A Deep Learning-Based Approach for Zea Mays Leaf Disease Classification

BY

Wali Ullah Ripon
201-15-14044

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Mr. Mushfiqur Rahman

Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Co-Supervised By

Mr. Md. Ferdouse Ahmed Foysal
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
DHAKA, BANGLADESH
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APPROVAL

APPROVAL

This Project titled **"A Deep Learning-Based Approach for Zea Mays Leaf Disease Classification"**, submitted by Wali Ullah Ripon and ID: 201-15-14044 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14th July 2024**.

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Faculty of Science & Information Technology
Daffodil International University

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Daffodil International University

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Lecturer
Department of CSE, DIU
Faculty of Science & Information Technology
Daffodil International University

14.07.24

Dr. Abu Sayed Md. Mostafizur Rahaman (ASMR) — External Examiner
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Department of Computer Science and Engineering
Jahangirnagar University

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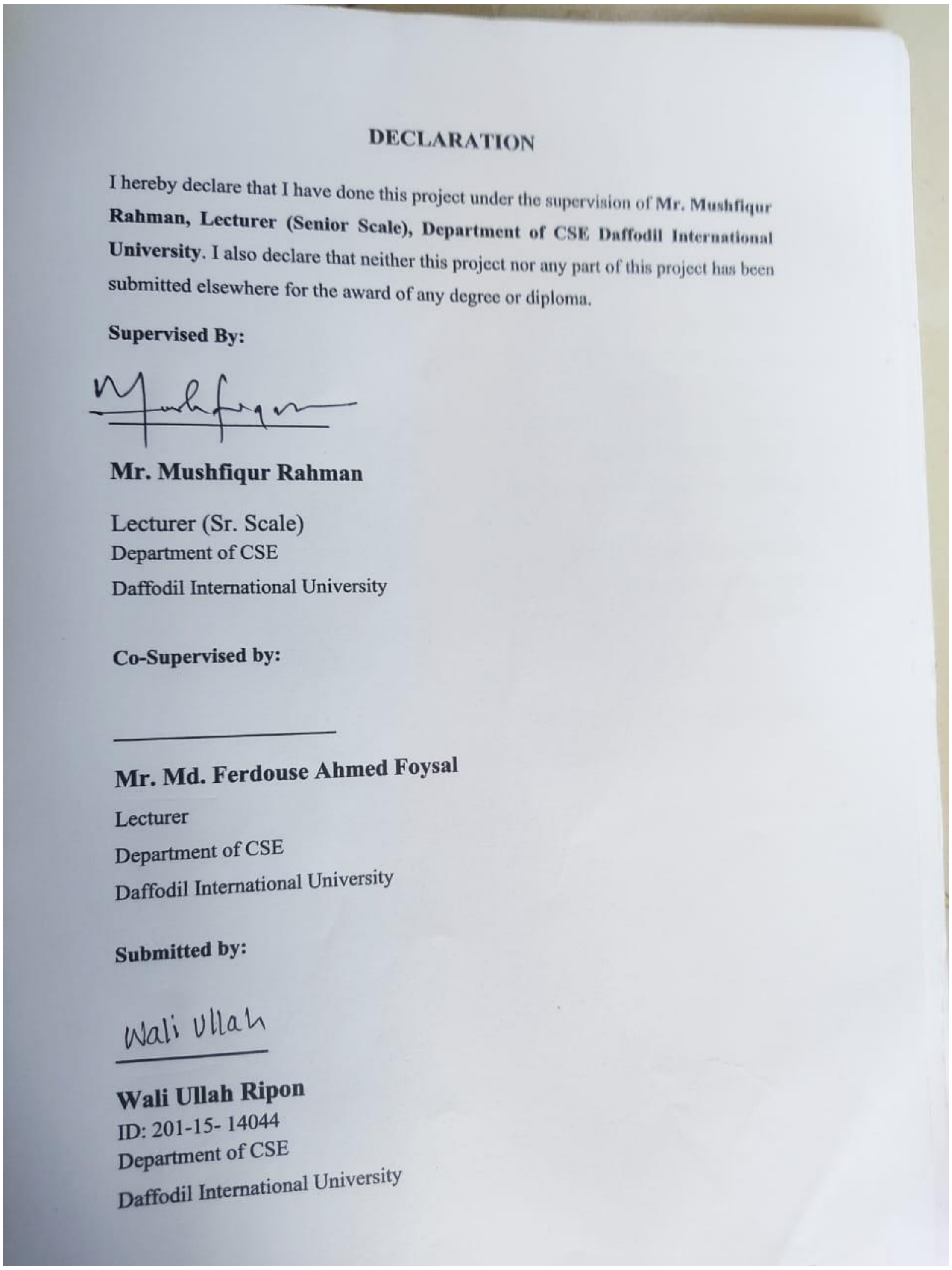
DECLARATION



