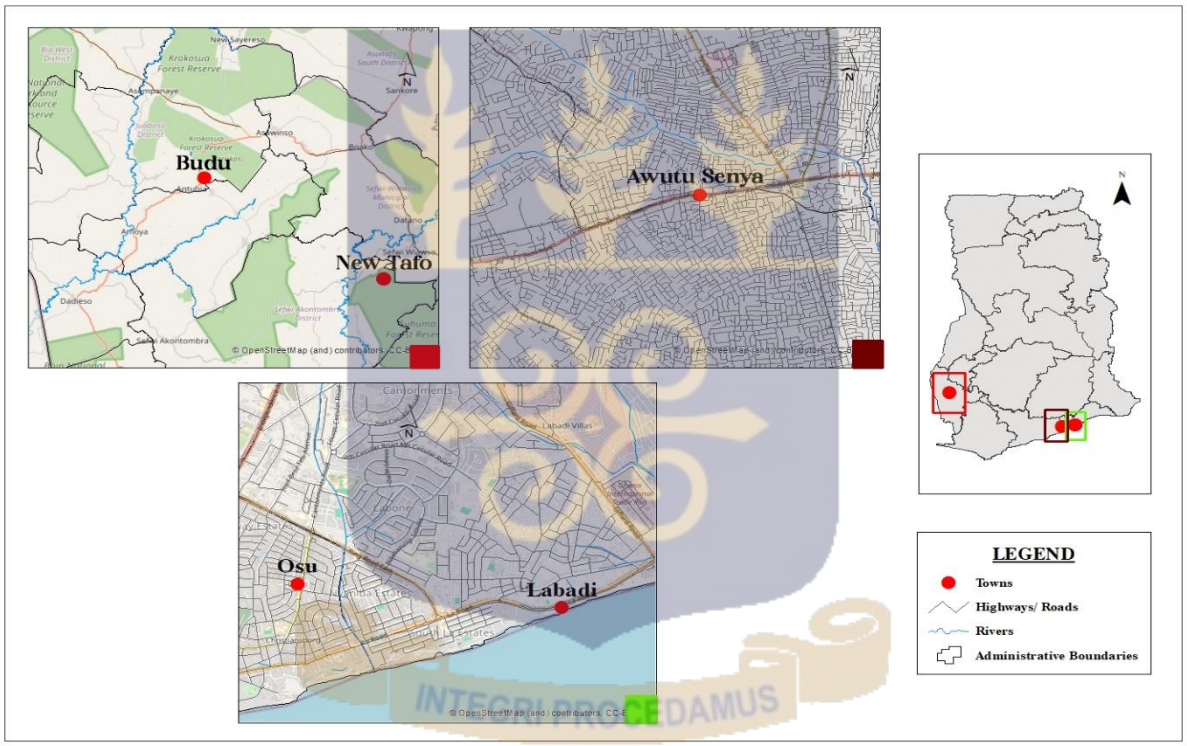


Figure 3. 1 Map of Ghana Showing the Study Regions

3.3.0 Research Design and Approach

3.3.1 Research Methodology

This research adopted a quantitative research paradigm, which emphasized the measurement and analysis of numerical data to draw conclusions. The use of quantitative methods is appropriate for assessing the performance of CNNs in crop disease detection (Leite et al., 2024). Thereby using objective metrics such as accuracy, precision, recall, and F1 score, the

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study provides measurable insights into the effectiveness of the models in classifying diseased and healthy plant leaves and pods.

Quantitative research enables a precise and replicable analysis, which is essential for validating the findings and offering scalable solutions for crop disease detection (Zyoud et al., 2024). The research design allows for the objective comparison of various CNN models' performances, providing concrete evidence of their strengths and weaknesses in agricultural applications.

3.3.2 Experimental Design

This study employed an experimental research approach, wherein variables were manipulated and controlled to observe their effects on the outcomes. In the context of this research, the two primary independent variables were the type of CNN architecture used (which were, ResNet 101, AlexNet, DenseNet 201, GoogLeNet, and DarkNet-53) and the T-T split ratio considered, while the dependent variables were the performance of these models in terms of disease detection accuracy (Cabanillas-Carbonell & Zapata-Paulini, 2025). The experiment involved training five different CNN models on a dataset of images of cassava, plantain, and cocoa leaves and pods, followed by testing the models on unseen data to evaluate their classification capabilities on two T-T split ratios of 80:20 and 90:10. Fig. 3.2 illustrates the flowchart of the CNN-based plant disease assessment method for cassava, plantain, and cocoa crops employed for the study.

By this experimental design, this study aims to establish cause-effect relationships between CNN architecture and model performance, providing empirical evidence that could inform future agricultural technologies. According to (Tzelepi et al., 2021; Shi et al., 2023), experimental research in DL is crucial for advancing model performance and refining predictive algorithms in agriculture.

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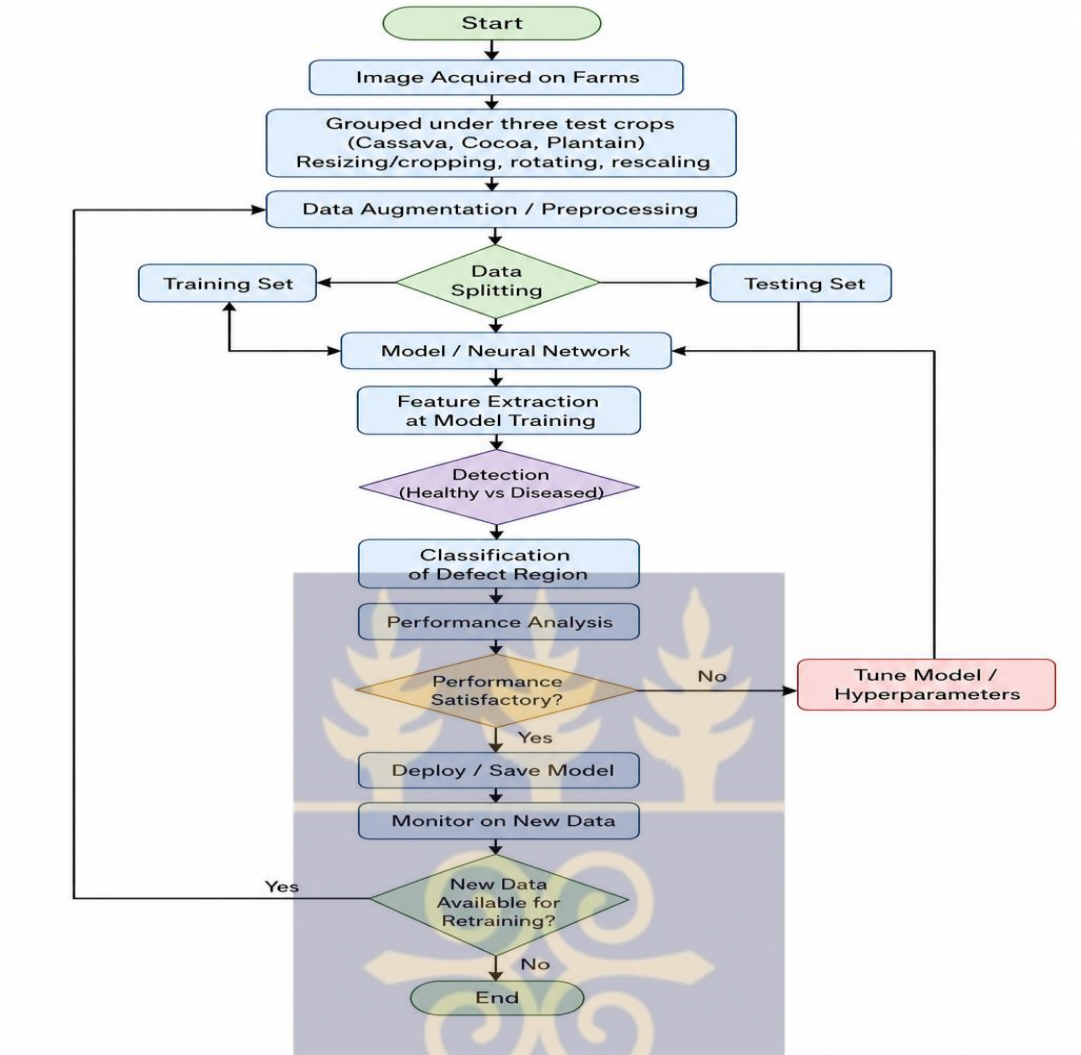


Figure 3. 2 Flowchart of the CNN-based plant disease assessment.

3.3.3 Image Classification Design using Convolutional Neural Networks

The study was designed around the task of image classification, which involved training CNNs to recognize and classify various crop diseases based on image data. Images were captured on the farm using a Digital Samsung WB250F Camera (Samsung Electronics, South Korea), as shown in Fig. 3.3. The camera features a 14.2-megapixel BSI CMOS sensor and an 18x optical zoom lens (24–432mm equivalent). This high-resolution device, equipped with Optical Image Stabilization (OIS) and a maximum resolution of 4320 x 3240 pixels, ensured the capture of sharp, detailed leaf and pod morphologies across varying field lighting conditions. The camera's technical profile was selected to provide consistent, high-fidelity visual data of both

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healthy and diseased leaves of cassava, plantain, cocoa leaves and pods essential for the precise feature extraction and classification required by the CNN architectures.



Figure 3. 3 Digital Samsung WB250F Camera used for field image acquisition.

Fig. 3.4 shows the conceptual framework of the study, illustrating the image capture, processing, and classification pipeline for crop disease detection. The CNN models were tasked with classifying plant leaves and pods into healthy or diseased categories, based on visual features learned from training images according to (Althuniyan et al., 2024). The dataset used for training and testing the models consisted of labeled images of cassava, plantain, and cocoa leaves and pods, captured under controlled conditions to represent both healthy and diseased states.

Image classification tasks are well-suited to CNNs due to their ability to extract hierarchical spatial features, which are essential for distinguishing between different types of diseases and healthy plant tissues (Zhang et al., 2020). CNNs have been widely recognized for their superior performance in image-based tasks, making them an ideal choice for crop disease detection (Ferentinos, 2018). The study will evaluate several different CNN architecture to determine which model provides the most accurate and efficient classification results.

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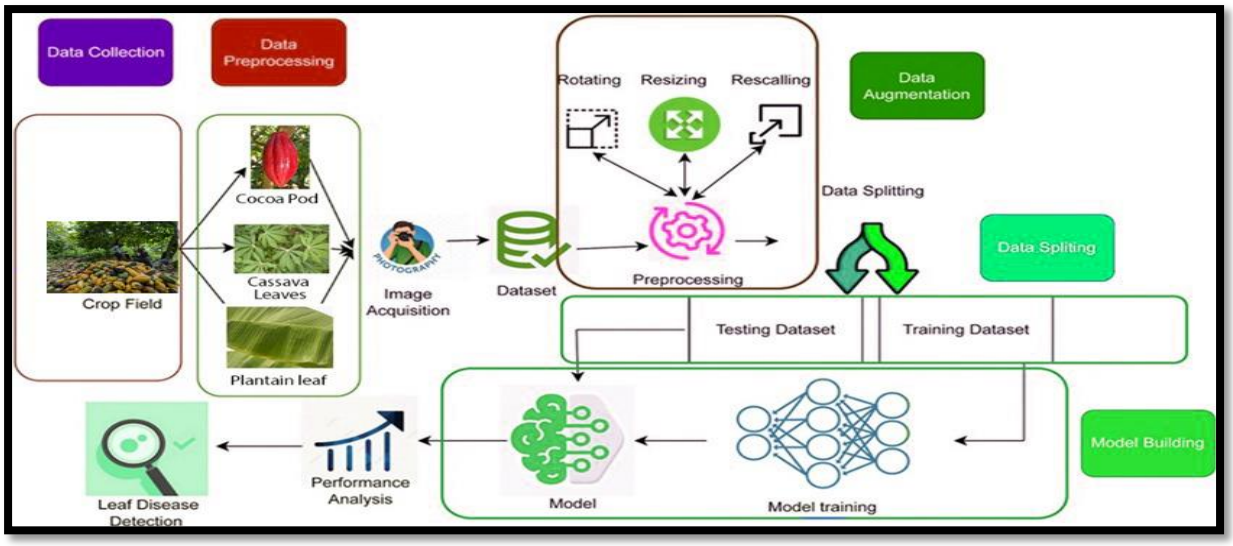


Figure 3. 4 Conceptual Framework for Disease Classification

3.3.4 Justification of the Use of CNNs for Crop Disease Detection

CNNs have proven to be highly effective for image classification tasks, particularly in fields like computer vision and agriculture. The rationale for choosing CNNs in this study is based on their ability to automatically extract important features from images without the need for manual feature engineering (Tripathy & Singh, 2022). In crop disease detection, this is particularly valuable as the symptoms of diseases such as Black Sigatoka, Cassava Mosaic Disease, and Black Pod Disease are often subtle and may vary depending on factors such as plant variety and disease progression (Aregbesola & Owombo, 2014) . CNNs, by virtue of their deep learning architecture, are capable of capturing complex patterns in images, making them highly effective at detecting and classifying these diseases with high accuracy (Haug et al., 2019).

Additionally, CNNs are robust to variations in lighting, orientation, and noise in images, which are common challenges in agricultural field conditions. Studies by (Zhang et al., 2020) and (Haug et al., 2019) emphasize CNNs' ability to generalize well across different types of crops and diseases, making them a versatile tool for agricultural applications. By leveraging CNNs, this study aims to offer an automated, scalable solution for crop disease detection that can be

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implemented across different regions, including sub-Saharan Africa, where crop diseases pose a significant threat to agricultural productivity.

Over the years, CNNs have been successfully employed in similar agricultural contexts, such as detecting diseases in crops like tomatoes, bananas, and wheat (Ferentinos, 2018). These successes reinforce the potential of CNNs in this study to accurately identify diseases in cassava, plantain, and cocoa, thereby contributing to the broader field of precision agriculture. The use of CNNs will also support future applications in integrated pest management, allowing for early detection and timely intervention to mitigate crop losses and enhance food security.

3.4.0 Disease Profile of Test Crops

3.4.1 Cassava (Manihot esculenta)

Cassava (*Manihot esculenta)* is a critical staple crop in Ghana, playing a vital role in food security and serving as a significant source of income for rural households. Known for its resilience to harsh climatic conditions and ability to grow in marginal soils, cassava is a dependable crop across all agroecological zones in Ghana. It is widely consumed in various forms, including gari, fufu, and tapioca, and is increasingly used in industrial applications such as starch production, contributing substantially to the nation's economy.

Ghana cultivates a variety of cassava types, which are broadly classified into traditional landraces and improved varieties. Local landraces, such as *Afisiafi, Bankyehemaa*, and *Esambankye*, are valued for their adaptability to local farming systems and traditional culinary uses (Acheampong et al., 2021). Improved varieties, developed by research institutions like the Crops Research Institute (CRI), include *Ampong, Bankye Botan,* and *Tekbankye* (Yeboah, 2022). These varieties are specifically bred for higher yields, industrial suitability, and resistance to diseases.

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Despite these advancements, cassava production in Ghana faces significant challenges from diseases. These diseases are broadly categorized as fungal, bacterial, and viral. Fig. 3.5 shows the healthy cassava class alongside representative diseases from each category.

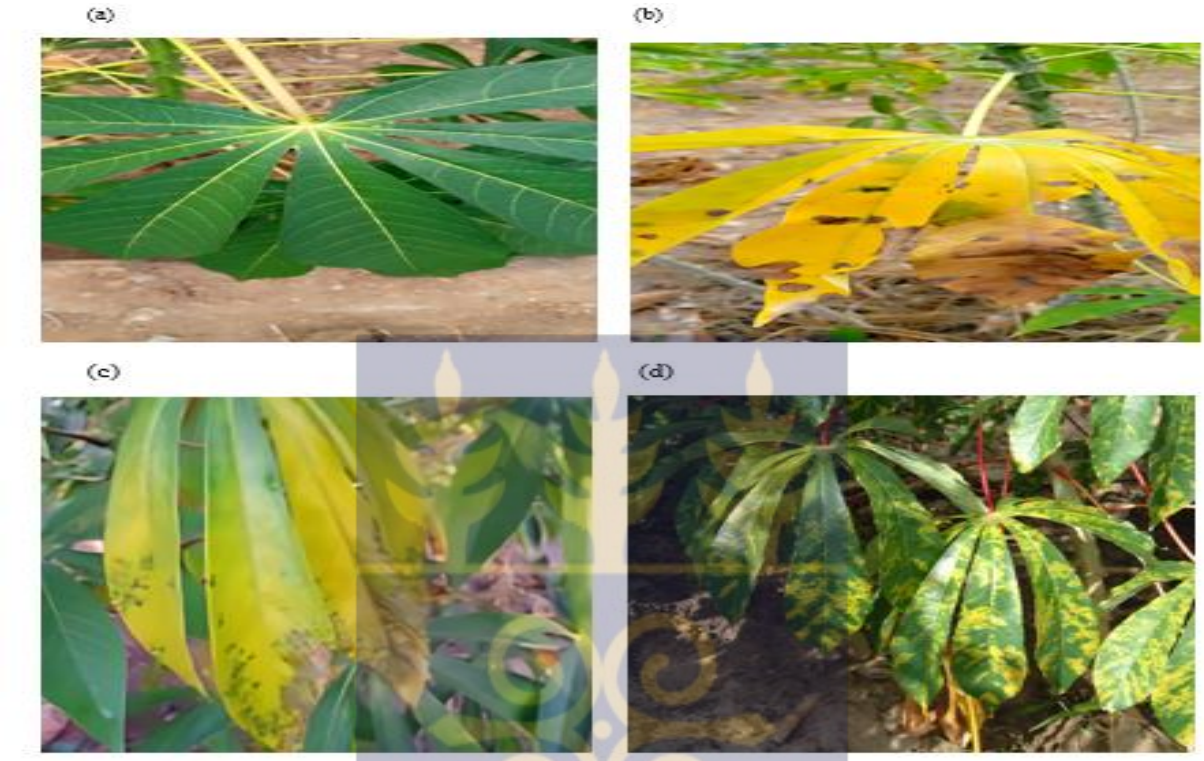


Figure 3. 5 Categorization of cassava diseases: (a) Healthy leaf, (b) Leaf spot (fungal), (c) Cassava bacterial blight (bacterial), (d) Cassava brown streak disease (viral).

Cassava Mosaic Disease, caused by viruses transmitted by whiteflies, is a major constraint, leading to stunted growth and yield loss. Similarly, Cassava Bacterial Blight, caused by *Xanthomonas axonopodis pv. manihotis*, manifests through leaf wilting, stem dieback, and crop failure in severe cases (Zárate-Chaves et al., 2021). It is therefore imperative to address cassava disease concerns through the strategic application of advanced technologies like the CNN models. Table 3.1 below presents the list of cassava diseases considered in this study.

Table 3. 1 Cassava Diseases Categorization

Disease Type	Diseases Affecting Cassava Leaves in Ghana
Fungal Diseases	1. Cassava Anthracnose Disease (CAD)

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	2. Leaf Spot (caused by various fungi, e.g., *Cercospora spp*.) 3. Nutrient Deficiency
Bacterial Diseases	Cassava Bacterial Blight (CBB)
Viral Diseases	1. Cassava Mosaic Disease (CMD) 2. Cassava Brown Streak Disease (CBSD)

3.4.2 Plantain (*Musa paradisiaca*)

Plantain (*Musa paradisiaca*) is a key staple crop in Ghana, widely cultivated across the country's tropical and subtropical regions. It plays a significant role in household food security and income generation, particularly in rural areas. Common varieties grown in Ghana include Apantu, Oniaba, and Asamienu, which are favored for their adaptability to local conditions, high yield, and versatility in culinary applications (CSIR & MOFA, 2012). Plantains are a vital source of carbohydrates and nutrients, forming the basis of traditional dishes such as *kelewele* and *ampesi*. Despite its economic importance, plantain cultivation faces significant challenges from diseases that reduce yield and quality. These diseases are broadly categorized as fungal, bacterial, and viral. Fig. 3.6 shows the healthy plantain class alongside representative diseases from each category.

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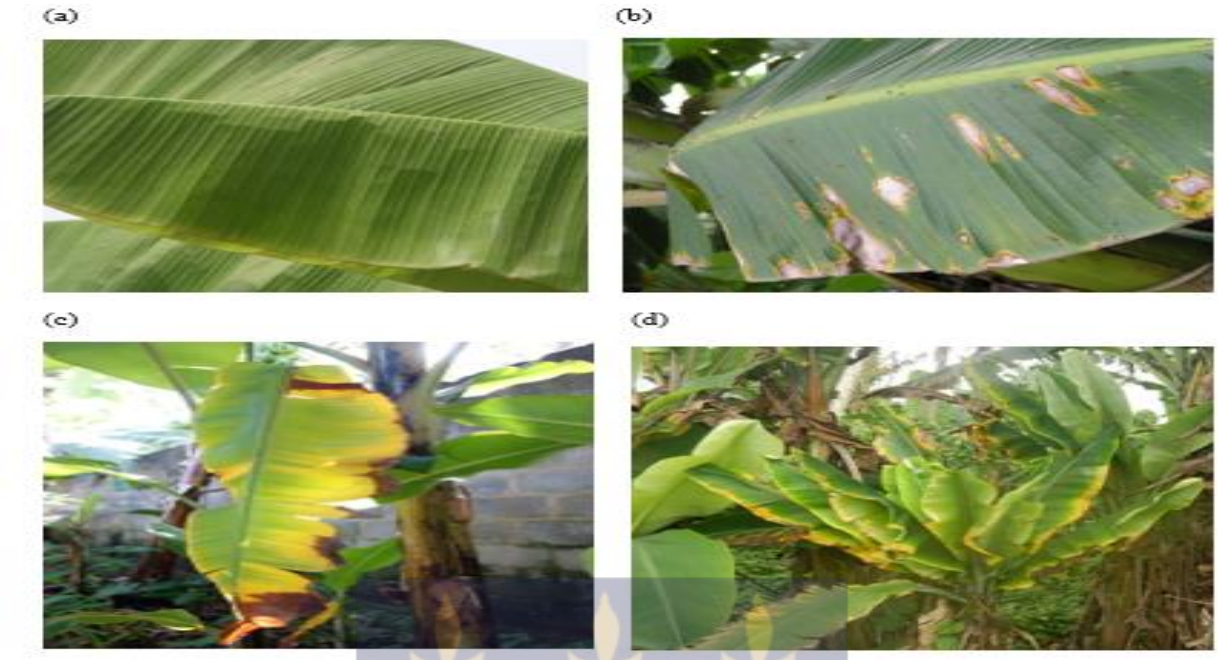


Figure 3. 6 Categorization of plantain diseases: (a) Healthy leaf, (b) Cordana leaf spot (fungal), (c) Xanthomonas wilt (bacterial), (d) Banana Bunchy Top Virus (viral).

Common diseases affecting plantain in Ghana include Black and Yellow Sigatoka (Moses & Woode, 2014). These diseases, if left unchecked, can lead to substantial losses for farmers. Addressing these challenges requires a combination of improved agronomic practices and innovative technological approaches. It is therefore imperative to address plantain disease concerns through the strategic application of advanced technologies like the CNN models. Table 3.2 below presents the list of plantain diseases considered in this study.