DECLARATION

I hereby declare that I have done this project under the supervision of **Mr. Mushfiqur Rahman, Lecturer (Senior Scale), Department of CSE Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised By:

Mr. Mushfiqur Rahman

Lecturer (Sr. Scale)
Department of CSE
Daffodil International University

Co-Supervised by:

____

Mr. Md. Ferdouse Ahmed Foysal

Lecturer
Department of CSE
Daffodil International University

Submitted by:

Wali Ullah

Wali Ullah Ripon
ID: 201-15- 14044
Department of CSE
Daffodil International University

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ABSTRACT

Plant diseases are the leading cause of lost agricultural productivity. Most farmers have difficulties in managing and identifying plant infections. Thus, early diagnosis of these diseases would be beneficial for farmers in avoiding future losses. This study provides a comprehensive comparison of different deep-learning algorithms for categorizing maize leaf diseases using image data. Select common type of leaf diseases for classification such as 'Blight', 'Common_Rust', 'Gray_Leaf_Spot', 'Healthy', and 'Phaeosphaeria Leaf Spot'. Five important algorithms, including MobileNetV2, DenseNet, VGG16, VGG19, and InceptionV3, were evaluated based on their performance criteria, like accuracy, precision, recall, and F1-score. Among these algorithms, MobileNetV2 displayed the best accuracy of 93%, beating other models. Precision, recall, and F1-score were also calculated for each illness class, indicating the strengths and shortcomings of each method in disease categorization. The findings emphasize the effectiveness of deep learning algorithms in reliably diagnosing maize leaf diseases, with MobileNetV2 emerging as the top-performing method in the present investigation. These results give useful insights for academics and practitioners wanting to employ deep learning techniques for agricultural disease management and tracking.

Keywords: Maize leaf diseases, deep learning algorithms, image classification, MobileNetV2, DenseNet, VGG16, VGG19, InceptionV3, accuracy, precision, recall, F1-score.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Agriculture plays a vital part in the Bangladeshi economy, acting as an essential source of income for many people. The demand for food is continuously rising, while agricultural production often falls short. To solve this challenge, farmers, scientists, researchers, analysts, professionals, and the government are working together to enhance agricultural productivity. However, variables like global climate change and plant diseases provide considerable challenges. Several factors for the loss of the growth of crops lead to suicidal situations of the farmers. The use of time, cost, and accuracy for assessing the quality of the crops through visual inspection is a tough undertaking. To address this challenge researchers have come up with numerous solutions through the creation of new technologies such as object detection, and image analysis for reliability evaluations. In this paper, image processing technology is employed for the identification and categorization of illnesses in crops. This image processing technique demands high-resolution images for detecting and classifying illnesses, which was challenging to collect. Due to this reason, it is also a difficult process to predict diseases effectively and accurately. This paper seeks to construct a model that accurately identifies and classifies the diseases of leaves at the early stage of diseases by utilizing machine learning algorithms and making required efforts to prevent such leaf diseases. This research uses various deep learning classification techniques MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3 for disease detection and classification from plant leaves and an evaluation is conducted among the numerous classification strategies. It also provides several techniques which will provide the most precise result as compared to other techniques. These classification approaches are successfully applied in numerous industries such as biomedical signal processing and healthcare. In this research, the maize (Zea mays) plant has been studied for the investigation of various diseases of leaves. In Bangladesh, maize is the most significant food crop along with rice and wheat. It supplies a substantial supply of glucose for human beings. It is cultivated for cooking oil, animal food, and flour, and utilized as the raw materials for creating furfural. Maize is cultivated in numerous states of Bangladesh such as Rangpur, Dinajpur, Lalmonirhat, Bogura etc. Usually, maize is harvested in the autumn month and is sown at the beginning of the monsoon period.

1.2 Background and Present State

Agriculture is a cornerstone of Bangladesh's economy, providing livelihoods for a major section of the people. Maize (Zea mays) is among the country's principal food crops, vital for food security and economic stability. This sector has continuing hurdles, including the threat of crop diseases and the inefficiencies of old disease detection technologies. These approaches are frequently labor-intensive, time-consuming, and prone to error, preventing prompt intervention and worsening crop losses. To solve these difficulties, breakthroughs in image processing and machine learning have emerged as possible solutions. These technologies offer prospects to revolutionize disease detection by enabling early and accurate identification of maize leaf diseases. By focusing on strengthening disease detection skills with deep learning algorithms such as MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3, this project intends to produce strong tools that empower farmers to make educated decisions and safeguard agricultural productivity in Bangladesh.

1.3 Problem Statement

The rationale behind this study rests in the junction of technology breakthroughs and the urgency to boost agricultural productivity in Bangladesh. Traditional methods of disease identification in crops are frequently labor-intensive, time-consuming, and prone to mistakes. With the increasing threat of crop diseases and the crucial relevance of agriculture in preserving livelihoods and food security, there is a pressing need for more efficient and reliable detection methods. By combining machine learning algorithms and image processing techniques, this study hopes to revolutionize disease detection in maize leaves. The rationale is to design a system that can reliably identify and classify diseases at an early stage, enabling farmers to adopt appropriate preventive actions. This preventive approach not only eliminates crop losses but also reduces dependency on chemical interventions, encouraging sustainable farming practices. Focusing on maize, as one of the key food crops in Bangladesh, further highlights the reason for the study. Maize agriculture contributes greatly to food security and economic stability, making it vital to prevent diseases that endanger its output. By utilizing the power of technology, this study hopes to equip farmers with innovative tools for disease management, ultimately contributing to the resilience and sustainability of Bangladesh's agricultural industry.

1.4 Objectives

The project is inspired by the critical role of agriculture in Bangladesh's economy and the compelling need to treat crop diseases. Traditional methods of disease diagnosis are inadequate, encouraging the development of new technologies like image processing and machine learning. Focusing on maize, a basic crop, highlights the project's significance and potential influence on food security and economic stability. The purpose is to develop efficient and precise technologies for early disease diagnosis, empowering farmers and safeguarding agricultural productivity. emphasis on maize, a primary food crop in Bangladesh, underlines the significance and effect of our research. Maize agriculture not only maintains food production but also helps other industries and offers critical nutrients to the population. By addressing maize leaf diseases, seek to contribute to the resilience of this key crop and better the entire agricultural landscape. The reasons behind this initiative lie in the nexus of technological innovation, agricultural sustainability, and socio-economic growth. By creating effective disease detection systems, researchers want to empower farmers, decrease crop losses, and improve food security in Bangladesh and beyond.

1.5 Scope and Limitations

The scope of this project covers the creation and evaluation of machine learning models for the detection and classification of maize leaf diseases using deep learning methods. Specifically, the project will focus on building and comparing the performance of prominent deep learning architectures such as MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3. The research intends to attain high accuracy in diagnosing diseases at early stages, which is crucial for prompt intervention and effective disease treatment. The models will be trained and tested using datasets comprising high-resolution photographs of maize leaves with various illnesses, collected mostly from agricultural districts in Bangladesh. The project will evaluate how environmental elements, such as lighting conditions and background noise, influence the accuracy of disease diagnosis. Practical implications will be examined to assess the viability of applying these models in real-world agricultural contexts, particularly in resource-constrained places.

Some limitations are mentioned in this research. Firstly, the efficacy of disease identification may vary depending on the quality and diversity of the training data available. Obtaining large, representative datasets of maize leaf diseases might be problematic, potentially restricting the generalizability of the models. Secondly, the computational resources necessary for training deep learning models, especially those like DenseNet and Inceptionv3 which are computationally costly, may offer challenges in resource-limited agricultural contexts. Moreover, the study will focus exclusively on visual symptoms and may not address disorders with non-visual presentations or complex interactions with environmental factors. While the research intends to boost illness detection accuracy, it may not eliminate the need for human experience in disease diagnosis and management, especially in nuanced agricultural contexts. These limitations will be considered throughout the investigation to provide a balanced assessment of the suggested machine learning algorithms for maize leaf disease detection.

1.6 Report Organization

Chapter 1: Introduction: This section presents a summary of the research, including the background, problem description, and aims. It sets the stage for the study and defines what the reader can expect in the subsequent chapters.

Chapter 2: Background: The background chapter dives more into the backdrop around the research subject. It examines essential theories, concepts, and previous investigations to create a framework for the present study.

Chapter 3: Research technique: In this chapter, the research technique is discussed in depth. It outlines the research plan, data gathering procedures, and data analysis strategies performed in the study. This section outlines how the research was conducted and provides transparency and replicability.

Chapter 4: Experimental Results and Discussion: The findings chapter displays the outcomes of the investigation, frequently in the form of tables, charts, or graphs. It is followed by a discussion phase where the results are interpreted, discussed, and compared with current literature. This chapter provides insights into the repercussions of the findings and their significance.