Table 3. 2 Plantain Disease Categorization

Disease Type	Diseases Directly Affecting Plantain Leaves in Ghana
Fungal Diseases	1. Black Sigatoka (caused by *Mycosphaerella fijiensis*) 2. Yellow Sigatoka (caused by *Mycosphaerella musicola*) 3. Cordana Leaf Spot (*Cordana musae*)
Bacterial Diseases	Xanthomonas Wilt (caused by *Xanthomonas campestris pv. musacearum*)

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Viral Diseases	Banana Bunchy Top Virus (BBTV)

3.4.3 Cocoa (Theobroma cacao)

Cocoa (*Theobroma cacao)* is a critical cash crop in Ghana, contributing significantly to the national economy and serving as the livelihood foundation for many rural households. Ghana is one of the world's largest cocoa producers, renowned for its high-quality beans (Adams et al., 2023). Cocoa cultivation thrives in the forested regions of the country, including the Ashanti, Western, and Eastern regions, where favorable climatic conditions and rich soils support its growth. Cocoa production is essential for global chocolate manufacturing and also contributes to by-products like cocoa butter and cocoa liquor.

Despite its significance, cocoa farming in Ghana is beset with numerous challenges, particularly diseases that severely impact yield and quality. These diseases are broadly categorized as fungal, bacterial, and viral. Fig. 3.7 shows the healthy cocoa class alongside representative diseases from each category. Common cocoa diseases include Black Pod Disease, Witches' Broom and Cocoa Swollen Shoot Virus Disease (Ameyaw, 2020). These diseases lead to considerable economic losses, affecting both farmers and the broader cocoa value chain.

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Figure 3. 7 Categorization of Cocoa diseases: (a) Healthy cocoa, (b) Black pod disease (fungal), (c) Cocoa pod borer (pest-related), (d) Cocoa swollen shoot (viral).

Given the scale and impact of these diseases, there is a pressing need for advanced technological interventions to improve disease detection and management. CNN models offer a transformative approach to early disease identification and classification, providing accurate and timely diagnostics that enhance cocoa crop management. Table 3.3 below highlights the cocoa diseases analyzed in this study.

Table 3. 3 Cocoa Disease Categorization

Disease Type	Diseases Affecting Cocoa Leaves	Diseases Affecting Cocoa Pods
Fungal Diseases	1. Witches' Broom (*Moniliophthora perniciosa*) 2. Vascular-Streak Dieback (*Ceratobasidium theobromae*) 3. Anthracnose (*Colletotrichum spp.)*	1. Black Pod Disease (*Phytophthora spp.)* 2. Frosty Pod Rot (*Moniliophthora roreri*) 3. Anthracnose (*Colletotrichum spp.)*

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Viral Diseases	Cocoa Swollen Shoot Virus (CSSV)	
Physiological Disorders		Cherelle Wilt
Pest-Related Issues		Cocoa Pod Borer (*Conopomorpha cramerella*)

3.5 Data Collection Methods

3.5.1 Image Dataset Collection

The first step in collecting data for this study involved collaborating with local farmers and agricultural research institutions. These stakeholders provided access to fields of cassava, plantain, and cocoa crops and helped identify diseased and healthy plants for image capture as shown from Figs. 3.8 to 3.10. The collaboration also ensured that the collected data accurately reflected real-world farming conditions, including the variability in disease symptoms across regions and crop varieties. Images were captured using the high-resolution digital camera to document both diseased and healthy leaves and pods. Photography sessions were conducted in natural lighting conditions to mimic real-life scenarios while minimizing artificial lighting effects. The captured images were cataloged with metadata such as the type of crop, disease symptoms, and geographic location to facilitate later analysis according to studies by (Baiju et al., 2025). To enhance the robustness of the dataset, images were captured from multiple angles and distances, ensuring diversity in visual perspectives. This diversity is critical for training models to recognize disease symptoms under varying conditions, such as changes in lighting, orientation, and scale (Misra & Mall, 2024). Resolutions were standardized for consistency, and images of varying sizes were included to simulate real-world input variability.

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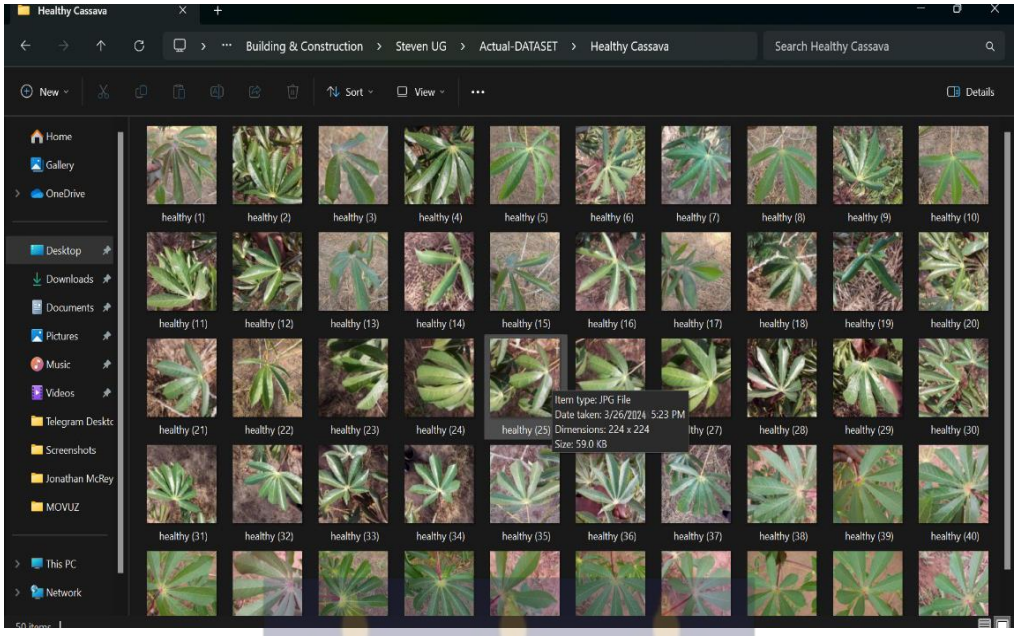


Figure 3. 8 Dataset containing Cassava images

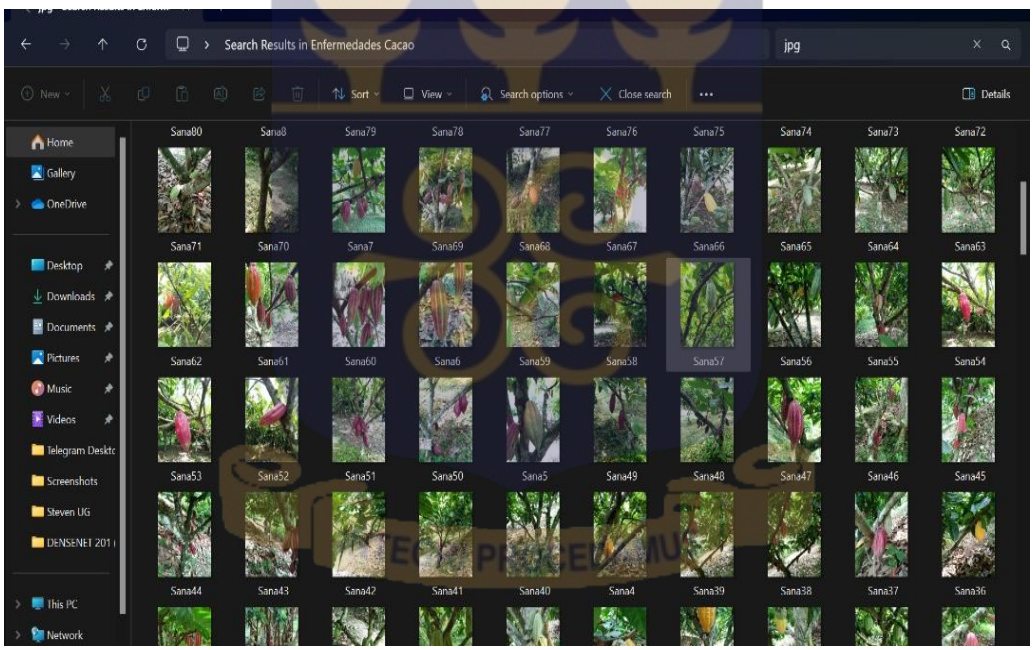


Figure 3. 9 Dataset containing Cocoa images

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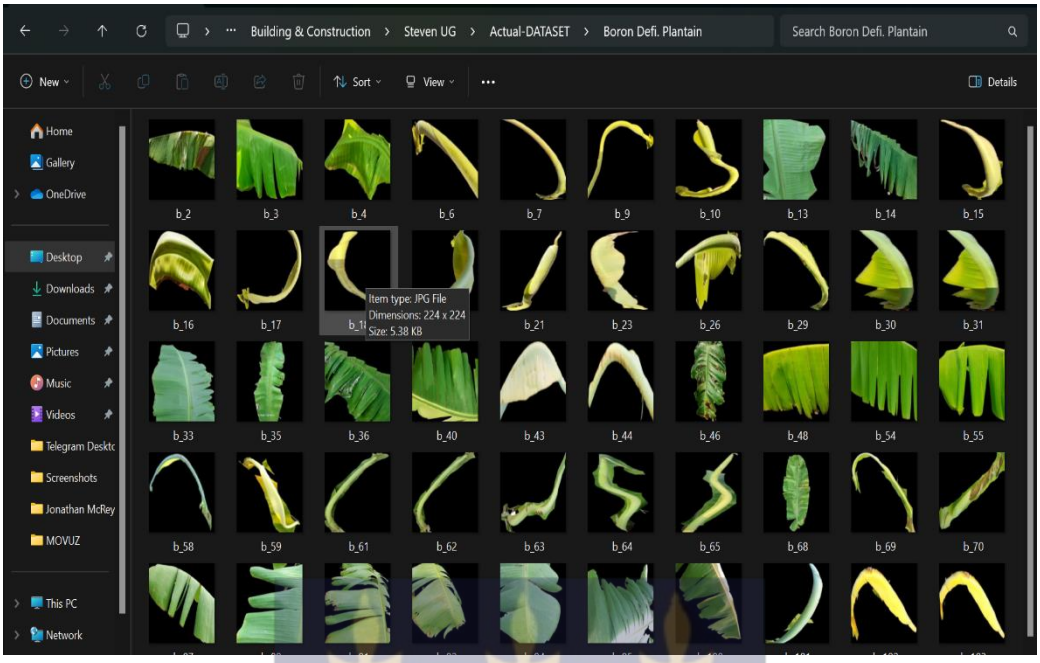


Figure 3. 10 Dataset containing Plantain images.

3.5.2 Data Preprocessing

To maintain consistency within the dataset, all images were resized to a standardized dimension of 224 × 224 pixels, suitable for CNN processing. Normalization techniques were applied to scale pixel values to a uniform range, typically [0, 1], improving the computational efficiency and performance of the models (Sane & Agrawal, 2017). To overcome the constraints of a limited dataset and reduce the risk of model overfitting, data augmentation techniques were applied to increase dataset diversity and enhance model robustness. These included rotating images to simulate different leaf orientations, applying horizontal and vertical flips to diversify visual patterns, and modifying brightness, contrast, and saturation through color jittering to mimic real-world variations in lighting conditions (Park et al., 2025). These augmentation strategies significantly expanded the dataset, providing more varied samples to improve the performance and generalization of the CNN models during the training phase. In this study, two T-T split ratios were employed: 80:20 and 90:10. For the 80:20 split, 80% of the images were used for training the CNN models, with the remaining 20% reserved for testing. Similarly, in the 90:10 split, 90% of the dataset was allocated for model training, while 10% was used for

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evaluation, allowing for assessment of model performance under varying training data proportions. The training set was used to develop the models' learning parameters, while the testing set evaluated their performance on unseen data. This split ensures that the models' performance metrics reflect their ability to generalize to new, real-world scenarios.

3.5.3 Sampling Strategy and Participants

A purposive sampling approach was employed to identify participants, including local farmers and agricultural research institutions. This method ensured access to experts familiar with crop health and disease identification, facilitating the collection of high-quality data. Farmers provided insights into prevalent diseases affecting cassava, plantain, and cocoa crops, while research institutions offered expertise in verifying disease symptoms and accessing specialized knowledge regarding agricultural practices and challenges. A stratified sampling method was used to ensure the dataset accurately represented the diversity of farming conditions and disease manifestations (Thomas, 2020). The regions were divided into strata based on specific factors such as the dominant crop type (cassava, plantain, or cocoa), the prevalence of diseases, and climate variations. This approach ensured balanced representation, capturing the variability of disease symptoms across different environmental and agricultural contexts. To achieve robust training and testing datasets, a total of 500 images was collected for each crop, with an equal distribution of healthy and diseased samples consistent with studies by (Tunio et al., 2025). This balanced sample size ensured the models could learn to differentiate effectively between healthy and diseased conditions, improving classification accuracy and generalization.

3.6 Instrumentation and Validation

3.6.1 Model Architecture Selection

To effectively classify and detect crop diseases, five CNN architecture were employed. ResNet 101, a deep residual network with 101 layers, was chosen for its ability to address vanishing gradient issues through skip connections, allowing for the extraction of intricate features

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necessary for disease identification (Sethy et al., 2024). AlexNet, a foundational CNN architecture, was selected for its computational efficiency and suitability for moderate-sized datasets, providing a balance between speed and accuracy (Klingler, 2024). DenseNet 201, with its densely connected layers, ensured efficient feature reuse and robust visual discrimination capabilities. GoogLeNet (Inception-v3) introduced multi-scale feature extraction through inception modules, making it both computationally efficient and accurate (Jin et al., 2023). DarkNet-53 (YOLOv3), widely recognized for real-time object detection, was integrated to evaluate its utility for rapid and precise disease detection in field conditions (Yang et al., 2023).

3.6.2 CNN Model Training

Model training was conducted in MATLAB R2022a for the five CNN architectures evaluated in this study: AlexNet, DarkNet-53, DenseNet-201, GoogLeNet and ResNet-101. The preprocessed and augmented images of the three test crops, Cassava, Cocoa, and Plantain, were divided into training and testing sets using 80:20 and 90:10 split. Each model was trained on the respective training sets with optimized hyperparameters, including batch size, learning rate, and number of epochs, to ensure effective convergence. Feature extraction was automatically performed within the neural network layers during training, enabling the models to learn distinguishing patterns of healthy versus diseased crop images. After training, the testing sets were used to evaluate model performance including accuracy, precision, recall and F1-score metrics. This procedure was repeated for each crop type to verify that the models could generalize across all classes. Additionally, performance results guided any necessary adjustments to hyperparameters, ensuring effective and reliable classification outcomes across the five different CNN architectures.

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3.6.3 Performance Metrics

Performance metrics are essential in evaluating the effectiveness of deep learning models, particularly in image classification and disease detection. The evaluation of CNN models for disease detection involves several metrics, each providing insight into different aspects of model performance. In this study, evaluation metrics including accuracy, precision, recall, and F1-score were used to quantitatively assess the model's ability to accurately detect and classify crop diseases from image datasets.

In addition to serving as a baseline for evaluating the performance of various CNN designs, these metrics also direct model optimization and improvement to satisfy particular application requirements. The metrics were computed from the resulting confusion matrix printed from the testing of the models using the test data. Below is an explanation of these metrics, their equations, and a tabular guide to interpret the results.

Accuracy – Accuracy quantifies the proportion of correctly classified instances, including both true positives and true negatives, relative to the total number of predictions. The equation below shows how accuracy is calculated (Saeik et al., 2021).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . Eq\ 1$$

Precision – Precision is the ratio of correctly predicted positive instances (TP) to the total predicted positive instances. The equation below shows how precision is calculated (Boesch, 2024).

$$Precision = \frac{TP}{TP + FP} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots Eq\ 2$$

Recall (Sensitivity) – Recall measures the ability of the model to capture all relevant positive cases as positive to the degree to which they are actually positive. The equation below shows how recall is calculated (Boesch, 2024).

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$$Recall = \frac{TP}{TP + FN} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . Eq\ 3$$

F1-Score – The F1-score represents the harmonic mean of precision and recall, providing a single metric that balances the trade-off between these two measures. The equation below shows how F1-Score is calculated (Kashyap, 2024).

$$F1\ Score = 2 \times \frac{PRECISION \times RECALL}{PRECSION + RECALL} \dots \dots \dots \dots \dots \dots \dots \dots . \dots Eq\ 4$$

Where:

TP (True Positive) – Correctly classified positive cases (e.g., diseased leaves).

TN (True Negative) – Correctly classified negative cases (e.g., healthy leaves).

FP (False Positive) – Healthy leaves misclassified as diseased.

FN (False Negative) – Diseased leaves misclassified as healthy.

3.6.4 Interpretation Guidelines for Classification Metrics

The table below outlines general guidelines for interpreting common classification metrics, drawing from established best practices in machine learning and data science. These guidelines are informed by insights from *Pattern Recognition and Machine Learning* by (Bishop, 2006), *Machine Learning: A Probabilistic Perspective* by (Murphy, 2012), and *Evaluation: From Precision, Recall and F-Factor to ROC, Informedness, Markedness & Correlation* by (Powers, 2020).

Table 3. 4 General Guidelines for Interpreting Common Classification Metrics

Metric	**Excellent**	**Good**	**Fair**	**Poor**
Accuracy	95%-100%	90%-94%	80%-89%	<80%

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Precision	95%-100%	90%-94%	80%-89%	<80%
Recall	95%-100%	90%-94%	80%-89%	<80%
F1 – Score	0.95-1.00	0.90-0.94	0.80-0.89	<0.80

3.7 Data Analysis

The data collected for this study was analyzed using MATLAB R2022a, employing descriptive statistics to summarize the dataset characteristics and inferential statistics to test hypotheses (Yellapu, 2019). Machine learning techniques was also applied to develop and optimize the CNN models for disease classification (Waheed et al., 2020). The analysis incorporated advanced visualization methods, with results presented in tables, figures, and graphs to offer a comprehensive understanding of the model's performance and insights into its effectiveness.

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CHAPTER FOUR

RESULTS

4.1 Introduction

This chapter presents the findings of the research, detailing the results from CNN models used for cassava, plantain, and cocoa disease detection. The analysis is organized to evaluate the performance metrics of the selected CNN architecture, including accuracy, precision, recall, and F1-score, as applied to the collected datasets. To evaluate model performance effectively, two T-T split ratios were employed, ensuring a strong assessment of the CNNs' learning and generalization capabilities.

4.2 Model Training and Testing Results

The performance of the CNN models during training and testing is visualized through graphical outputs generated by MATLAB R2022a. These graphs provide insights into the models' learning behaviour, highlighting validation accuracies achieved during the training phase and their performance on testing datasets.

The analysis of these graphs helps determine the robustness and efficiency of each CNN architecture in disease detection across cassava, plantain, and cocoa leaves and pods. Two distinct training patterns were employed:

1. Training each crop (cassava, plantain, cocoa) individually on specific CNN models to assess crop-specific model performance.

2. Training each individual CNN model across all three crops to identify the most versatile and efficient architecture for multi-crop disease detection.

Each training approach is detailed below, with corresponding images of the validation accuracy graphs to support the discussion.

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4.3 Data Split Considerations on Model Learning

An essential aspect of training CNNs for crop disease detection is determining an appropriate T-T split, as it directly impacts the model's ability to generalize to unseen data. In this study, two widely used data partition ratios 80:20 and 90:10 was employed to evaluate how varying the amount of training data affects model performance. The 80:20 split offers a balanced approach with sufficient data for both learning and evaluation (Muraina, 2022), while the 90:10 split emphasizes maximizing training data, potentially enhancing learning at the cost of fewer evaluation samples (Altamimi & Abu Al-Haija, 2024).

These ratios were applied across two distinct training strategies: training each CNN model across combined datasets of cassava, plantain, and cocoa leaves and pods to identify the most versatile model, and training individual CNN models on each crop to assess crop-specific performance. This dual-layered evaluation aimed to reveal how both the data split and training scope influence the accuracy and reliability of the models. The results from this analysis are presented in the section below.

4.4 Analysis of Training Patterns on Model Performance of Crops

Both multi-crop and crop-specific (individual) model performance were assessed based on accuracy, precision, recall, and F1-score metrics under the two T-T splits. The aim of this comparison was to determine the most efficient architecture for crop disease detection and classification across the cassava, plantain, and cocoa leaves and pods dataset. These performance metrics reveals distinct trends across the selected CNN architecture.

4.4.1 CNN Model Performance on Individual Crops

In this approach, cassava, plantain, and cocoa leaves and pods datasets were trained separately using a single CNN model. This approach was designed to evaluate how well each crop dataset performed when paired with a specific architecture. For instance, cassava images were trained

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and validated on DenseNet 201, plantain on ResNet 101, and cocoa leaves and pods on AlexNet. The graphs from MATLAB display the validation accuracies achieved during each training iteration, showing convergence trends, overfitting risks, or underfitting behavior.

4.4.2 Model Performance on Individual Crops at 80:20 T-T Split

All five models were trained and tested under the 80:20 T-T split ratio on individual crop datasets to investigate how well each model could perform when exposed to distinct disease images from cassava, plantain, and cocoa leaves and pods. Figs. 4.1 to 4.15 illustrate the accuracy performance of the individual crop models across different architecture.

Each graph represents the validation accuracy of the respective model for cassava, plantain, and cocoa leaves and pods, providing insights into how well the model is generalizing to unseen data. As shown below, the accuracy plots display the rate of improvement over epochs, offering a clear comparison between the different architecture and highlighting the optimal convergence points for each crop.

The validation accuracies achieved by each model across the individual crop datasets; cassava, plantain, and cocoa leaves and pods are as follows: AlexNet (93.45%, 94.95%, 94.56%), DarkNet-53 (95.11%, 96.23%, 95.55%), DenseNet 201 (96.63%, 97.61%, 97.25%), GoogLeNet (95.59%, 96.43%, 96.19%), and ResNet 101 (96.31%, 97.05%, 96.80%), as illustrated in the figures below.

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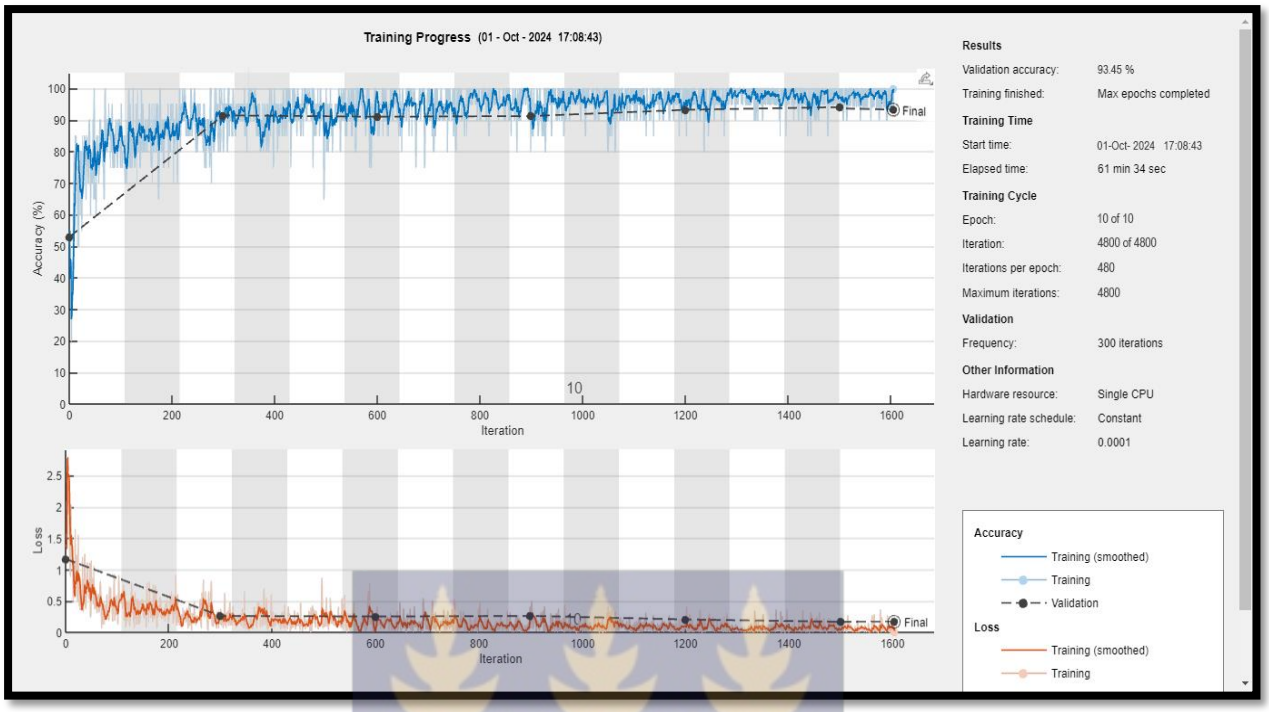


Figure 4. 1 Validation Accuracy of AlexNet on Cassava at 80:20 T-T Split

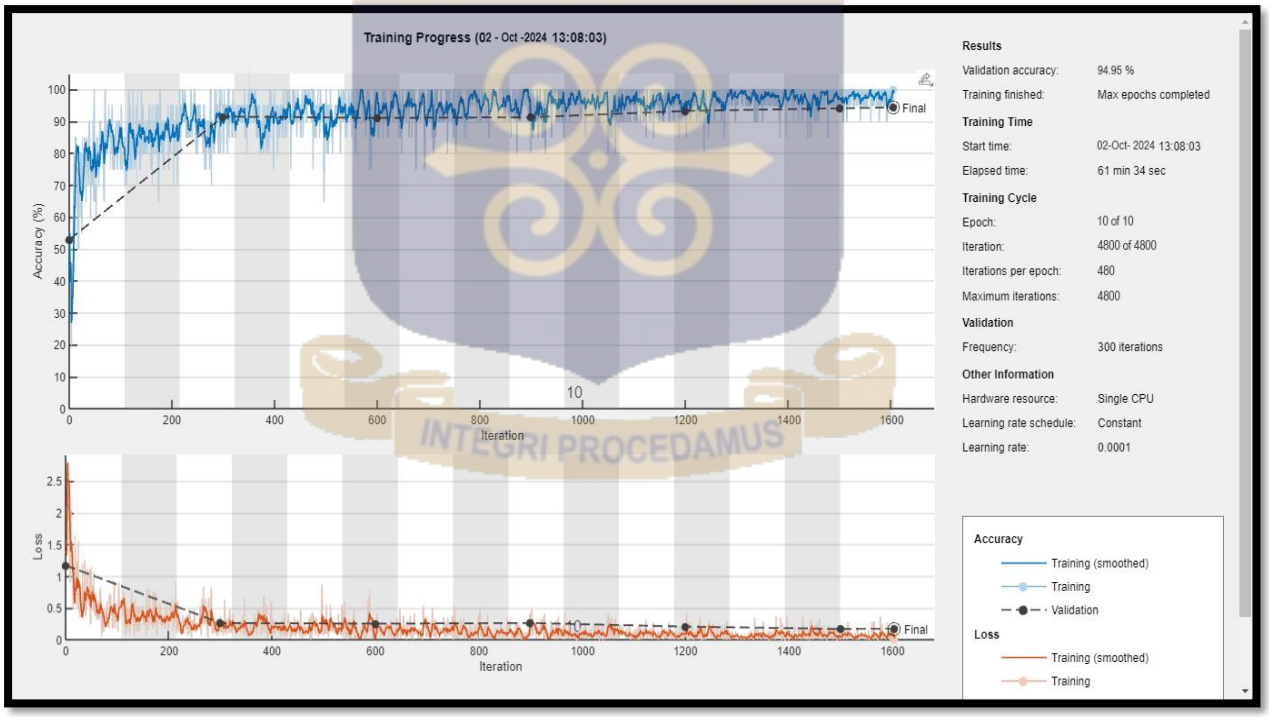


Figure 4. 2 Validation Accuracy of AlexNet on Plantain at 80:20 T-T Split

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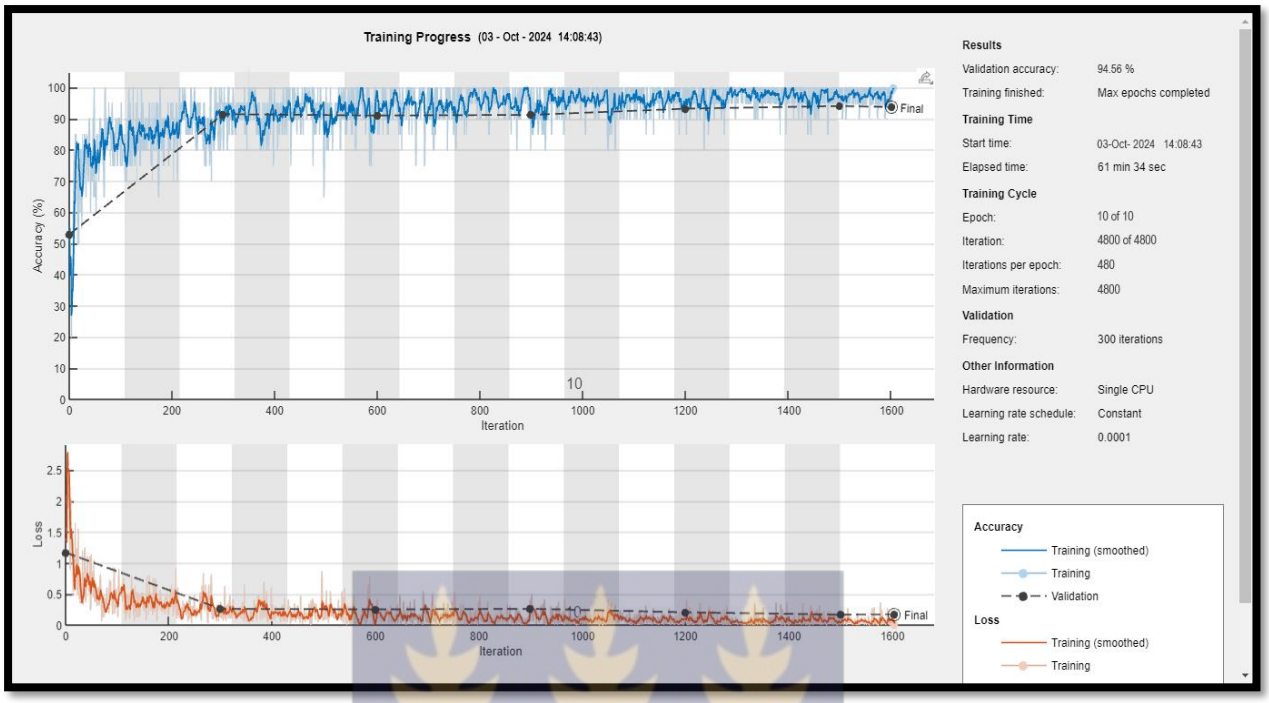


Figure 4. 3 Validation Accuracy of AlexNet on Cocoa Leaves and Pods at 80:20 T-T Split

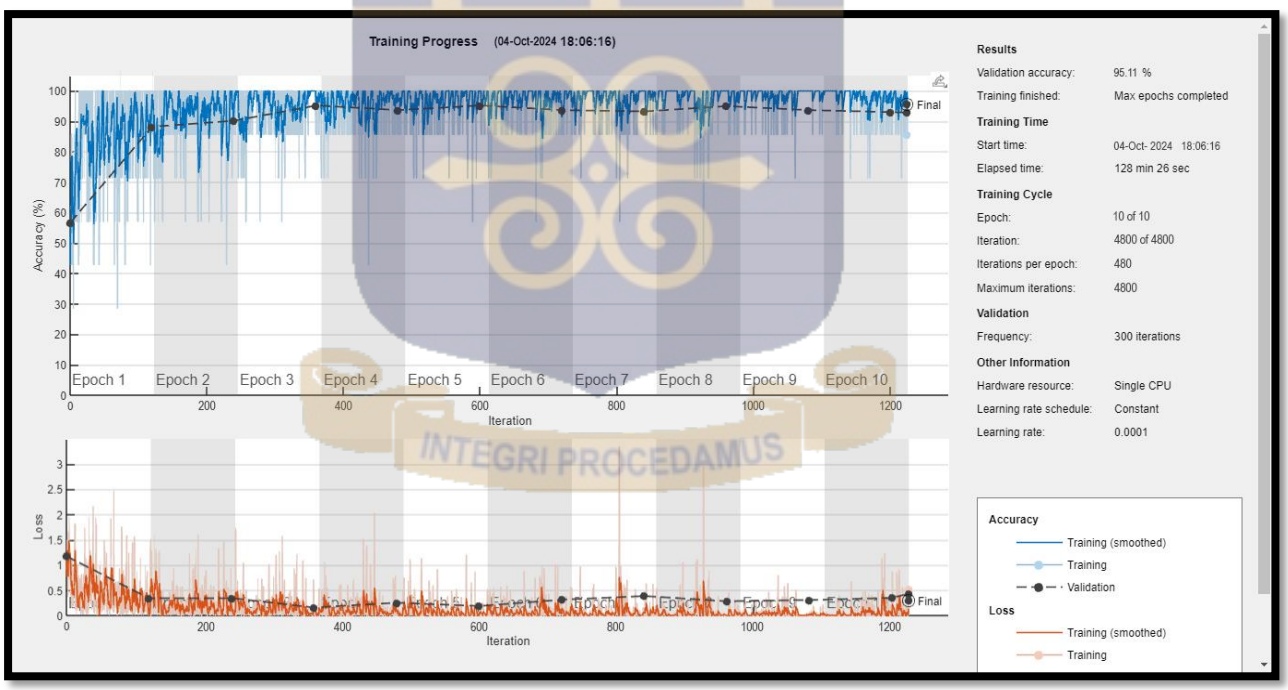


Figure 4. 4 Validation Accuracy of DarkNet-53 on Cassava at 80:20 T-T Split

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Figure 4. 5 Validation Accuracy of DarkNet-53 on Plantain at 80:20 T-T Split

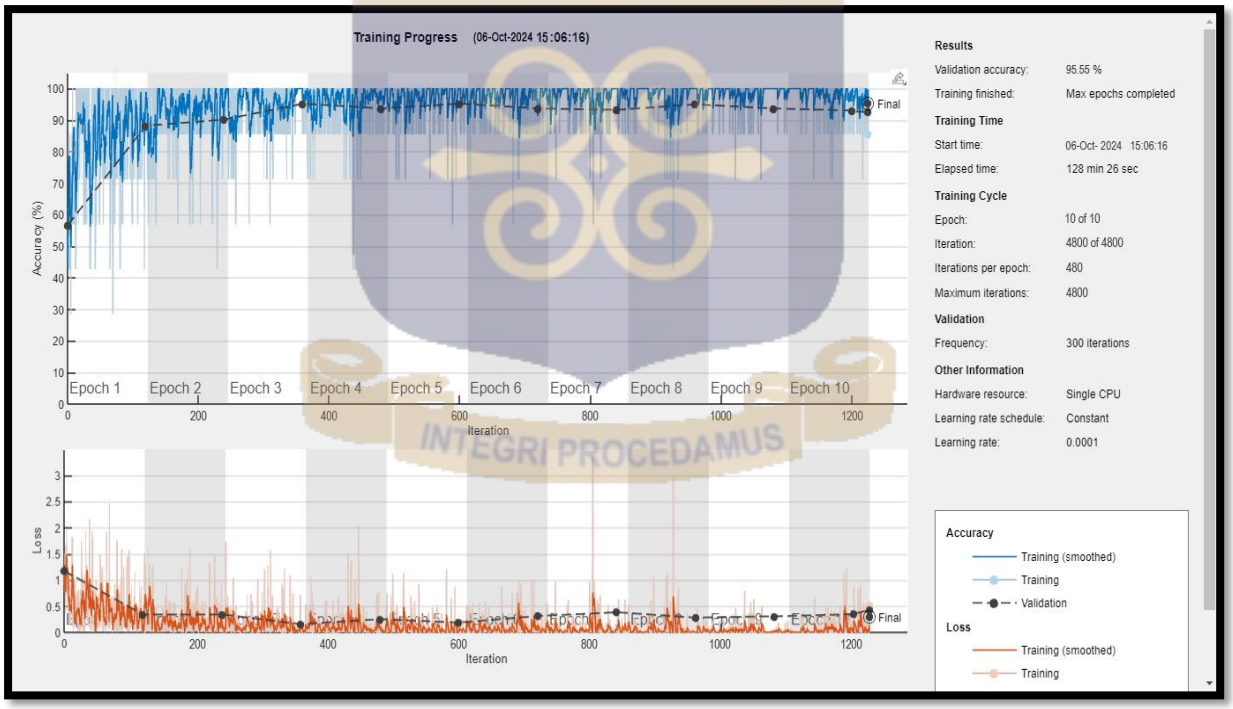


Figure 4. 6 Validation Accuracy of DarkNet-53 on Cocoa Leaves and Pods at 80:20 T-T Split

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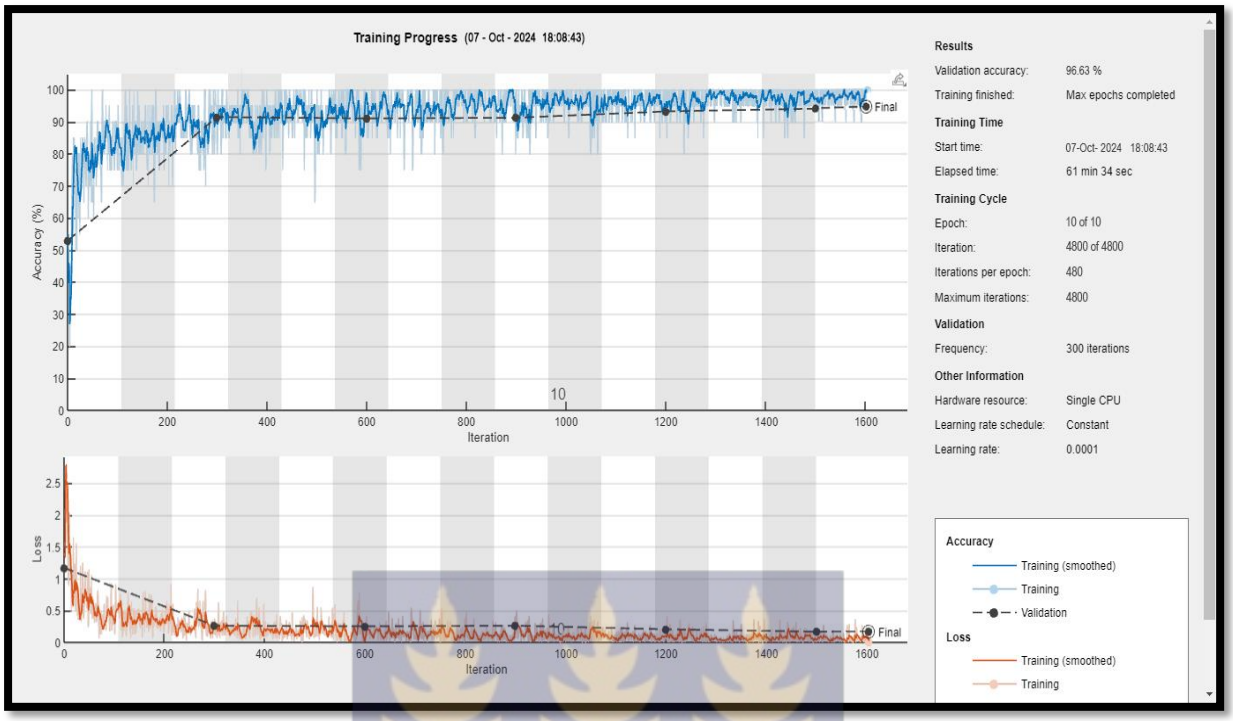


Figure 4. 7 Validation Accuracy of DenseNet-201 on Cassava at 80:20 T-T Split

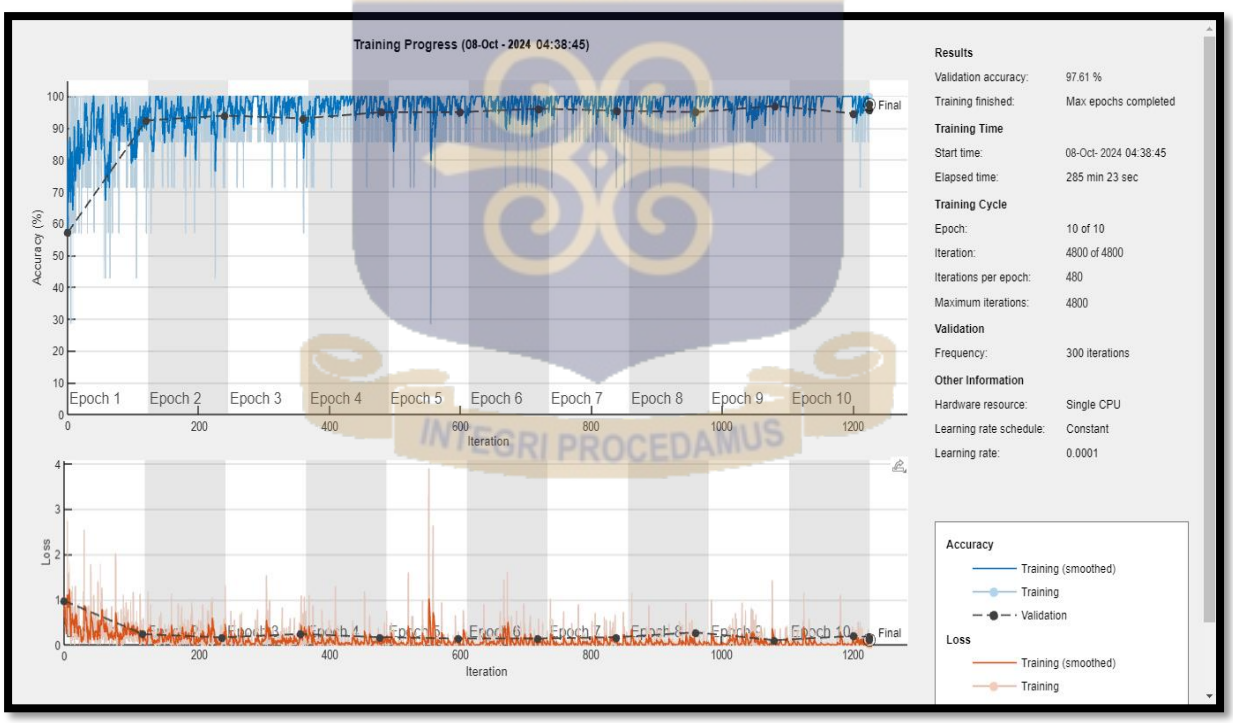


Figure 4. 8 Validation Accuracy of DenseNet-201 on Plantain at 80:20 T-T Split

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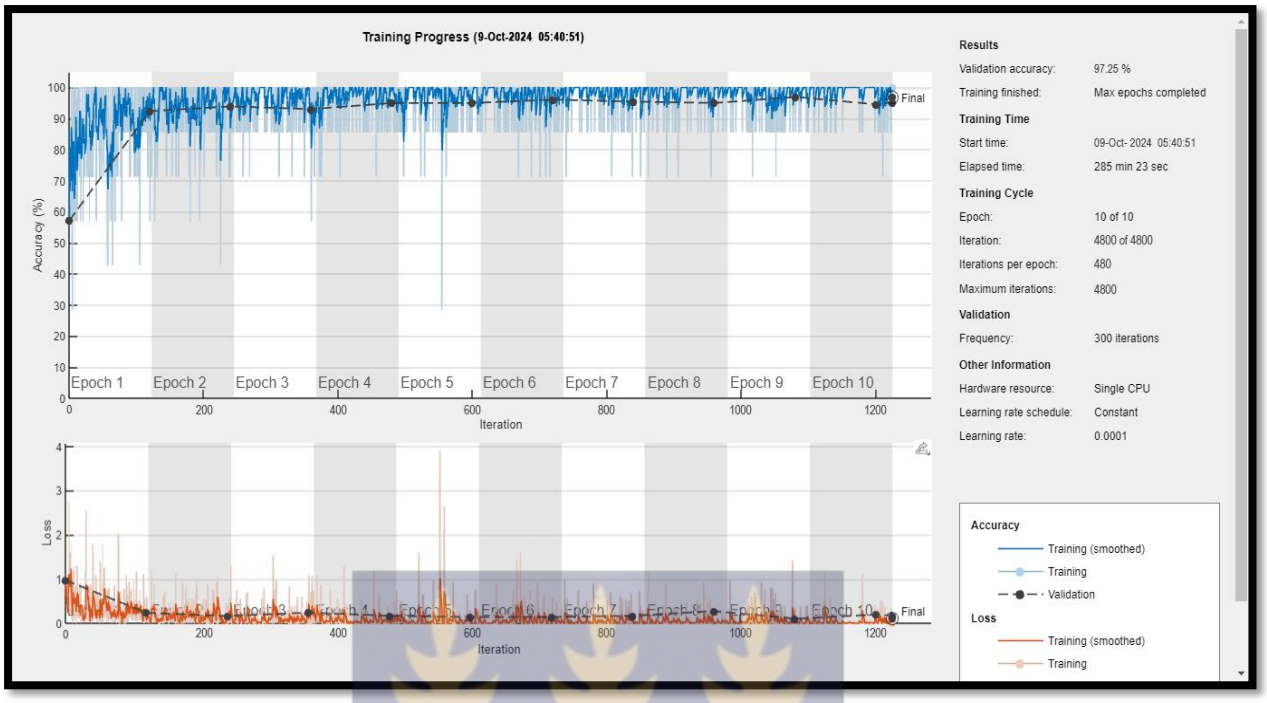


Figure 4. 9 Validation Accuracy of DenseNet-201 on Cocoa Leaves and Pods at 80:20 T-T Split