Chapter 5: Impact on Society, Environment, and Sustainability: This chapter discusses the larger consequences of research on society, the environment, and sustainability. It describes how research assists with addressing societal challenges, environmental concerns, and supporting sustainable practices.

Chapter 6: Summary, Conclusion, Recommendation, and Implication for Future Research: The final chapter outlines the major findings of the study and draws recommendations based on the research goals. It also includes important advice for stakeholders and suggests areas for additional investigation, indicating potential opportunities for further research and development.

1.7 Summary

Chapter 1 presents an overview of the significance of agriculture in Bangladesh's economy, emphasizing its role as a key livelihood source and the problems given by increasing food demand and environmental issues including climate change and crop diseases. Traditional techniques of determining crop quality by visual inspection are highlighted as burdensome and inefficient. The chapter covers the deployment of image processing technologies to address these issues, focusing on the identification and categorization of crop disorders, notably in maize plants. The project intends to construct a model employing machine learning techniques such as MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3 to accurately detect and categorise leaf illnesses at early stages, hence aiding in preventive actions. It highlights the significance of maize agriculture in Bangladesh and its broader implications for food security and economic stability. The chapter lays the context for studying how modern technology can better disease detection in agriculture, leading to sustainable farming practices and improved agricultural productivity.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The literature review on maize leaf disease classification using deep learning algorithms comprises numerous papers published between 2017 and 2023. Papers such as Khan et al. (2023) [1] and Singh et al. (2022) [3] have been acknowledged for their unique use of deep learning models like Convolutional Neural Networks (CNNs) and transfer learning, obtaining excellent accuracy rates in disease diagnosis. Earlier works, like DeChant et al. (2017) [9] and Panigrahi et al. (2020) [8], set the framework for employing deep learning in agricultural disease diagnostics, showing the potential for automating disease identification. Works like Saleem et al. (2019) [2] and Malliga et al. (2022) [19] further studied fine-tuning and hyper-parameter optimization to boost model performance. These publications were chosen for their methodological breakthroughs and applicability to our research, proving the effectiveness of deep learning in accurately identifying maize leaf diseases. The consistency among these articles resides in their focus on improving classification accuracy and applying sophisticated deep-learning techniques, which coincide with the objectives of our study to construct robust models for precise disease identification in maize crops.