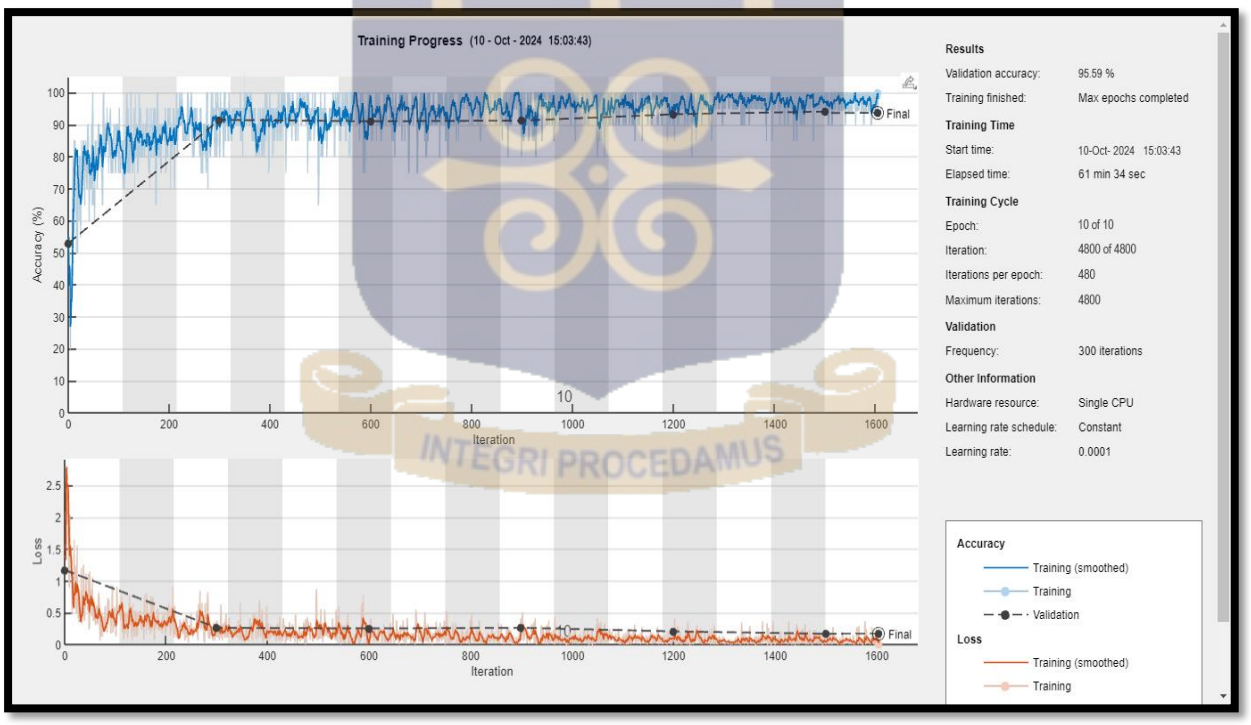


Figure 4. 10 Validation Accuracy of GoogLeNet on Cassava at 80:20 T-T Split

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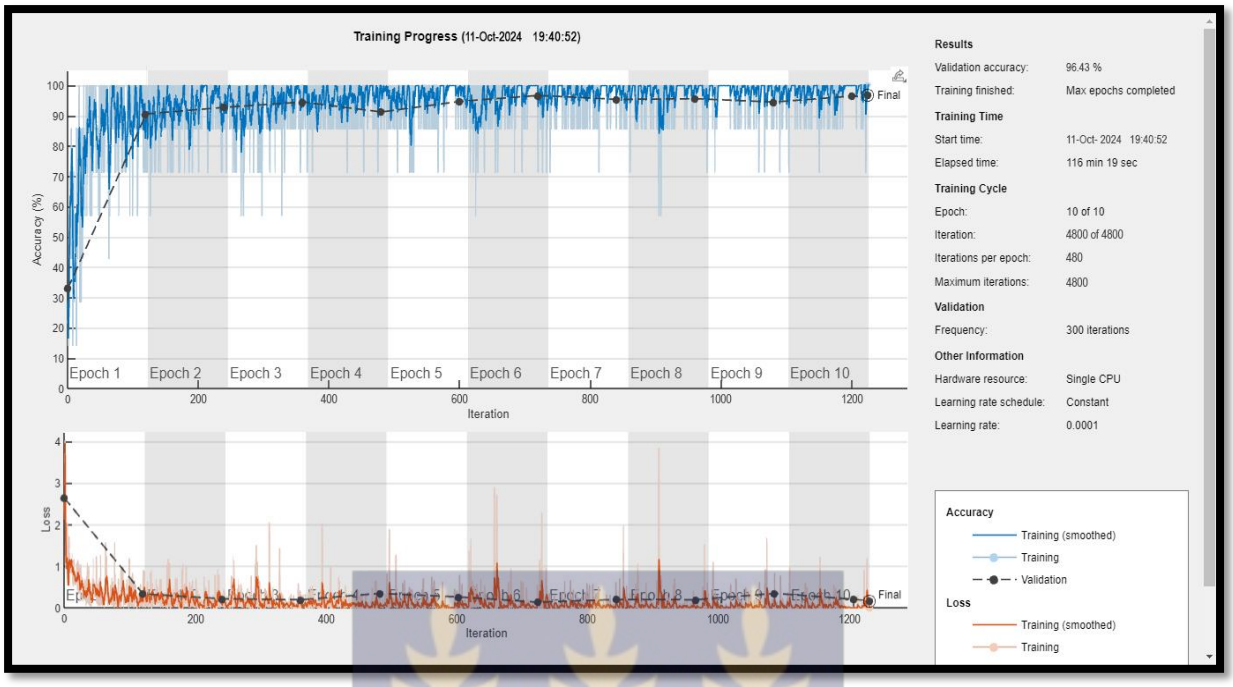


Figure 4. 11 Validation Accuracy of GoogLeNet on Plantain at 80:20 T-T Split

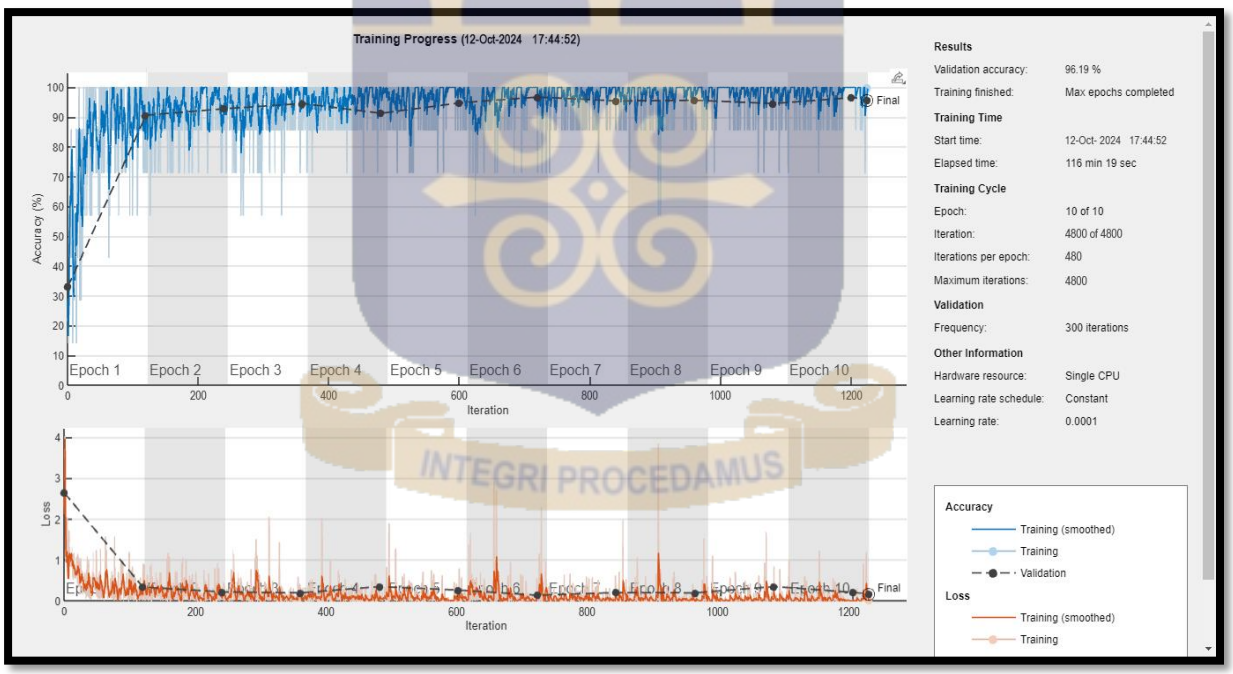


Figure 4. 12 Validation Accuracy of GoogLeNet on Cocoa Leaves and Pods at 80:20 T-T Split

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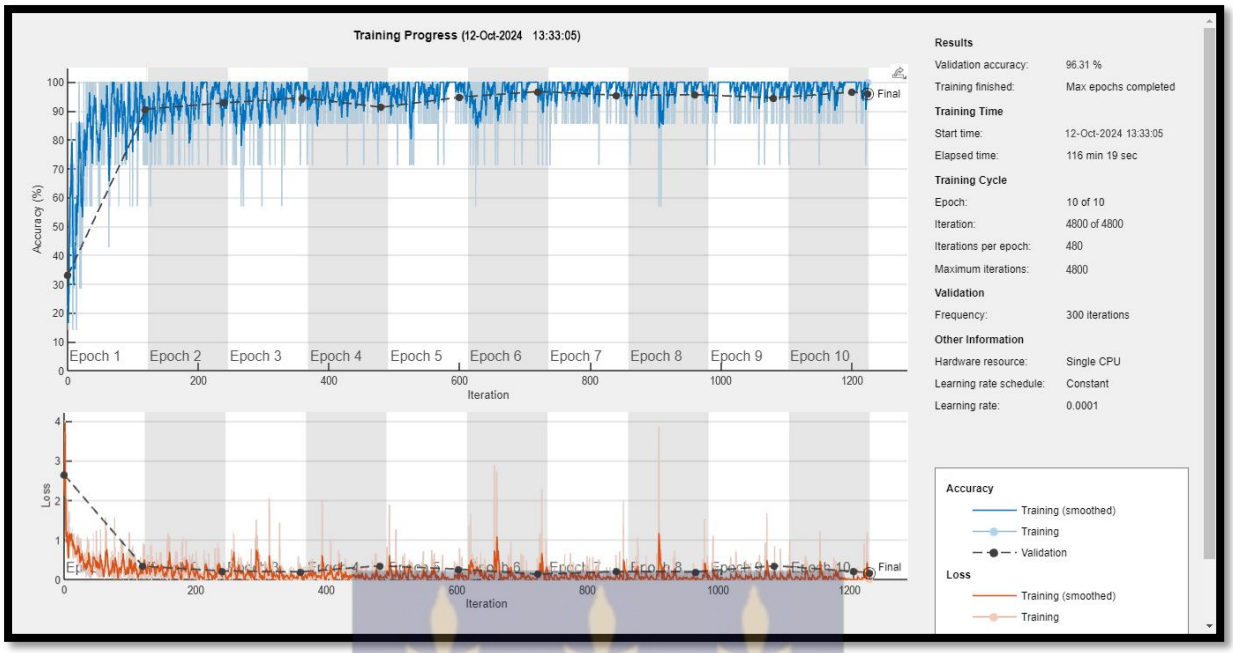


Figure 4. 13 Validation Accuracy of ResNet-101 on Cassava at 80:20 T-T Split

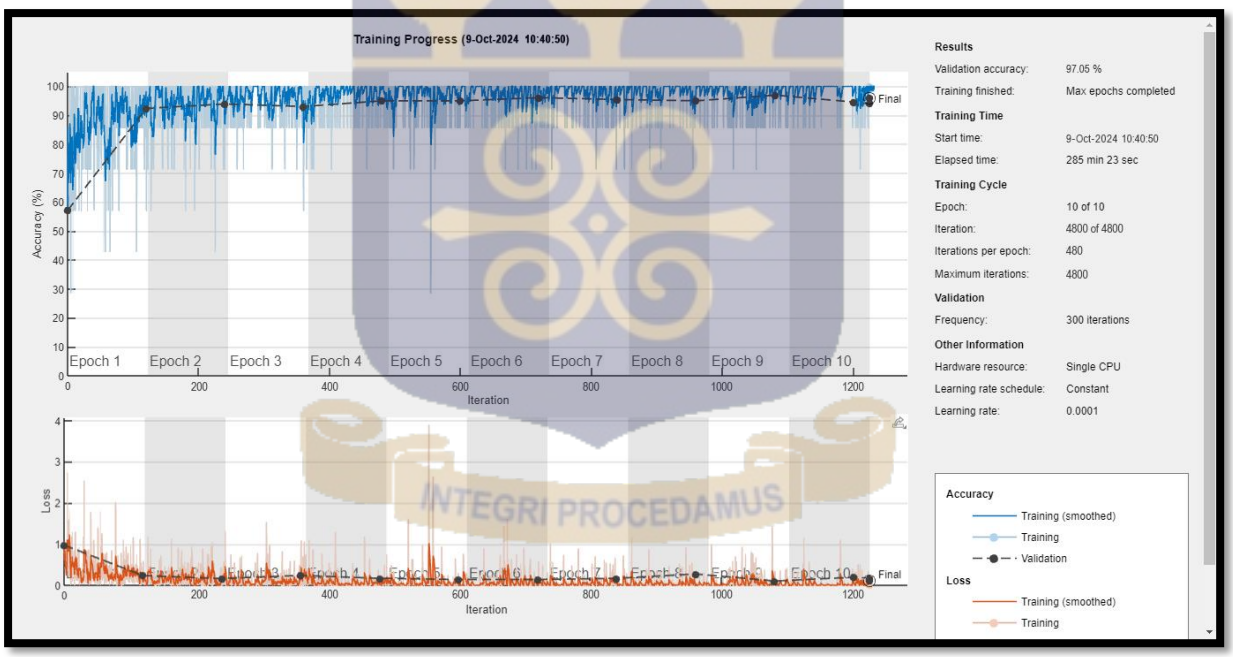


Figure 4. 14 Validation Accuracy of ResNet-101 on Plantain at 80:20 T-T Split

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Figure 4. 15 Validation Accuracy of ResNet-101 on Cocoa Leaves and Pods at 80:20 T-T Split

4.4.3 Model Performance Evaluation on Individual Crops at 80:20 T-T Split

The performance evaluation of the CNN models on individual crop datasets (cassava, plantain, cocoa leaves and pods) under the 80:20 T–T split is presented below in Fig. 4.16. The results are illustrated through accuracy, precision, recall, and F1-score metrics, providing insights into the classification effectiveness of each model across the different crops. Across the individual crops under the 80:20 T–T split, DenseNet-201 consistently achieved the highest performance, recording accuracy of 96.63%, 97.61%, and 97.25% for cassava, plantain, and cocoa respectively, with corresponding superior precision, recall, and F1-Score values. ResNet101 and GoogLeNet followed closely, with accuracies above 96% for all crops and balanced scores across the remaining metrics. DarkNet-53 also maintained strong results, with accuracies ranging from 95.11% to 96.23% across the crops. AlexNet, while showing commendable performance with accuracies between 93.45% and 94.95%, consistently underperformed relative to the other models across all four metrics.

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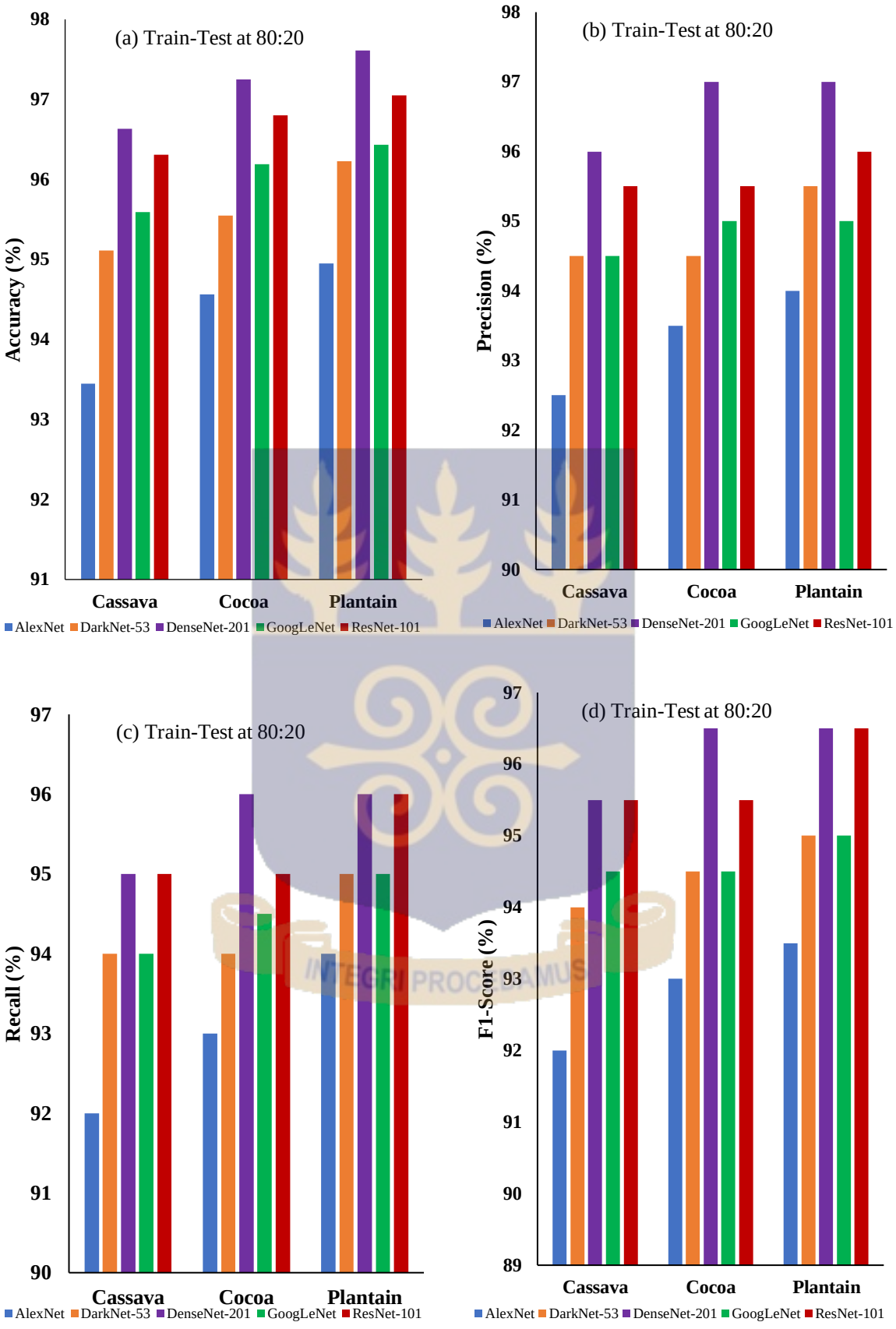


Figure 4. 16 Model Performance Evaluation on Individual Crops at 80:20 T-T split: (a) Accuracy, (b) Precision, (c) Recall, and (d) F1-Score across the CNN architecture.

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4.4.4 Multi-Crop Model Accuracy with 80:20 T-T Split

In this training pattern, each CNN architecture (ResNet 101, AlexNet, DenseNet 201, GoogLeNet, and DarkNet-53) was trained on combined cassava, plantain, and cocoa leaves and pods datasets using an 80:20 split. The 80:20 split provided a balanced distribution of data for training and evaluation, enabling the models to learn from a substantial dataset while maintaining a strong test set for performance assessment (Bichri et al., 2024).

This method also aimed to identify which architecture exhibited the best generalizability and adaptability for disease detection across multiple crops. The validation accuracy graphs below reveal the models' performance under varying multi-crop datasets at 80:20 T-T split. The performance of each CNN model across the three crops is illustrated in Fig. 4.17 - 4.21.

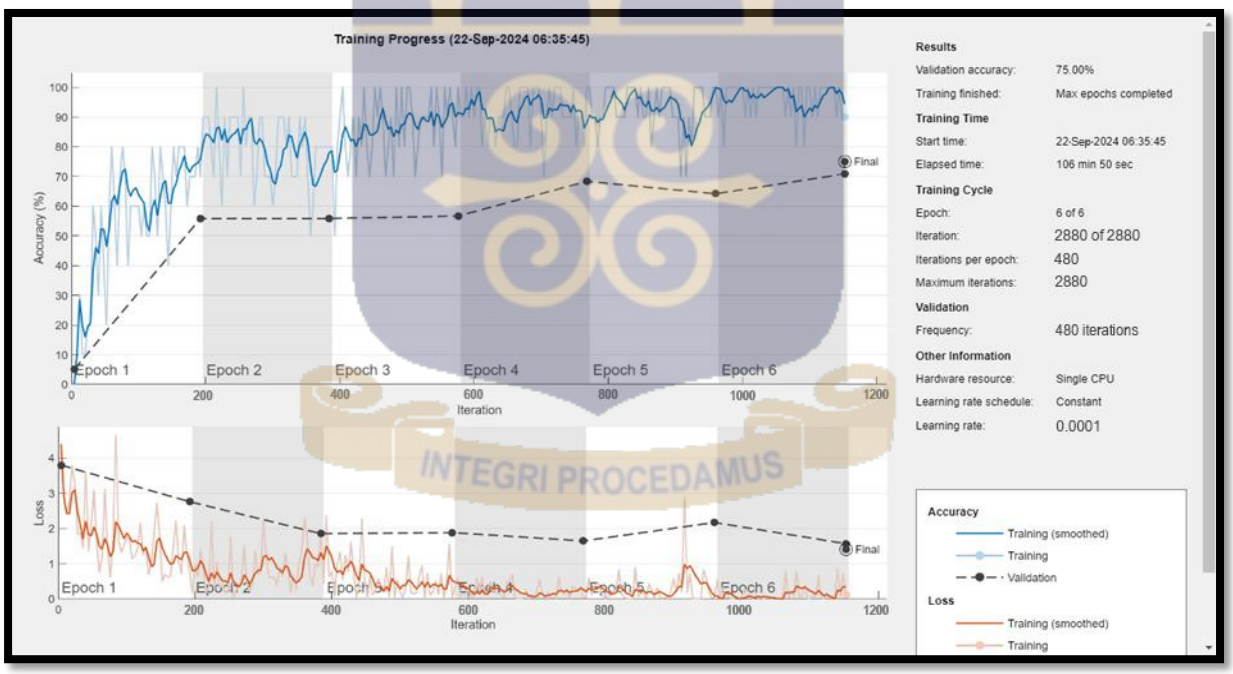


Figure 4. 17 Validation Accuracy of AlexNet on multi-crop at 80:20 T-T Split

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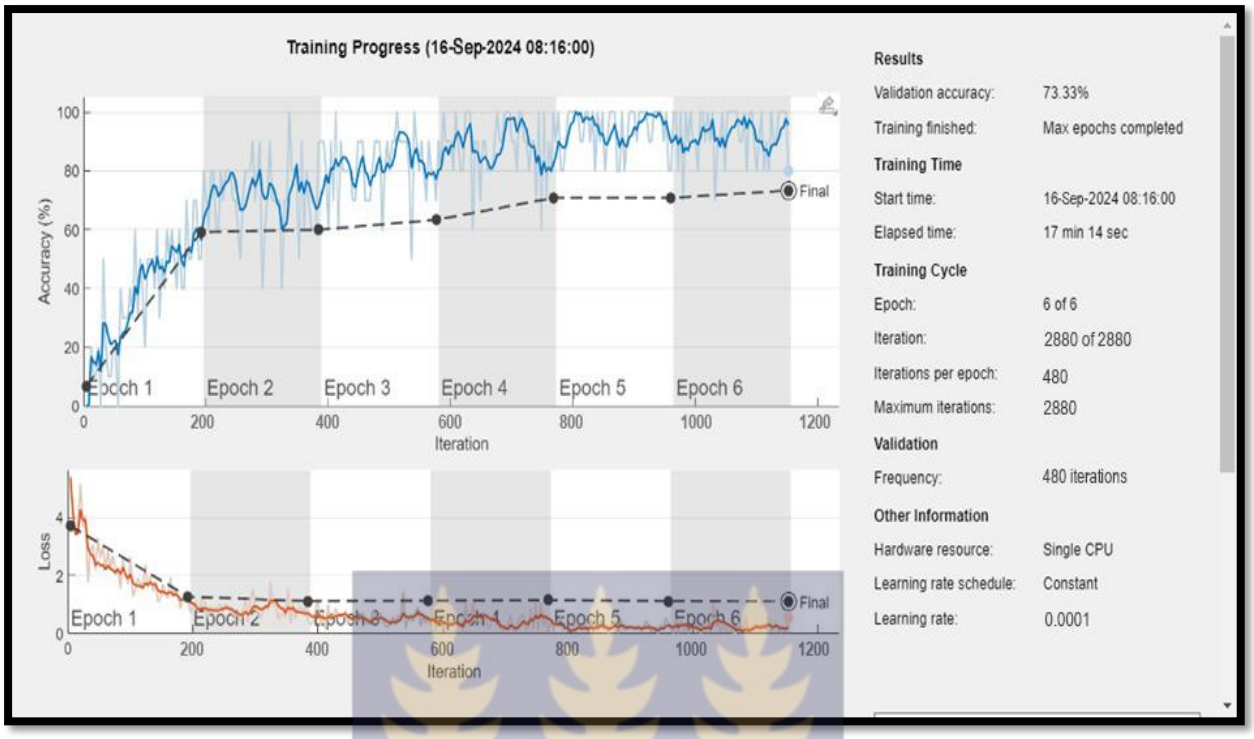


Figure 4. 18 Validation Accuracy of DarkNet-53 on multi-crop at 80:20 T-T Split



Figure 4. 19 Validation Accuracy of DenseNet 201 on multi-crop at 80:20 T-T Split

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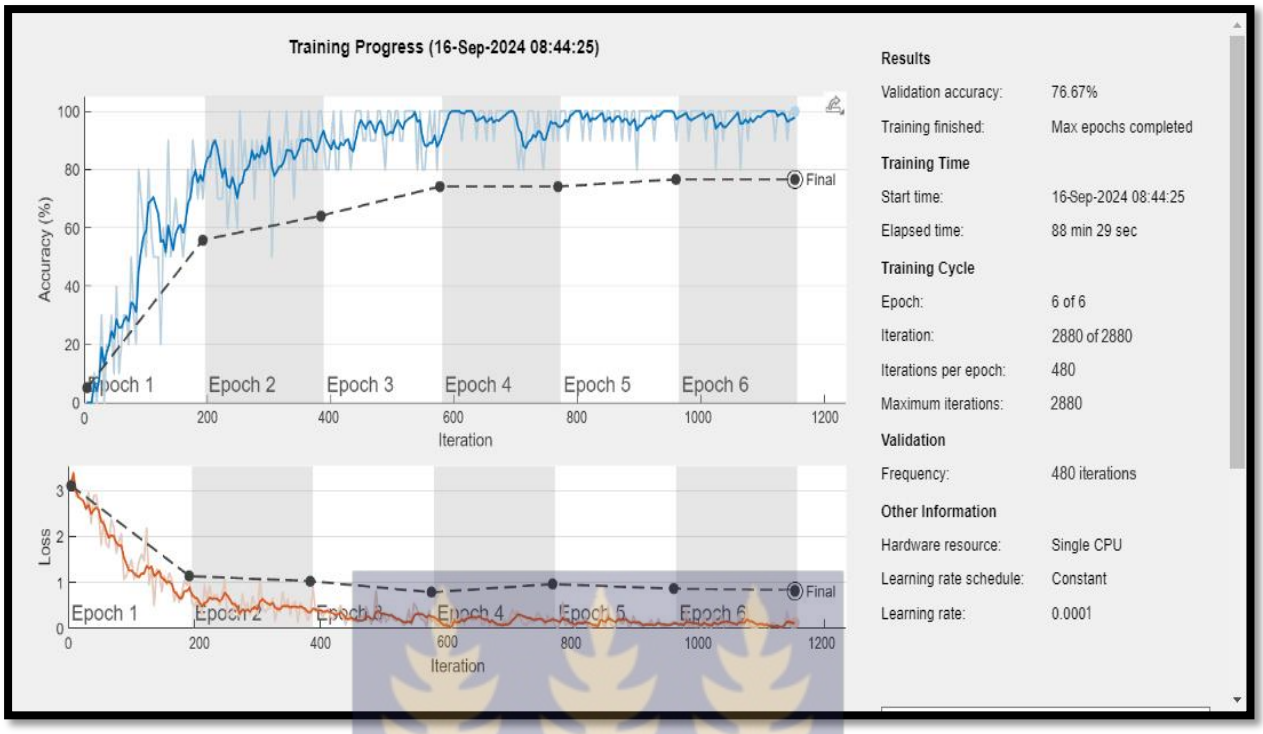


Figure 4. 20 Validation Accuracy of GoogLeNet on multi-crop at 80:20 T-T Split

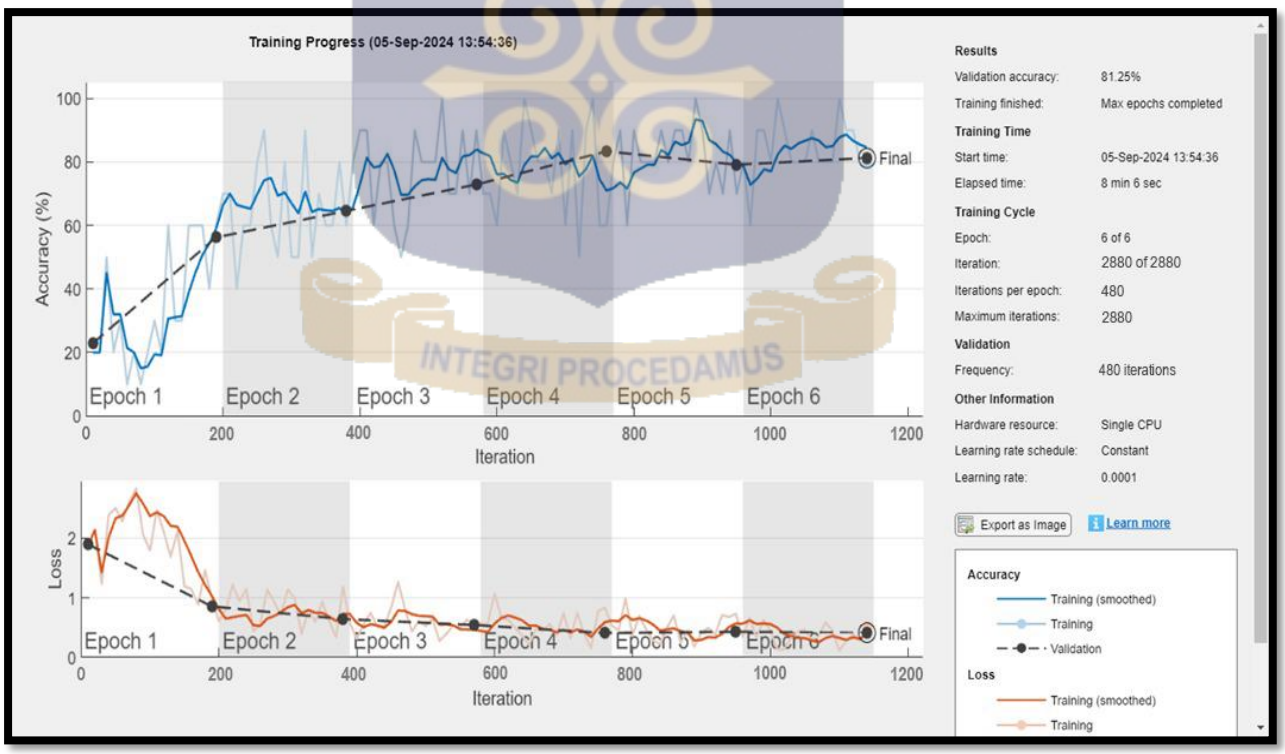


Figure 4. 21 Validation Accuracy of ResNet 101 on multi-crop at 80:20 T-T Split

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A summary of the models' accuracy performance is presented in Table 4.1. This table provides a concise overview of the average accuracy achieved by each model across the three crops, facilitating a direct comparison of their performance.

Table 4. 1 Model Accuracy Performance at 80:20 T-T Split

CNN Models	Multi-Crop Validation Accuracy (%)
AlexNet	75.00
DarkNet-53	73.33
DenseNet 201	89.58
GoogLeNet	76.67
ResNet 101	81.25

4.4.5 Model Performance Evaluation on Multi-Crops at 80:20 T-T Split

The graph presented below in Fig. 4.22 shows the performance of the CNN models on the multi-crop dataset under the 80:20 T–T split, highlighting variations across accuracy, precision, recall, and F1-score. Among the models evaluated, DenseNet-201 attained the highest performance across all metrics (Accuracy: 89.58%, Precision: 90.00%, Recall: 89.00%, F1-Score: 89.00%), followed by ResNet-101 (Accuracy: 81.25%), while AlexNet, GoogLeNet, and DarkNet-53 recorded comparatively lower but consistent outcomes within the 72–77% range across metrics.

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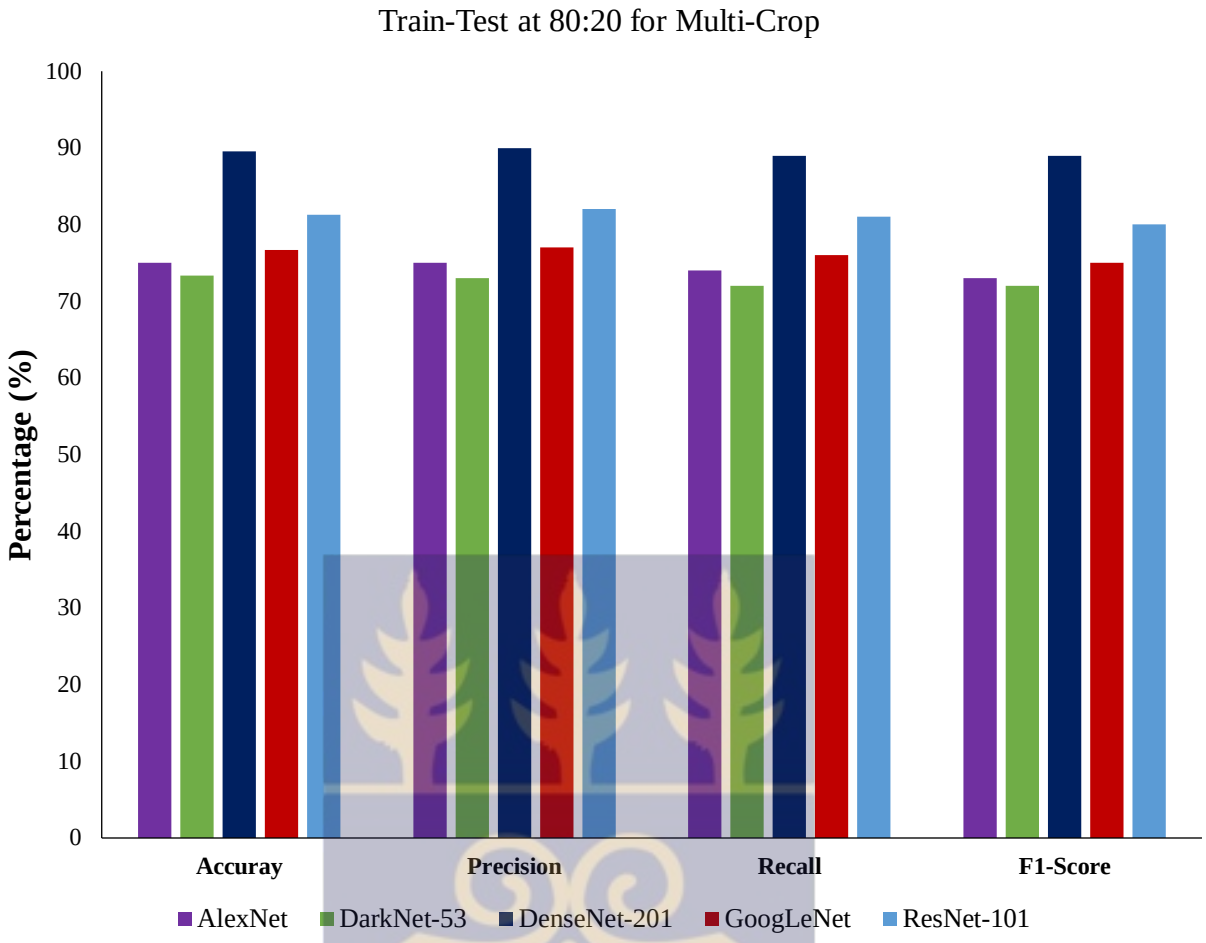


Figure 4. 22 Model Performance Evaluation on Multi-Crops at 80:20 T-T Split

4.4.6 Model Performance on Individual Crops at 90:10 T-T Split

All five models were trained and tested under the 90:10 T-T split ratio on individual crop datasets to investigate how well each model could perform when exposed to distinct disease images from cassava, plantain, and cocoa leaves and pods. Figs. 4.23 to 4.37 illustrate the accuracy performance of the individual crop models across different architecture. Each graph represents the validation accuracy of the respective model for cassava, plantain, and cocoa leaves and pods, providing insights into how well the model is generalizing to unseen data. As shown, the accuracy plots display the rate of improvement over epochs, offering a clear comparison between the different architecture and highlighting the optimal convergence points for each crop. The validation accuracies achieved by each model across the individual crop datasets; cassava, plantain, and cocoa leaves and pods are as follows: AlexNet (95.90%,

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96.50%, 96.10%), DarkNet-53 (96.60%, 97.80%, 97.20%), DenseNet 201 (98.20%, 99.00%, 98.70%), GoogLeNet (97.00%, 97.60%, 97.30%), and ResNet 101 (98.10%, 98.90%, 98.60%), as illustrated in the figures below.

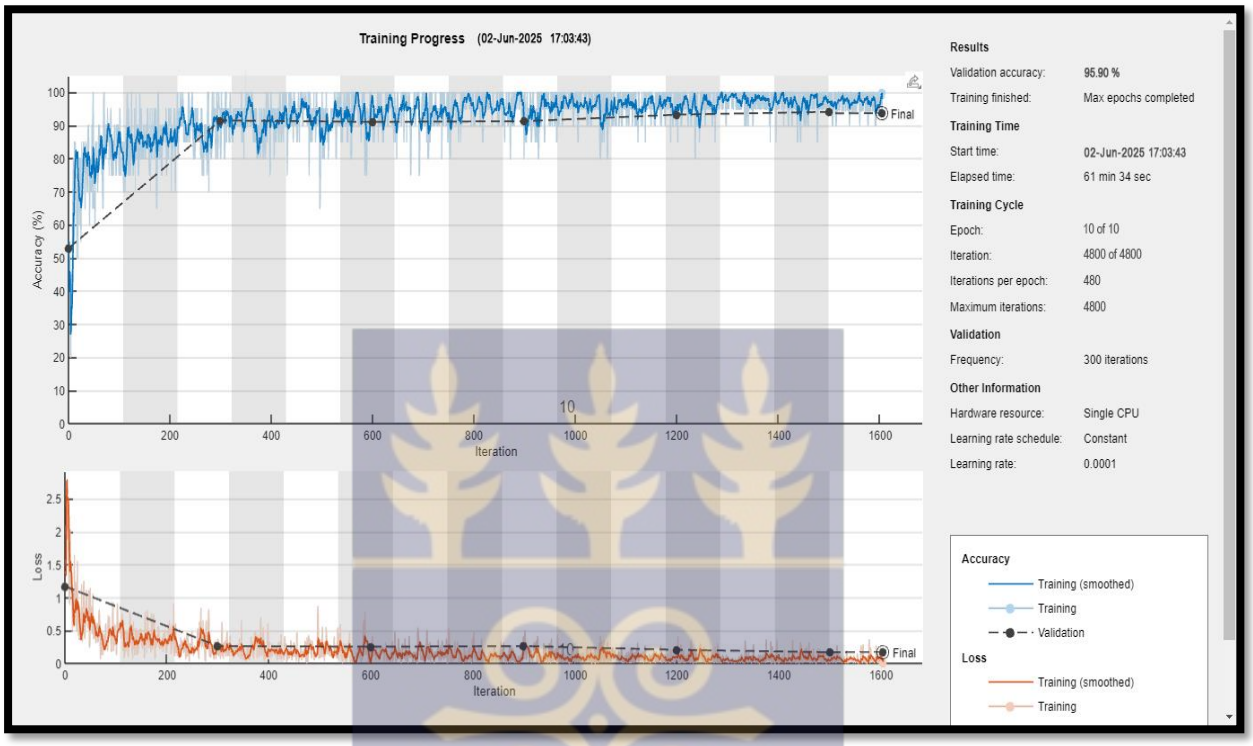


Figure 4. 23 Validation Accuracy of AlexNet on Cassava at 90:10 T-T Split

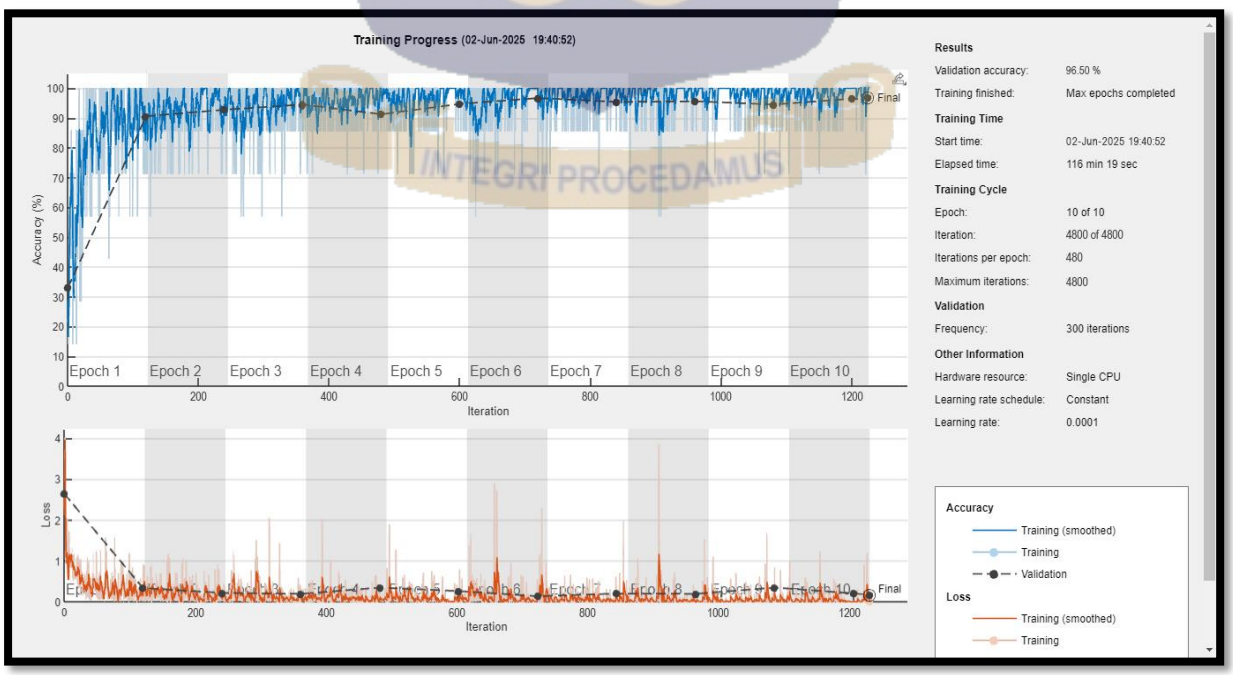


Figure 4. 24 Validation Accuracy of AlexNet on Plantain at 90:10 T-T Split

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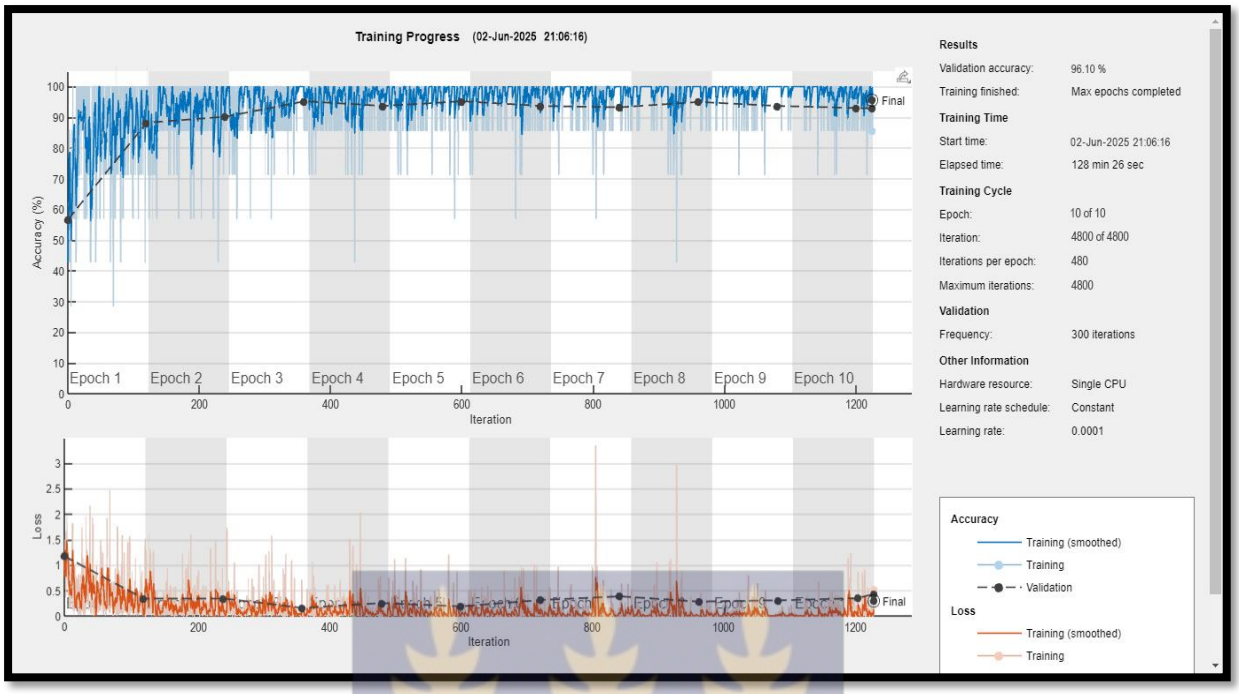


Figure 4. 25 Validation Accuracy of AlexNet on Cocoa Leaves and Pods at 90:10 T-T Split

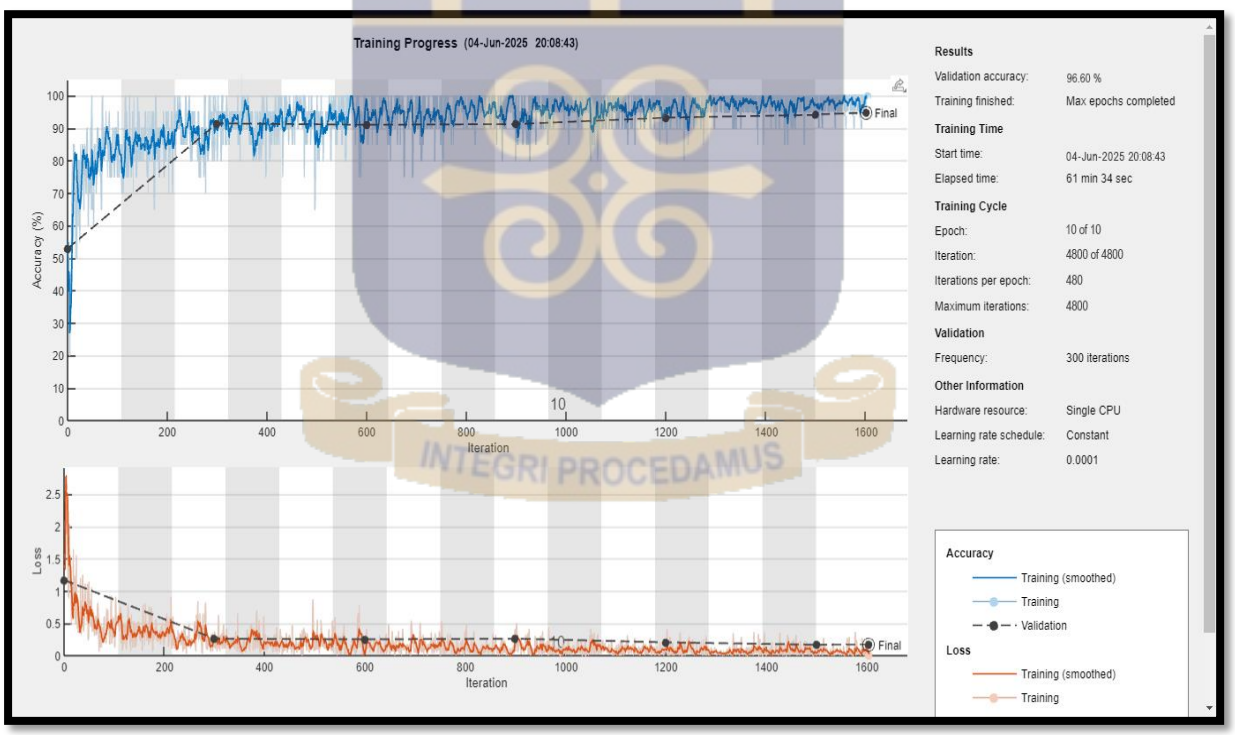


Figure 4. 26 Validation Accuracy of DarkNet-53 on Cassava at 90:10 T-T Split

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Figure 4. 27 Validation Accuracy of DarkNet-53 on Plantain at 90:10 T-T Split

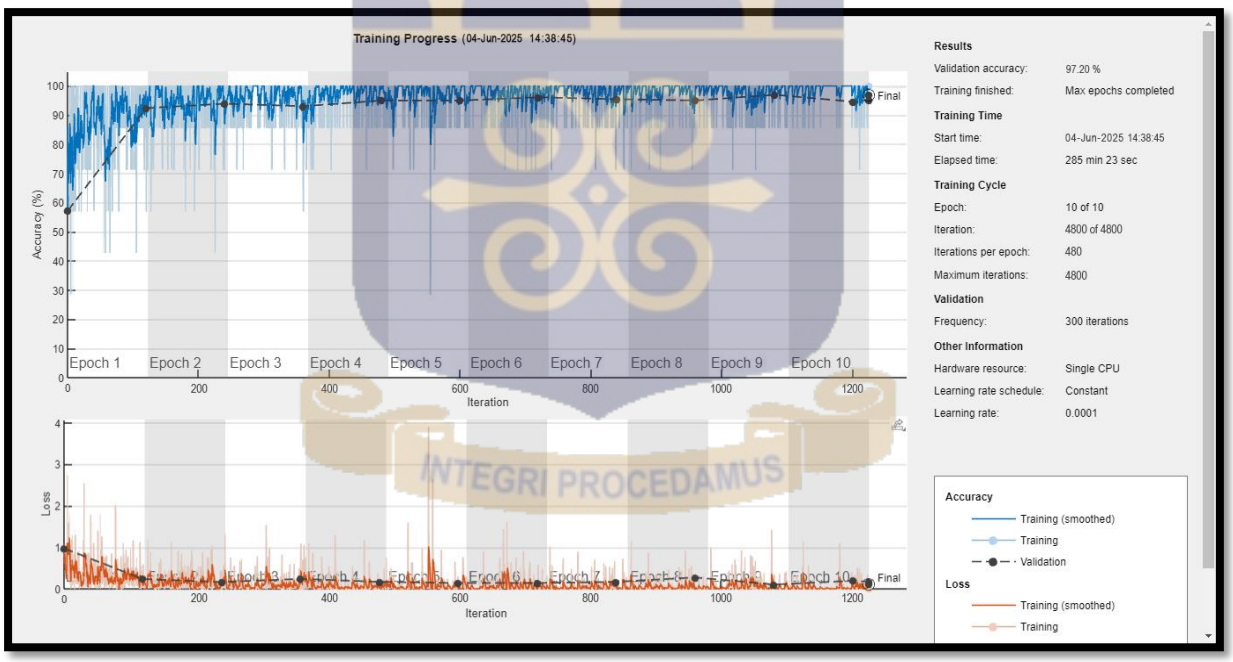


Figure 4. 28 Validation Accuracy of DarkNet-53 on Cocoa Leaves and Pods at 90:10 T-T Split

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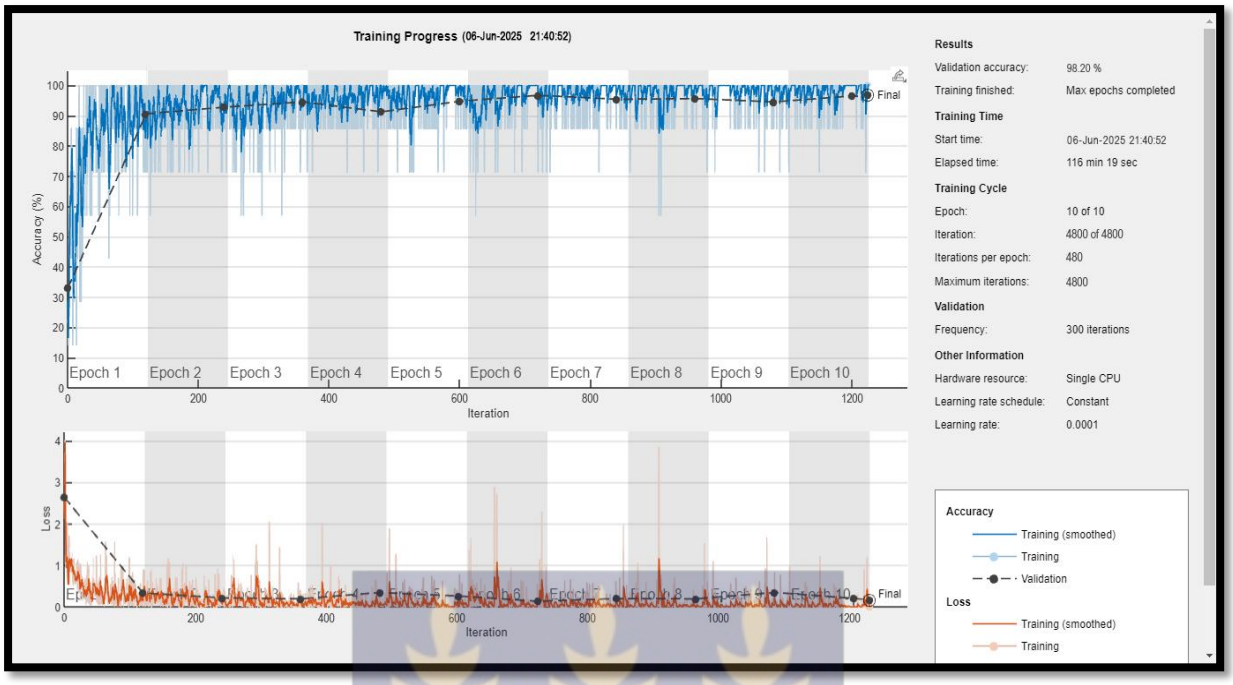


Figure 4. 29 Validation Accuracy of DenseNet-201 on Cassava at 90:10 T-T Split

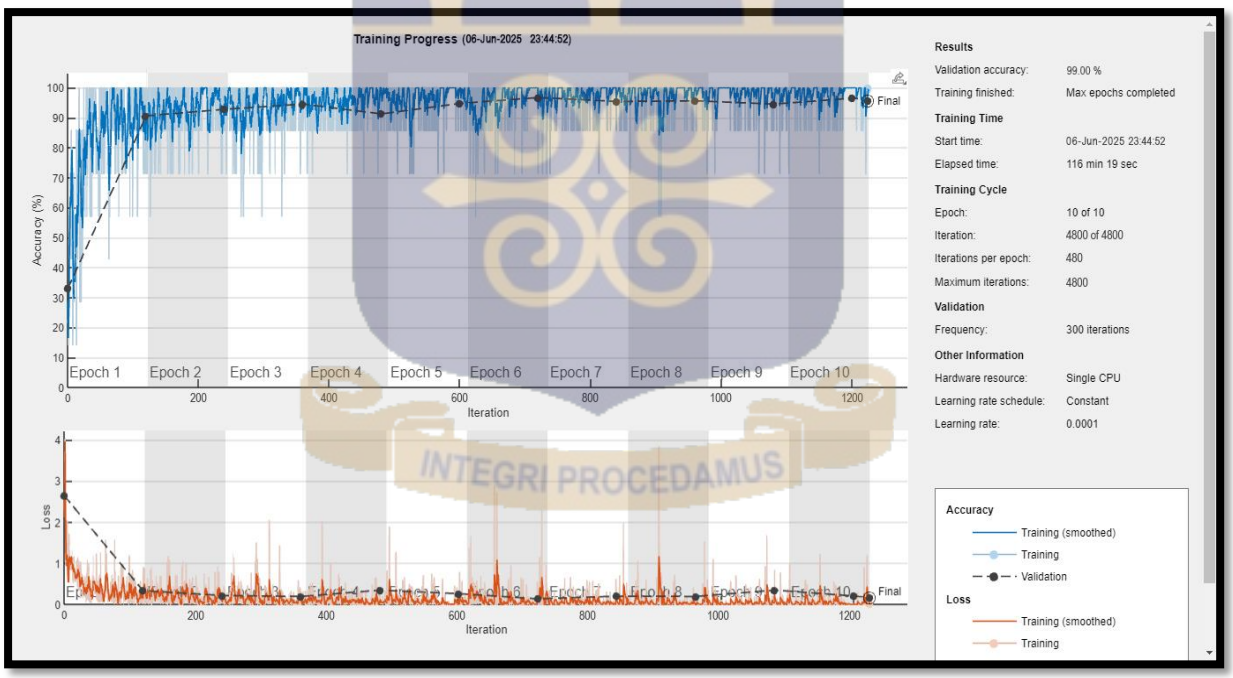


Figure 4. 30 Validation Accuracy of DenseNet-201 on Plantain at 90:10 T-T Split

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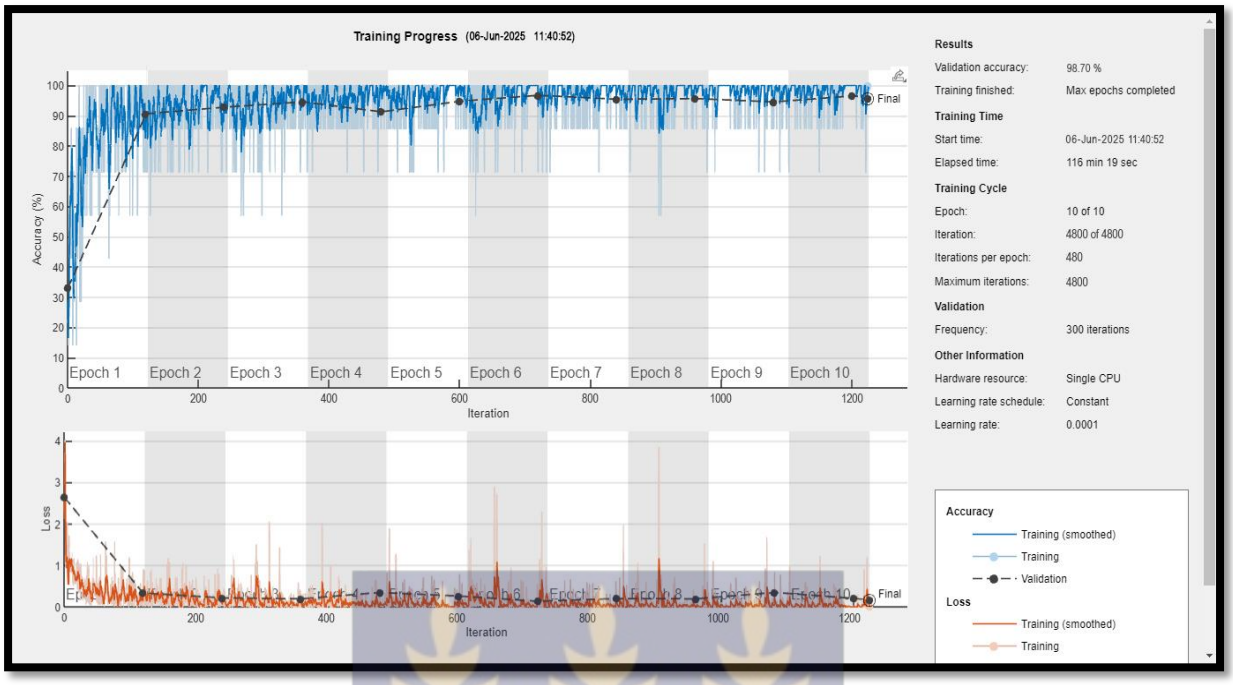


Figure 4. 31 Validation Accuracy of DenseNet-201 on Cocoa Leaves and Pods at 90:10 T-T Split

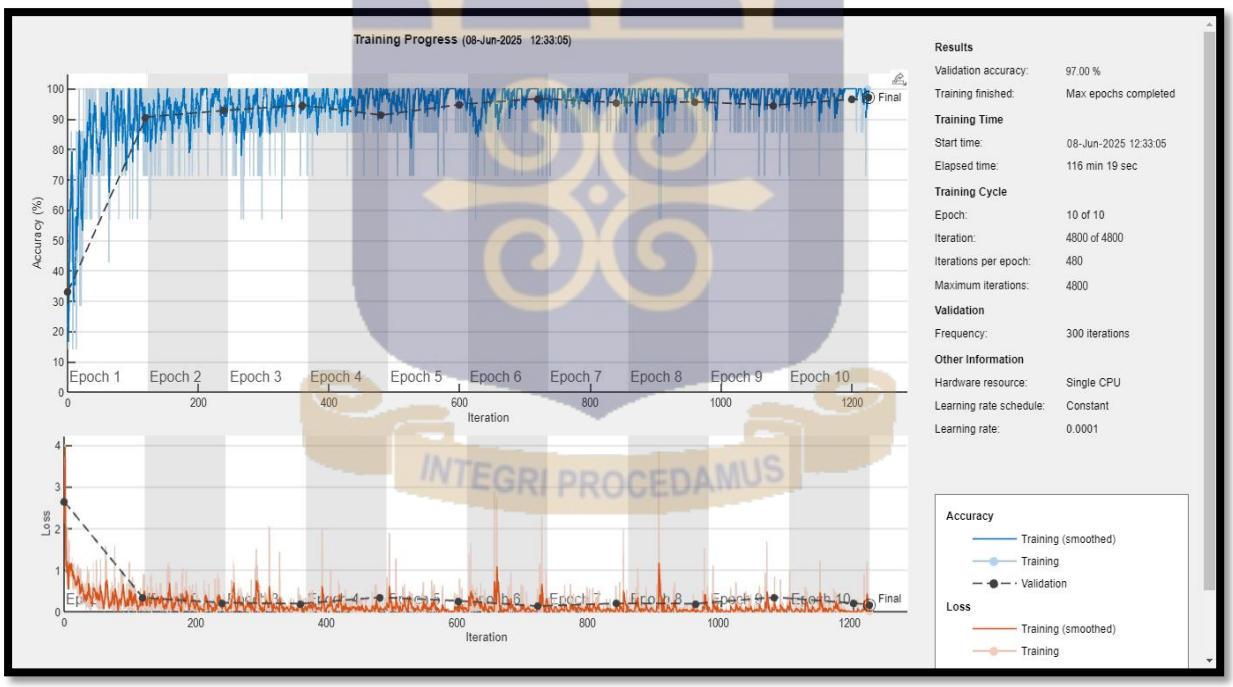


Figure 4. 32 Validation Accuracy of GoogLeNet on Cassava at 90:10 T-T Split

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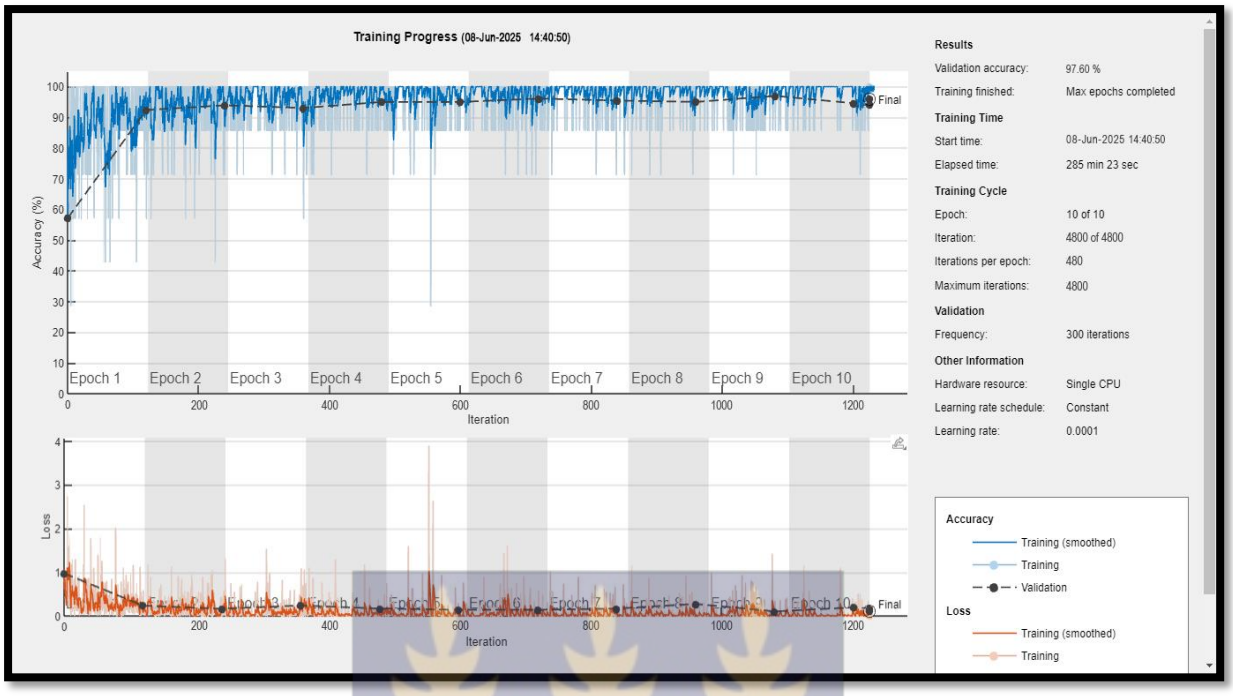


Figure 4. 33 Validation Accuracy of GoogLeNet on Plantain at 90:10 T-T Split

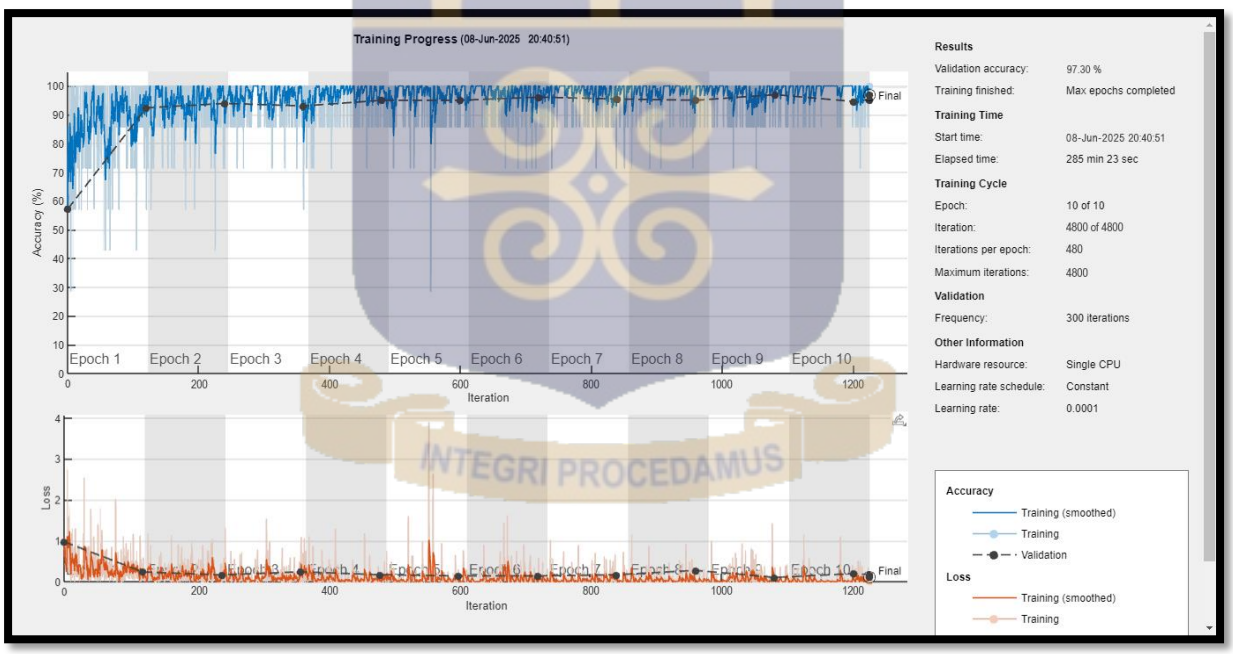


Figure 4. 34 Validation Accuracy of GoogLeNet on Cocoa Leaves and Pods at 90:10 T-T Split

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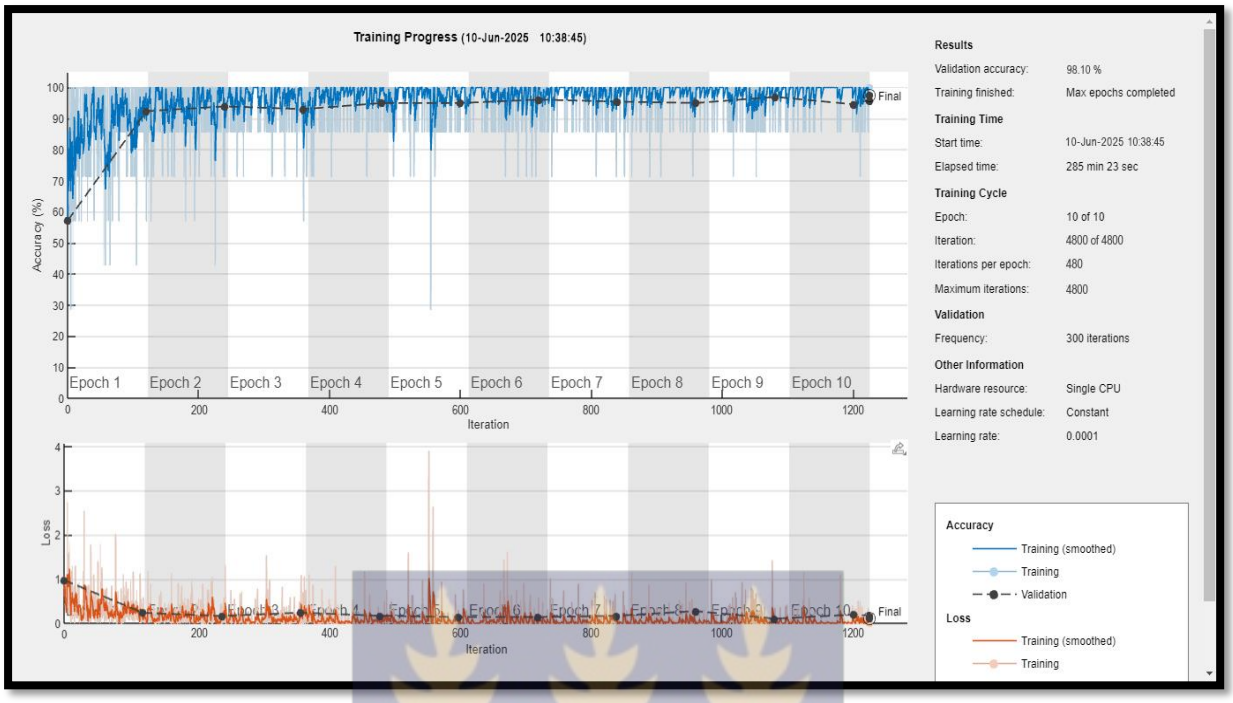


Figure 4. 35 Validation Accuracy of ResNet-101 on Cassava at 90:10 T-T Split

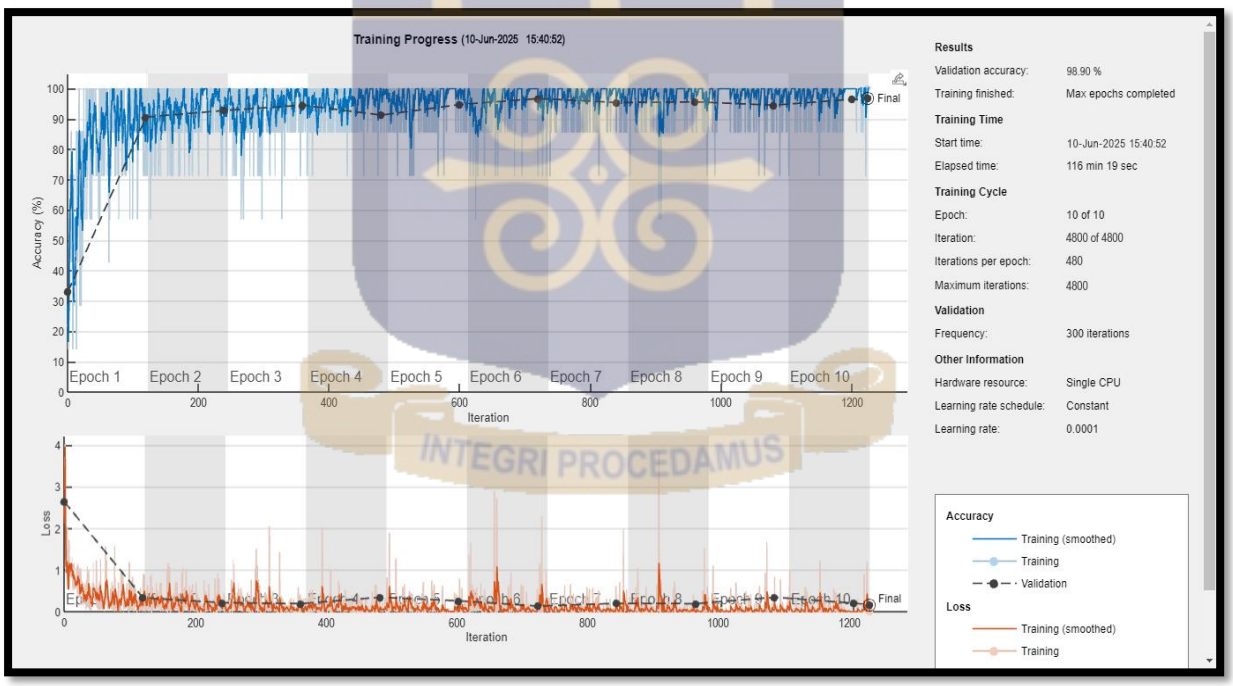


Figure 4. 36 Validation Accuracy of ResNet-101 on Plantain at 90:10 T-T Split

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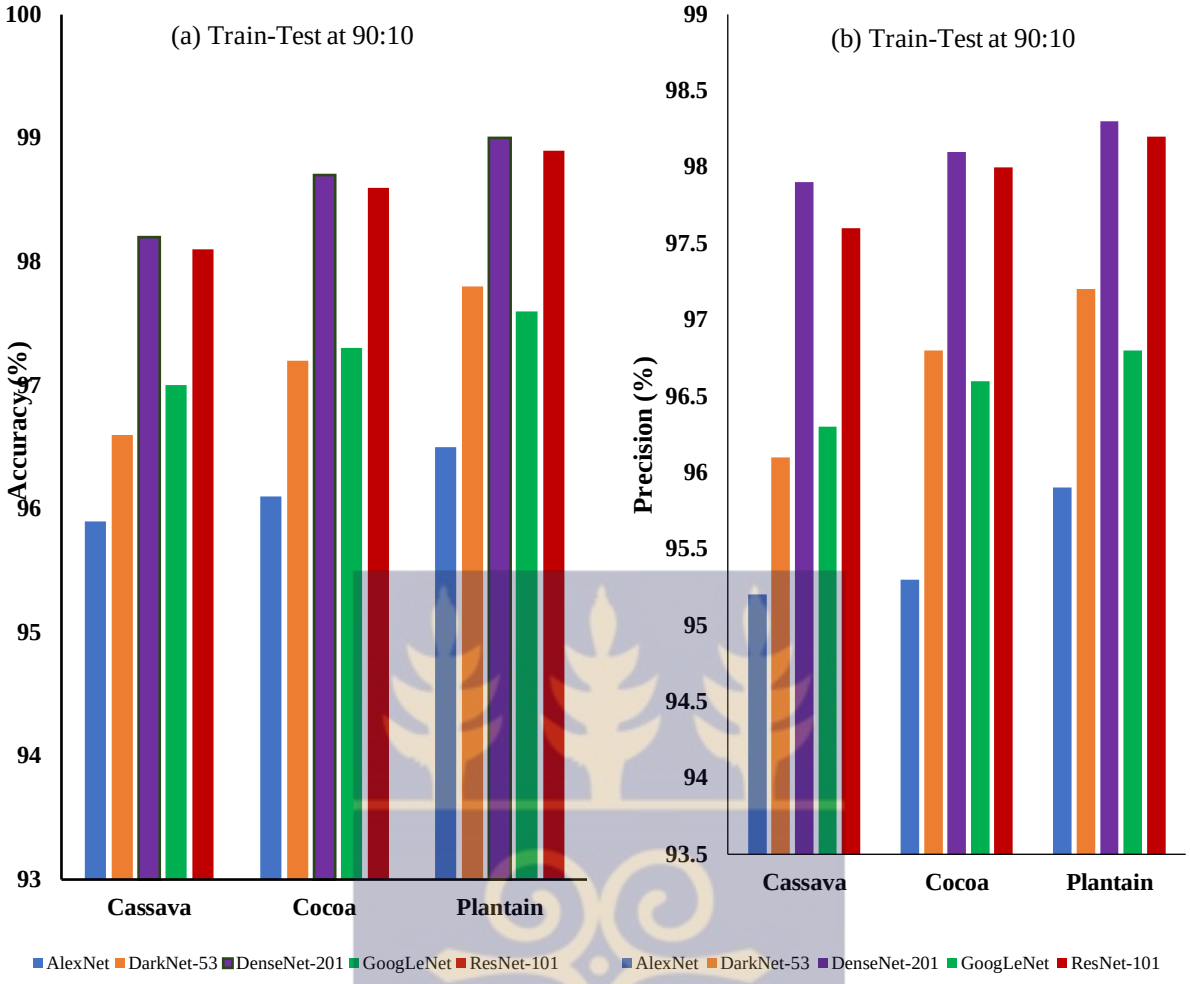


Figure 4. 37 Validation Accuracy of ResNet-101 on Cocoa Leaves and Pods at 90:10 T-T Split

4.4.7 Model Performance Evaluation on Individual Crops at 90:10 T-T Split

The performance evaluation of the CNN models on individual crop datasets (cassava, plantain, cocoa leaves and pods) under the 90:10 T–T split is presented below in Fig. 4.38. The results are illustrated through accuracy, precision, recall, and F1-score metrics, providing insights into the classification effectiveness of each model across the different crops. Under the 90:10 T–T split, DenseNet-201 recorded the highest overall performance, with accuracies of 98.20%, 99.00%, and 98.70% for cassava, plantain, and cocoa respectively, alongside superior precision, recall, and F1-Score values. ResNet-101 closely followed, achieving accuracies above 98% across all crops with strong supporting metrics. GoogLeNet and DarkNet-53 also demonstrated strong performance, maintaining accuracies between 96.60% and 97.80%. AlexNet, while improving compared to the 80:20 split, remained the lowest-performing model, with accuracies ranging from 95.90% to 96.50% and consistently lower precision, recall, and F1-Score values relative to the other models.

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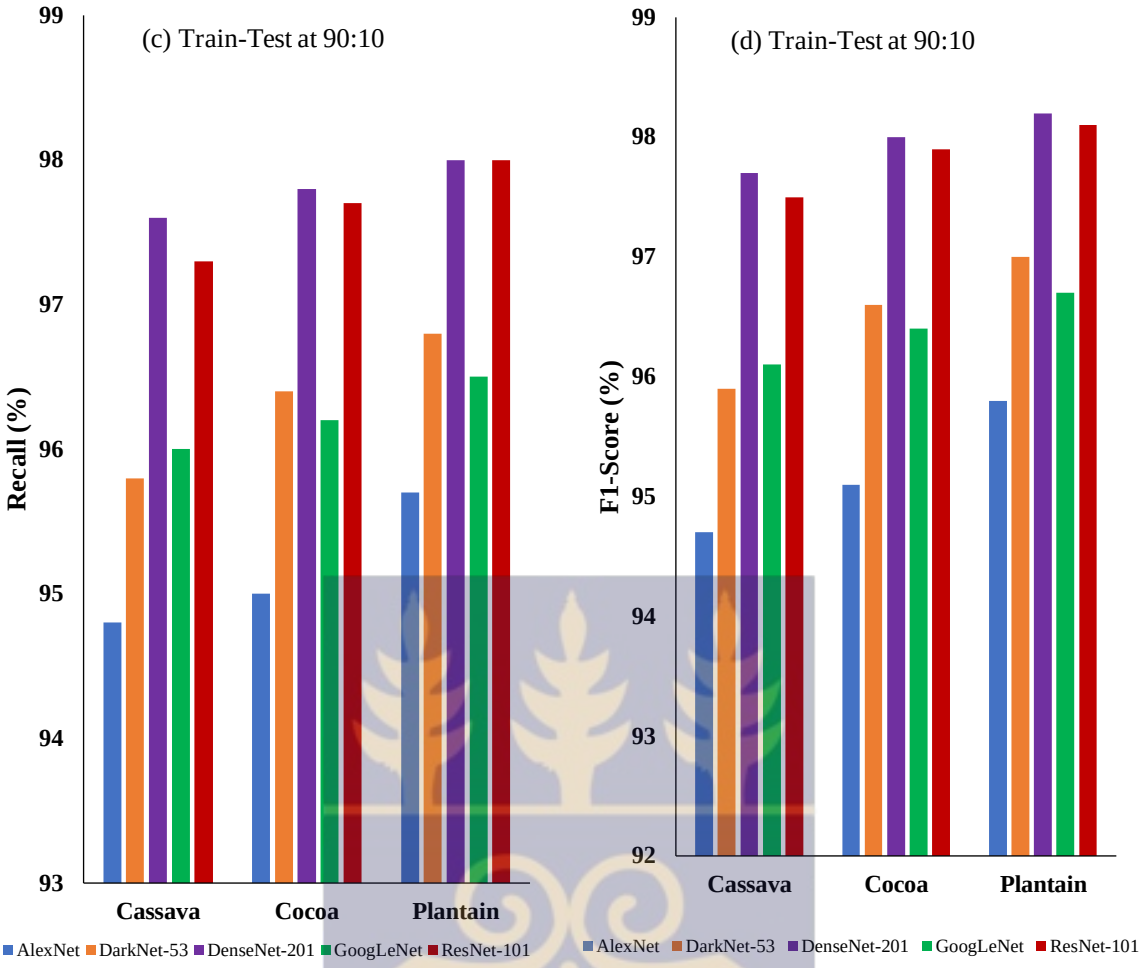


Figure 4. 38 Model Performance Evaluation on Individual Crops at 90:10 T-T split: (a) Accuracy, (b) Precision, (c) Recall, and (d) F1-Score across the CNN architecture.

4.4.8 Multi-Crop Model Accuracy with 90:10 T-T Split

In this training pattern, 90% of the dataset was allocated to training and 10% to testing, thereby maximizing the learning phase with a broader range of input samples. This resulted in higher training accuracy due to increased exposure to data, although the smaller test set could potentially limit the comprehensiveness of performance evaluation. Comparatively, some CNN models under the 90:10 split recorded marginally higher accuracies than their 80:20 models, suggesting enhanced learning efficiency; however, in certain cases, the improvement was minimal, indicating that additional training data does not always guarantee significantly better generalization as reported by (Aliferis & Simon, 2024). The validation accuracy graphs below

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reveal the models' performance under varying multi-crop datasets at 90:10 T-T split. The performance of each CNN model across the three crops is illustrated in Figs. 4.39 - 4.43.

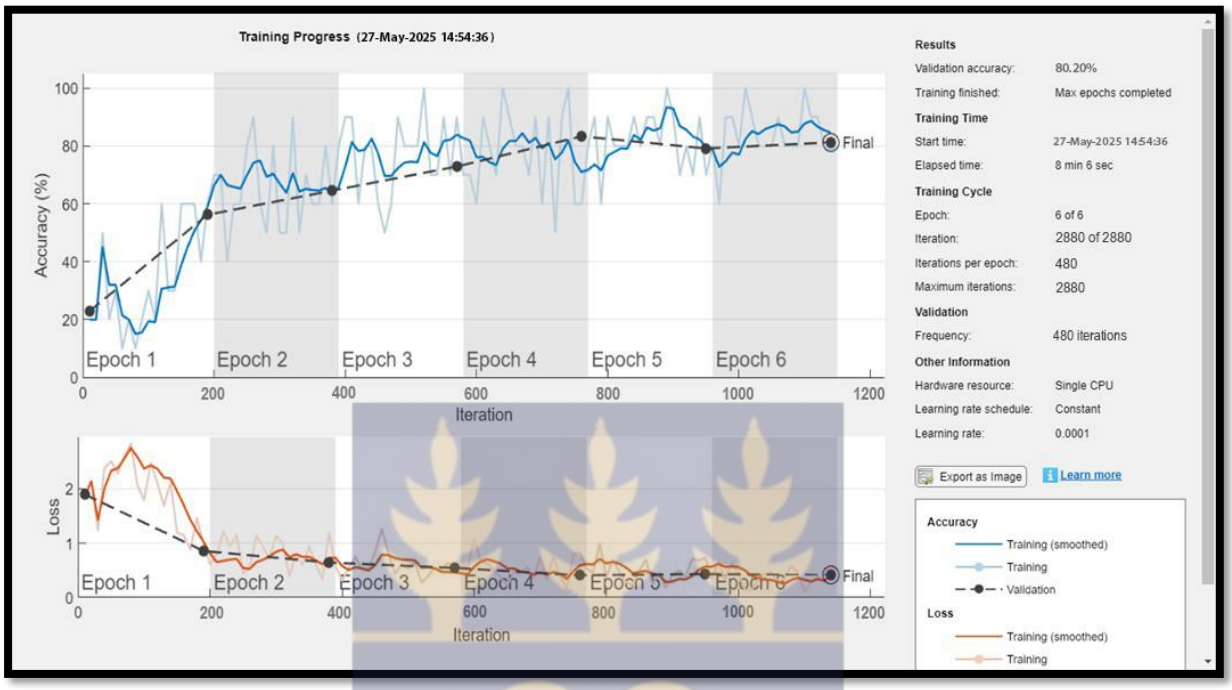


Figure 4. 39 Validation Accuracy of AlexNet on multi-crop at 90:10 T-T Split



Figure 4. 40 Validation Accuracy of DarkNet-53 on multi-crop at 90:10 T-T Split

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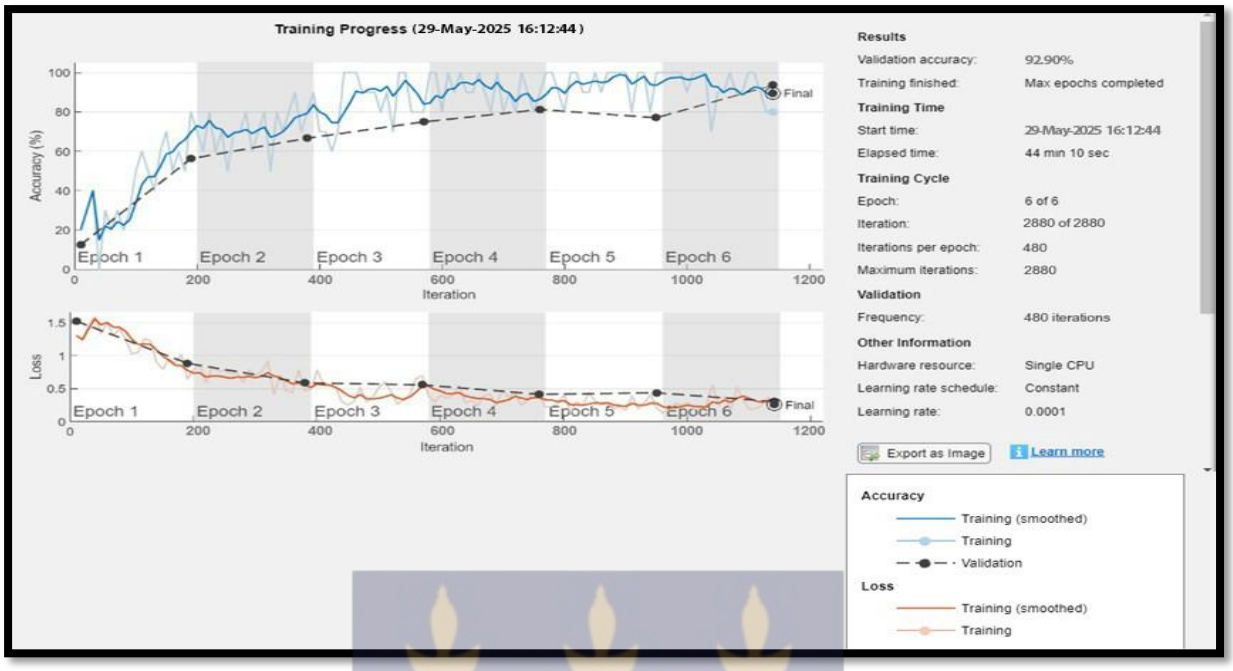


Figure 4. 41 Validation Accuracy of DenseNet 201 on multi-crop at 90:10 T-T Split

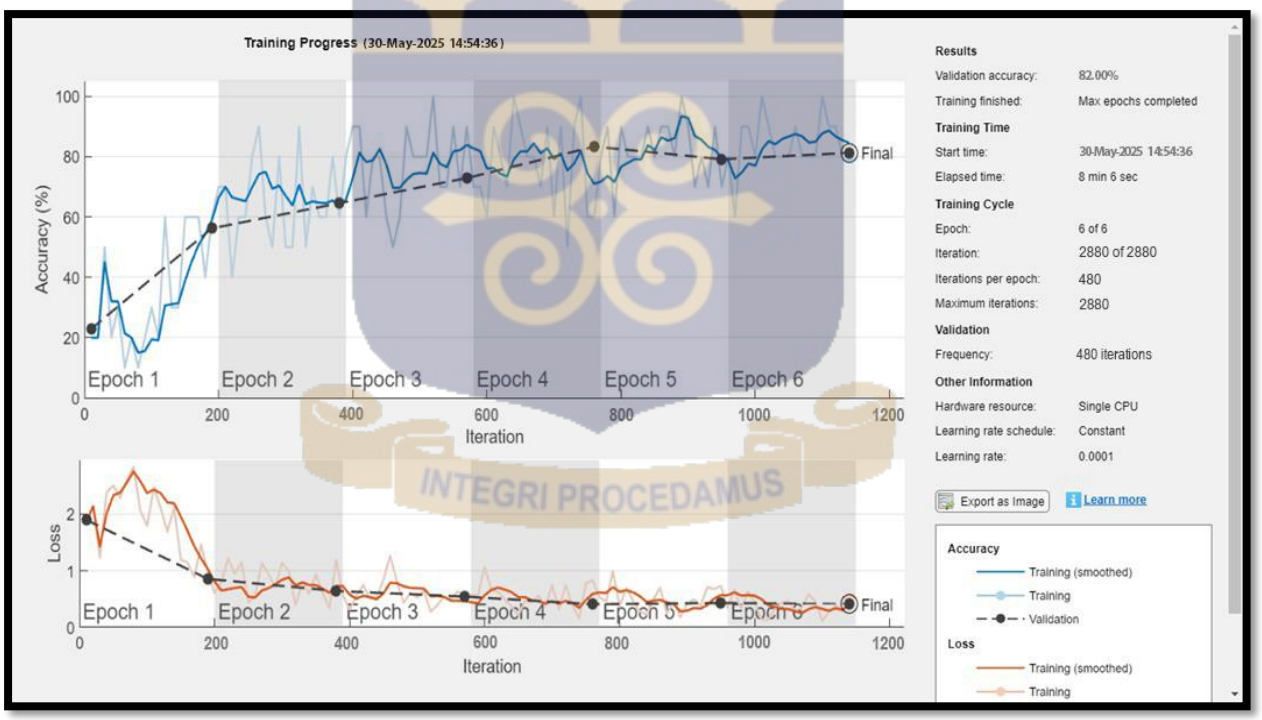


Figure 4. 42 Validation Accuracy of GoogLeNet on multi-crop at 90:10 T-T Split

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Figure 4. 43 Validation Accuracy of ResNet 101 on multi-crop at 90:10 T-T Split

The summary of the CNN models' multi-crop performance under the 90:10 T-T split is presented in Table 4.2.

Table 4. 2 Model Accuracy Performance at 90:10 T-T Split

CNN Models	Multi-Crop Validation Accuracy (%)
AlexNet	80.20
DarkNet-53	78.80
DenseNet 201	92.90
GoogLeNet	82.00
ResNet 101	86.20

4.4.9 Model Performance Evaluation on Multi-Crops at 90:10 T-T Split

The graph below in Fig. 4.44 presents the results for the CNN model performance on the multi-crop dataset under the 90:10 T–T split; demonstrating consistent improvements across all evaluation metrics compared to the 80:20 split. DenseNet-201 again achieved the highest performance (Accuracy: 92.90%, Precision: 93.00%, Recall: 92.00%, F1-Score: 92.30%), followed by ResNet-101 (Accuracy: 86.20%). GoogLeNet and AlexNet showed moderate

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outcomes within the 80–82% range across metrics, while DarkNet-53 produced the lowest performance, though still exhibiting balanced results (Accuracy: 78.80%).

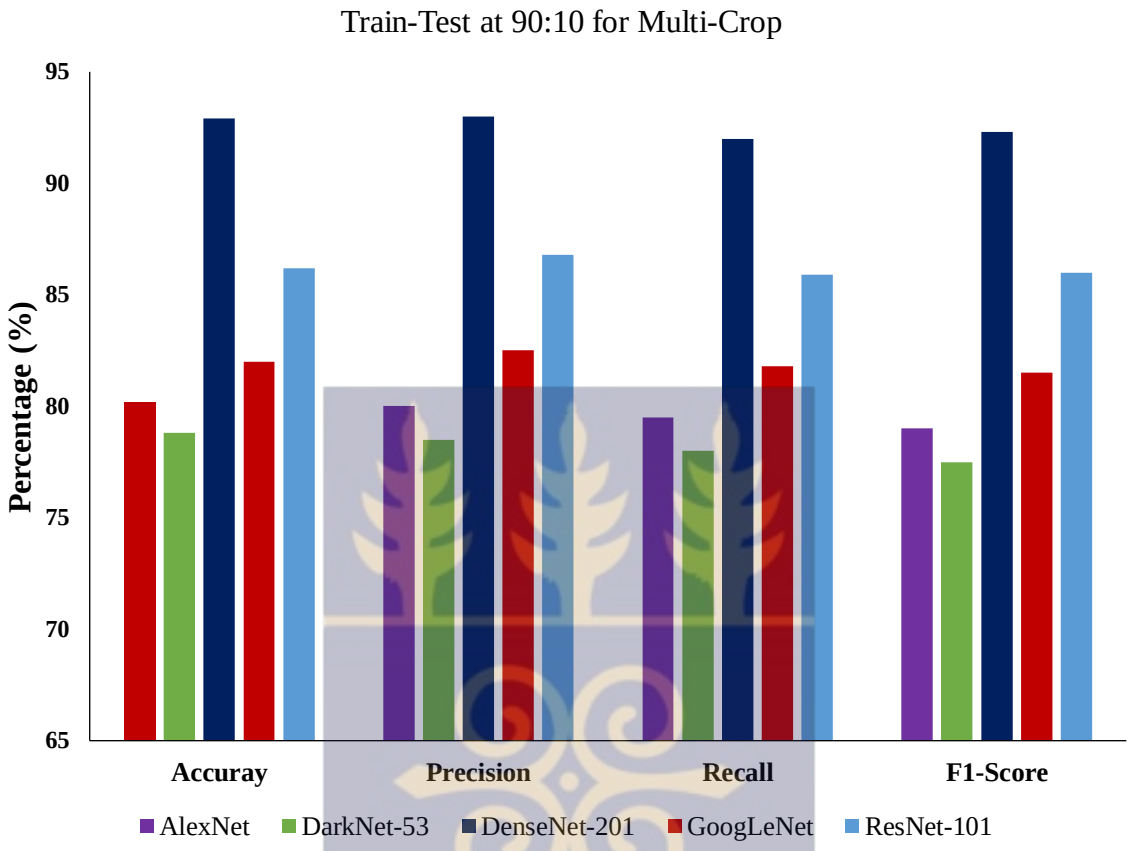


Figure 4. 44 Model Performance Evaluation on Multi-Crops at 90:10 T-T Split

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CHAPTER FIVE

DISCUSSION

5.1 Introduction

This chapter interprets the results presented in Chapter four, in relation to the study's objectives and existing literature. The discussion highlights key trends, explains variations in model performance across crops and CNN architecture, and examines the influence of T–T splits on classification outcomes. Furthermore, the chapter discusses the implications of the results in light of existing literature and highlights the potential applications and limitations of the models in agricultural disease management. The research objectives, which include evaluating the CNN models, their classification capabilities, and comparative analysis, are revisited to provide context for the findings.

5.2 Evaluation of the Individual Crop Model Performance

5.2.1 Accuracy Comparison for Individual Crops under 80:20 and 90:10 T-T Splits

The accuracy of the CNN models for individual crops under the 80:20 and 90:10 T-T splits were compared to evaluate how varying training data proportions affect classification performance.

Under the 80:20 split in Fig. 4.16 (a), performance across all crops was strong, with most models achieving excellent classification accuracy. DenseNet-201 achieved the highest scores, 96.63% (cassava), 97.61% (plantain), and 97.25% (cocoa), indicating superior capacity to extract discriminative features across diverse crop diseases consistent with findings by (Salim et al., 2023). ResNet-101 closely followed, maintaining above 96% for all crops, reflecting robust feature generalization. GoogLeNet and DarkNet-53 also performed excellently (≥95%) across all crops, with DarkNet-53 reaching 96.23% for plantain. AlexNet recorded the lowest values within this split, 93.45% for cassava, 94.95% for plantain, and 94.56% for cocoa;

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placing it in the good category. These results suggest that while AlexNet can still perform reliably, its shallower architecture limits its ability to fully exploit complex feature hierarchies in crop imagery compared to deeper networks like DenseNet 201 as reported by (Kumar et al., 2025).

For the 90:10 split in Fig. 4.38 (a), accuracies increased slightly across all models and crops, consistent with the principle that more training data can enhance learning efficiency (Barbierato & Gatti, 2024). DenseNet 201 again led, achieving 98.20% (cassava), 99.00% (plantain), and 98.70% (cocoa), all excellent classifications and the highest across the board as shown in Fig. 4.38 (a). ResNet101 performed nearly on par, with results above 98% for all crops. GoogLeNet and DarkNet-53 also delivered excellent performance, with DarkNet-53 showing notable improvement from its 80:20 values, reaching 97.80% for plantain. AlexNet improved into the excellent range for all crops (95.90–96.50%), confirming that additional training data benefits shallower architecture as reported by (Pasupa & Sunhem, 2016).

Comparatively, the 90:10 split consistently outperformed the 80:20 split across all models and crops as seen in Fig. 4.38, although the magnitude of improvement was more pronounced for lower-capacity models like AlexNet. DenseNet-201 remained the most accurate and reliable network under both splits, with its ability to capture fine-grained spatial details likely contributing to consistent performance across cassava, plantain, and cocoa disease classification.

5.2.2 Precision Comparison for Individual Crops under 80:20 and 90:10 T-T Splits

The precision of the CNN models for individual crops under the 80:20 and 90:10 T–T splits were compared to assess their ability to correctly identify true positive disease cases. Under the 80:20 split in Fig. 4.16 (b), DenseNet-201 consistently achieved the highest precision for all three crops (96.00% for cassava, 96–98% for plantain, and 97.00% for cocoa), indicating

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its superior ability to minimize false positives as confirmed by (S. N. Patil et al., 2024) across different plant types. This was closely followed by ResNet-101 and DarkNet-53, both of which maintained precision values above 94% for all crops. AlexNet, while delivering solid results (92.50–94.00%), trailed slightly behind the other architecture, particularly for cassava.

With the 90:10 split on Fig. 4.38 (b), overall precision values improved for all models, consistent with the principle that a larger proportion of training data can enhance model learning (Barbierato & Gatti, 2024). DenseNet 201 again led with precision scores nearing or exceeding 98% for all crops, followed closely by ResNet-101 and DarkNet-53, each showing notable gains compared to the 80:20 results. The performance gap between AlexNet and the more advanced architecture narrowed under this split, though AlexNet still recorded the lowest precision among the tested models. Overall, the results highlight DenseNet-201's strong and consistent precision across both splits and crop types, reaffirming its reliability for high-specificity disease classification tasks as reported by (Srinivasan et al., 2025).

5.2.3 Recall Comparison for Individual Crops under 80:20 and 90:10 T-T Splits

The recall of the CNN models for individual crops under the 80:20 and 90:10 T–T splits were compared to evaluate their effectiveness in identifying all true disease instances.

Under the 80:20 split in Fig. 4.16 (c), DenseNet-201 consistently achieved the highest recall across cassava (95.00%), plantain (95–97%), and cocoa (96.00%), reflecting its strong sensitivity in detecting diseased samples as reported by (Salim et al., 2023). ResNet-101 and DarkNet-53 followed closely, each maintaining recall values above 94% for all crops. GoogLeNet also demonstrated solid recall (94–95%), while AlexNet recorded the lowest, though still appreciable, recall rates (92–94%). These findings indicate that while AlexNet is reasonably sensitive, deeper architecture better capture subtle disease features, reducing false negatives consistent with studies by (Samuel, 2024).

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With the 90:10 split in Fig. 4.38 (c), recall values improved for all CNN models, consistent with the benefit of larger training sets (Barbierato & Gatti, 2024). DenseNet-201 again led the performance, achieving excellent recall scores above 97% for all crops. ResNet101 closely followed with recall values at or above 97%, and GoogLeNet and DarkNet-53 also showed strong improvements, exceeding 96%. AlexNet improved to near or above the 95% threshold, reaching excellent recall for all crops. This progression confirms that increasing training data enhances models' abilities to detect diseased cases accurately, particularly benefiting architecture with previously lower recall as reported by (Barbierato & Gatti, 2024) and aligning with best practices that larger training datasets improve model sensitivity in classification tasks.

5.2.4 F1-Score Comparison for Individual Crops under 80:20 and 90:10 T-T Splits

The F1-score of the CNN models for individual crops under the 80:20 and 90:10 T–T splits were compared to assess the balance between precision and recall in disease classification.

Under the 80:20 T-T split in Fig. 4.16 (d), DenseNet-201 achieved the highest F1-scores across cassava (95.50%), plantain (96–97%), and cocoa (96.50%), demonstrating a superior balance between minimizing false positives and false negatives consistent with findings by (Talukder, 2025). ResNet-101 closely followed, with F1-scores consistently above 95% for all crops, confirming its reliable classification capability. GoogLeNet and DarkNet-53 also maintained strong performance, with F1-scores in the 94–95% range. Meanwhile, AlexNet exhibited the lowest F1-scores, though still respectable (92.00–93.50%), indicating it is less effective at balancing precision and recall compared to deeper models.

With the 90:10 split in Fig. 4.38 (d), all models showed improved F1-scores, consistent with enhanced learning from increased training data (Barbierato & Gatti, 2024). DenseNet-201 again led with excellent F1-scores exceeding 97% across all crops. ResNet101 closely matched these results, with F1-scores above 97%. GoogLeNet and DarkNet-53 demonstrated solid

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improvements, reaching F1-scores above 96%, while AlexNet improved into the excellent range (94.70–95.80%).

DenseNet 201 consistently exhibited the best F1-scores, reflecting its effectiveness in maintaining a favorable trade-off between precision and recall. The 90:10 split generally provided superior F1-scores across all models and crops, reaffirming the advantage of a larger training set in optimizing model performance for crop disease classification by (Barbierato & Gatti, 2024).

5.3 Evaluation of the Multi-Crop Model Performance

5.3.1 Multi-Crop Accuracy Performance on both T-T Splits

Under the 80:20 split, DenseNet-201 demonstrated the highest accuracy (89.58%) as summarized in Table 4.1, indicating strong feature extraction and generalization capability as reported by (Chauhan et al., 2021) across multiple crops. ResNet-101 followed with 81.25%, reflecting good performance but lower robustness compared to DenseNet-201. GoogLeNet (76.67%) and AlexNet (75.00%) achieved moderate accuracy, suggesting reasonable learning capacity but limited adaptability as reported by (Syed et al., 2022) to multi-crop variability. DarkNet-53 recorded the lowest accuracy (73.33%), highlighting weaknesses in generalization under the more balanced evaluation setting as reported by (Yang et al., 2023). Under the 90:10 split, some CNN models recorded marginally higher accuracies (Table 4.2) than their 80:20 models, suggesting enhanced learning efficiency.

5.3.2 Multi-Crop Model Performance Comparison on both T-T

For accuracy at 90:10 shown in Fig. 4.44, DenseNet-201 achieved the highest accuracy (92.90%) which is classified Good in Table 3.4, outperforming all other models, while DarkNet-53 recorded the lowest (78.80%, Poor). At 80:20 shown in Fig. 4.22, DenseNet-201 again led (89.58%, Fair), with DarkNet-53 performing worst (73.33%, Poor). This indicates

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that DenseNet-201 consistently generalizes better (Chauhan et al., 2021) in multi-crop classification, while DarkNet-53 struggles with diverse crop data.

Precision, followed a similar trend. At 90:10 shown in Fig. 4.44, DenseNet-201 (93.00%, Good) was most reliable in minimizing false positives consistent with studies by (Aliferis & Simon, 2024), whereas DarkNet-53 (78.50%, Poor) was least effective as shown in Fig. 4.11(b). At 80:20, DenseNet-201 (90.00%, Good) again topped the performance chart, with DarkNet-53 (73.00%, Poor) trailing as shown in Fig. 4.22. This reinforces DenseNet-201's robustness in correctly identifying diseased cases without over-predicting confirming findings by (Alam et al., 2024).

Recall, which measures the proportion of actual positive cases correctly classified, showed DenseNet-201 as the most acceptable model under both splits (92.00% at 90:10, Good; 89.00% at 80:20, Fair) in Figs. 4.44 and 4.22 respectively. DarkNet-53 consistently underperformed (78.00% at 90:10; 72.00% at 80:20), suggesting difficulty in capturing all true positive cases, potentially missing diseased instances.

F1-score, further confirmed DenseNet-201's superior balance between sensitivity and specificity (92.30% at 90:10, Good; 89.00% at 80:20, Fair) in Figs. 4.44 and 4.22 respectively. DarkNet-53 remained the weakest performer (77.50% at 90:10; 72.00% at 80:20), indicating limited capability in achieving an optimal trade-off between precision and recall which confirms findings of (Junos et al., 2022).

DenseNet-201 emerged as the most acceptable model across all metrics and both splits, aligning with guidelines from (Bishop, 2006; Murphy, 2012) that emphasize architecture capable of capturing complex, multi-scale features. DarkNet-53's consistent underperformance highlights its limitations in multi-crop scenarios, possibly due to less effective feature representation for diverse disease patterns. Notably, the 90:10 split in Fig. 4.44 generally

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yielded marginally higher metric values across models, consistent with the principle that more training data can enhance learning, however, the gain in performance was not substantial for every model (Barbierato & Gatti, 2024).

5.4 Analysis of the Models Accuracy Performance

The CNN model's accuracy performance in detecting crop diseases was influenced by several critical factors, most notably the quality of input images, the visual distinctiveness of disease symptoms, and the diversity of the training dataset. One of the key determinants of model performance was image quality, which affected the ability of CNNs to learn and generalize relevant features (Zech et al., 2018). Images that were blurry, poorly lit, or partially obscured reduced the effectiveness of feature extraction during training. This was especially evident in cases where fine-grained visual cues such as discoloration or small lesions were essential for accurate classification.

In addition, the severity and visual clarity of disease symptoms significantly impacted classification performance. Diseases that presented with distinct patterns or color contrasts such as necrotic spots, widespread chlorosis, or localized pod lesions were more readily identified by the models. In contrast, conditions that exhibited mild or diffuse symptoms, particularly in the early stages of infection, posed challenges. This was particularly true for diseases with symptoms that visually overlapped with other physiological stressors like nutrient deficiencies or environmental damage (Grant-Downton et al., 2014).

The ability of each model to detect different disease types also varied based on architecture complexity (Shewale & Daruwala, 2023). Deeper networks with more layers, such as DenseNet and ResNet, tended to perform better across all models in identifying subtle visual patterns and distinguishing between classes. Both models achieved superior performance exceeding 96%, which is considered excellent in deep learning evaluations (Bishop, 2006; Powers, 2020),

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aligning with findings by (Lu et al., 2021). These architectures are inherently more capable of capturing hierarchical representations, which is particularly advantageous for detecting diseases that manifest with nuanced symptoms (Zhao et al., 2024). Simpler models, such as AlexNet, showed limitations in handling more complex or visually ambiguous disease classes, often leading to confusion between healthy and mildly infected samples.

5.5. Analysis of Classification Performance

The classification performance of the CNN models was influenced by a range of interrelated factors. One of the primary determinants was the visual distinctiveness of disease features, which played a critical role in enabling the model to learn discriminative patterns. Diseases with clear, consistent symptoms such as Black Pod Disease in cocoa and Cassava Mosaic Disease were more accurately classified across all models. In contrast, diseases with subtle, early-stage symptoms, or those resembling physiological disorders, posed significant classification challenges aligning with findings by (Aregbesola & Owombo, 2014).

Another factor that affected performance was the architecture depth and learning capacity of each CNN model (Chen & Tsou, 2022). Deeper models like DenseNet 201 and ResNet 101 were able to retain and propagate spatial and contextual information through dense connections and residual paths, enhancing their capability to differentiate between visually similar disease classes. On the other hand, shallower architecture such as AlexNet, while faster to train, lacked the representational depth necessary for handling complex classification scenarios.

Again, environmental variation in image backgrounds, leaf orientation, lighting conditions, and disease progression stages contributed to classification discrepancies. Some misclassifications were linked to overlapping symptom patterns between diseases, such as nutrient deficiency and viral infections in cassava, and between Black Sigatoka and Cordana Leaf Spot in plantain.

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5.6 Relating Findings to Research Objectives

The primary aim of this research was to assess the efficacy of various CNN models in detecting and classifying crop diseases, particularly in cassava, plantain, and cocoa leaves and pod dataset.

The first research objective focused on evaluating the ability of the selected CNN models to accurately detect and classify leaf diseases in the selected test crops under investigation. The results indicate that this objective was successfully achieved, as all five CNN models, AlexNet, DarkNet-53, DenseNet 201, GoogLeNet, and ResNet 101 demonstrated high classification accuracy, particularly in crop-specific training scenarios. The models also performed particularly well in recognizing diseases with clear, well-defined visual symptoms, such as Black Pod Disease in cocoa and Cassava Mosaic Disease. DenseNet-201 emerged as the top-performing model across both multi-crop and crop-specific evaluations, indicating a strong capacity for generalization and feature discrimination across different disease types and plant structures.

The second objective sought to conduct a comparative analysis to determine which model demonstrated superior performance and efficiency. This was addressed through a comprehensive comparison using performance metrics including accuracy, precision, recall, and F1-score. DenseNet-201 and ResNet-101 consistently achieved higher scores across these metrics, validating their effectiveness in crop disease detection tasks. The insights gained from this comparative analysis directly inform recommendations for deploying these models in practical large scale agricultural contexts.

The third and final objective focused on investigating the impact of different T-T split ratios on the performance of CNN models for crop disease detection. Across both multi-crop and individual crop experiments, the 90:10 T-T split consistently produced slightly higher

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accuracy, recall, and F1-scores than the 80:20 split, indicating that a larger training set generally enhances model performance. Based on these findings, the 90:10 split is recommended for agricultural crop disease detection, as it maximizes learning while maintaining sufficient data for reliable evaluation.

The implications for cassava, plantain, and cocoa leaves and pod disease management are significant. Early detection of diseases such as Cocoa Black pod disease, Cassava Bacterial Blight and Black Sigatoka can drastically reduce crop losses and improve yield through timely intervention. The integration of CNN-based disease detection tools in rural farming communities particularly those with limited access to agricultural extension services can empower farmers with rapid, accessible diagnostic support using mobile or handheld devices

5.7 Limitations of the Study

Despite the promising results, the study is not without limitations. One notable constraint was the reliance on a finite and context-specific dataset, which may not capture the full variability of disease presentations under different climatic conditions, or growth stages. This can lead to reduced generalizability when applied outside the trained domain. Second, there was variability in image quality across the dataset, influenced by factors such as lighting conditions, image resolution, and background interference. These inconsistencies can introduce noise into the training process and potentially impact the models' ability to maintain high accuracy in less controlled environments. There is also the challenge of interpretability in CNN-based models. While they achieve high accuracy, understanding how and why specific predictions are made remains difficult, posing a challenge for stakeholder trust and transparency, especially in field deployment scenarios. Additionally, the scope of this study did not include real-time testing in field conditions or integration with IoT or mobile platforms, which would have further tested the models' robustness in uncontrolled environments.

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CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1.0 CONCLUSION

An experimental computational study was carried out to investigate the performance of five CNN architecture, AlexNet, DarkNet-53, DenseNet 201, GoogLeNet, and ResNet 101 in detecting and classifying diseases in cassava, plantain, and cocoa leaves and pods using both multi-crop and individual crop training approach. The analysis was conducted under two T–T split ratios, 80:20 and 90:10, to evaluate the impact of dataset partitioning on model performance.

1. The results demonstrated that DenseNet 201 consistently achieved the highest accuracy, precision, recall, and F1-score across both T–T split ratios and in both multi-crop and individual-crop contexts. ResNet-101 and DarkNet-53 followed closely, while AlexNet generally recorded the lowest performance metrics. The consistent high performance of DenseNet 201 and ResNet 101 suggests these models are well-suited for practical deployment in precision agriculture, where early and accurate disease identification is critical for effective crop protection. Their ability to capture subtle symptom variations makes them ideal candidates for real-time disease monitoring in both smallholder and commercial farms.
2. Model performance improved under the 90:10 split compared to the 80:20 split, confirming that a larger training set enhances CNN learning capacity. This improvement was consistent across multi-crop and individual-crop scenarios, although the magnitude varied between metrics and crops. Among the crops, plantain generally recorded the highest classification metrics, while cassava and cocoa followed closely.

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3. This research contributes to plant disease management by demonstrating that advanced DL architecture can reliably detect multiple crop diseases with high accuracy, offering potential for early detection and timely intervention. For cassava, plantain, and cocoa which is the backbone crops of many tropical agricultural economies, rapid and reliable disease detection can substantially reduce the spread of pathogens, improve yield quality, and enhance food security. The results also show the importance of high-quality datasets, as model performance is closely tied to data diversity and representation.

6.2.0 RECOMMENDATIONS

I. Integrate DenseNet-201 and ResNet-101 into mobile-based decision support systems. These architectures demonstrated the highest classification accuracy and feature sensitivity during testing, making them the most reliable engines for real-time field diagnostics by farmers and extension officers.

II. Future training cycles should prioritize datasets that represent a wider range of climatic conditions and growth stages. Research data indicates that model robustness across regions is highly dependent on exposure to environmental variables like varying solar intensity and background foliage complexity.

III. Expand the diagnostic scope to include more disease types and phenotypic symptom variations from additional agro-ecological zones. This expansion is necessary to increase the model's generalization capability, allowing it to identify early-stage symptoms and multi-infection scenarios across diverse geographic landscapes.

IV. Investigate lightweight architectures and model compression techniques such as pruning or quantization. Optimizing the DenseNet and ResNet backbones for low-resource mobile hardware is essential to maintain high-speed inference without requiring high-end GPUs in rural agricultural settings.

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PUBLICATION

Mensah, S. A., Amoatey, P. K., Ofori, P. A., Owusu-Nketia, S., Sabi, E. B., Dwomoh, F. A., Simpson, A. R., & Asenso, E. (2026). Evaluating the Efficacy of Convolutional Neural Networks: Disease Detection in Crops. Advances in Agriculture, 2026, 2026:3578866. https://doi.org/10.1155/aia/3578856



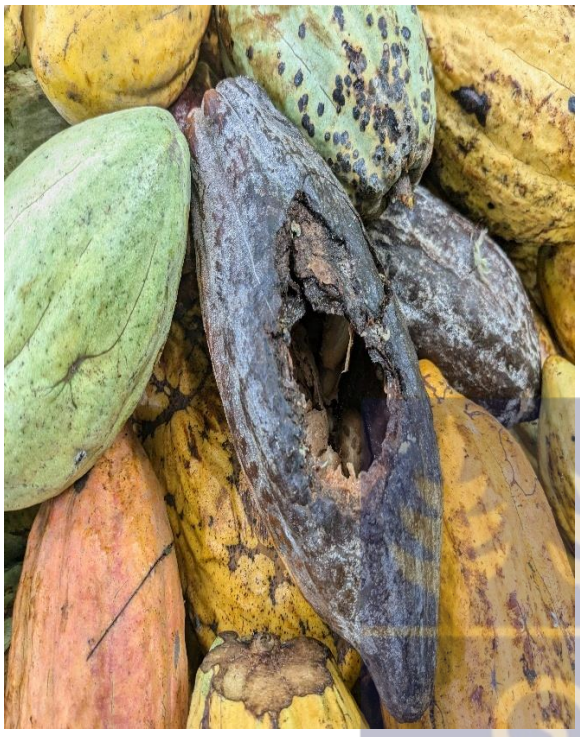
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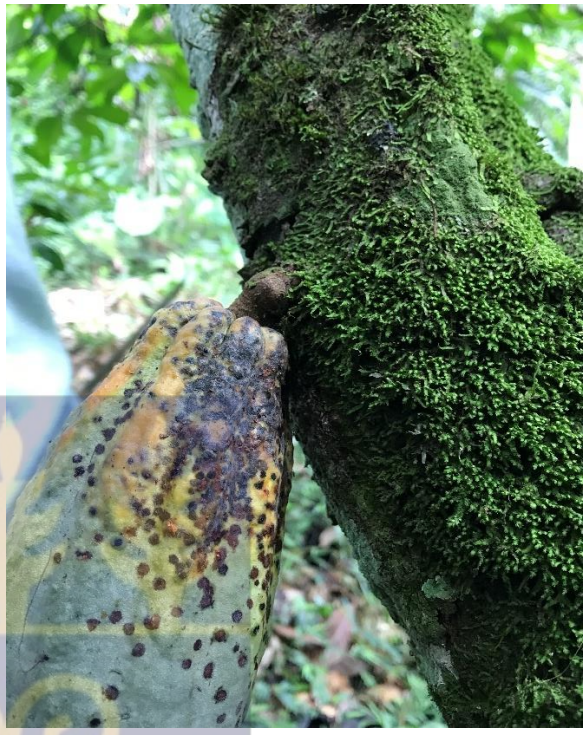
APPENDIX: Sample Images from Dataset

Cocoa leaf and pod images captured for classification, illustrating variations between healthy and infected samples.



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Cassava leaf images collected from the field showing both healthy and diseased conditions.



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Plantain leaf images representing diverse conditions for model training and evaluation