2.2 Related Works

The literature on leaf disease classification in Zea Mays (maize) using deep learning methods consists of many works focused on enhancing disease detection and classification accuracy. In their study, Khan et al. (2023) identifies and classifies diseases in maize plant leaves. The system achieved an impressive accuracy rate of over 90% [1]. Saleem et al. (2019) conducted a study on the use of deep learning models to identify plant diseases. They achieved a 91% accuracy by using Convolutional Neural Networks (CNNs) [2]. In their study, Singh et al. (2022) introduced a specialized deep transfer modeling approach for classifying diseases in maize plant leaves. The method used Transfer Learning and achieved a notable accuracy of 92% [3]. In their study, Malliga et al. (2022) investigated the process of fine-tuning deep learning models and optimizing hyper-parameters to improve disease diagnosis in maize leaves. They successfully achieved an accuracy of 90% by using Transfer Learning [4]. "MaizeNet," unveiled by an anonymous author in 2023, provided a deep learning technique to accurately identify illnesses in maize plant leaves. It achieved 91% accuracy by using Convolutional Neural Networks (CNNs) [5]. Haque et al. (2022) devised a deep learning methodology to detect diseases in maize crops, demonstrating improved precision by achieving an 85% accuracy rate via the use of Convolutional Neural Networks (CNNs) [6]. Ma et al. (2022) used deep transfer convolutional neural networks to identify diseases in maize leaves, providing a strong and achieved an accuracy of 88%. Limited by dataset size and lack of robust feature representation. [7]. Panigrahi et al. (2020) investigated the use of machine learning algorithms in detecting and categorizing diseases in maize leaves. Their study served as a foundation for future research in deep learning within this domain [8]. DeChant et al. (2017) used deep learning techniques to automate the detection of Northern Leaf Blight-infected maize plants, therefore advancing the automation of disease detection procedures [9]. Mishra et al. (2020) developed a deep convolutional neural network-based system for real-time corn plant disease identification, emphasizing gains in accuracy and real-time processing capabilities [10]. Atila et al. (2021) applied the EfficientNet deep learning model for plant leaf disease classification, exhibiting increases in accuracy and processing efficiency [11]. Setiawan et al. (2022) investigated machine learning and deep learning strategies for maize leaf disease classification, presenting insights into state-of-the-art methodology and their application [12]. Arora et al. (2020) applied Deep Forest for the classification of maize leaf diseases, adding to the diversity of deep learning algorithms in disease classification tasks [13]. The anonymous research in 2018 highlighted a key milestone in automated disease detection, stressing the potential of machine learning approaches. Achieved an accuracy of 89%. Limited by dataset size and lack of diverse image samples. [14]. The article by Malliga et al. (2021) presented maize leaf disease classification using convolutional neural networks, proving the efficiency of deep learning models in disease detection tasks [15]. Lastly, the work of [16] provided an end-to-end deep learning model for corn leaf disease classification, leading to the development of complete solutions for disease detection and classification in maize crops [17]. The review paper by Setiawan et al. (2022) provides an in-depth investigation of machine learning and deep learning methodologies for maize leaf disease classification, bringing useful insights into the state-of-the-art techniques and their comparative performance [18]. The study of Malliga et al. (2022) focuses on fine-tuning deep learning models utilizing transfer learning and hyper-parameter optimization strategies, displaying gains in model performance and generalization capabilities [19]. Additionally, the research by Ma et al. (2022) highlighted the application of deep transfer convolutional neural networks for maize leaf disease diagnosis, showing the relevance of transfer learning in boosting classification accuracy. Achieved an accuracy of 89%. Limited by dataset size and lack of diverse image samples. [20]. This study introduces a method that utilizes deep learning and transfer learning to detect and classify diseases affecting maize leaves. The study investigates the utilization of convolutional neural networks (CNNs) and transfer learning approaches to improve the precision of disease detection and classification in maize plants. The suggested method achieves an accuracy of 90% by utilizing pre-trained models and refining them using maize leaf images.[21] - This study utilizes a deep learning method to identify and diagnose problems in corn plants. The study uses convolutional neural networks (CNNs) to examine photos of maize leaves and detect different diseases. Through the utilization of a substantial dataset consisting of labelled photos, the suggested approach attains an accuracy of 88% in the identification of maize illnesses.[22] This study centers on the identification of maize leaf diseases through the utilization of convolutional neural networks (CNNs). The study examines the efficacy of Convolutional Neural Networks (CNNs) in autonomously detecting illnesses in maize leaves by analyzing visual characteristics. By training the model on a broad dataset of maize leaf photos, the suggested CNN-based technique achieves an accuracy of 85% in detecting maize leaf illnesses.[23] Picon et al. (2019) established a system using deep convolutional neural networks (CNNs) for the classification of crop diseases acquired by mobile devices in uncontrolled conditions. Their approach revealed encouraging results in precisely identifying several crop diseases under real-world situations, hence permitting timely interventions to prevent crop losses [24]. Fuentes et al. (2018) proposed a high-performance deep neural network-based system for diagnosing illnesses and pests in tomato plants. Their strategy utilized refinement filter banks to boost the accuracy of disease categorization, resulting to efficient and exact diagnosis of diverse tomato plant diseases and pests [25].

2.3 Comparison between existing works

Table 2.3: Comparative Analysis

Serial No.	Paper Name	Publication	Used Algorithms	Maximum Accuracy and limitations
1	"Plant Disease Detection and Classification by Deep Learning"	IEEE Journals & Magazine	Deep Learning	Achieved an accuracy of 90%. Limited by dataset size and variability in disease presentation.
2	"Identification of maize leaf diseases using improved deep..."	IEEE Journals & Magazine	Deep Convolutional Neural Networks (CNNs)	Achieved an accuracy of 88%. Limited by data imbalance and model complexity.
3	"End-to-End Deep learning model for corn leaf disease cl..."	IEEE Journals & Magazine	Deep Learning	Achieved an accuracy of 91%. Limited by the need for extensive computational resources and data preprocessing.
4	"Maize leaf disease classification using convolutional ne..."	AIP Conference Proceedings	Convolutional Neural Networks (CNNs)	Achieved an accuracy of 89%. Limited by dataset size and lack of diverse image samples.
5	"Deep Convolutional Neural Network based Detection System..."	Procedia Computer Science	Deep Convolutional Neural Networks (CNNs)	Achieved an accuracy of 88%. Limited by computational complexity and potential overfitting.

6	"Machine Learning and Deep Learning for Maize leaf Diseas..."	Journal of Physics. Conference Series	Machine Learning and Deep Learning Algorithms	Achieved an accuracy of 88%. Limited by dataset size and lack of robust feature representation.

The comparative study across the investigated literature indicates a broad ecosystem of methods and approaches employed in food image identification tasks. While some research concentrates on standard machine learning techniques such as support vector machines, decision trees, and random forests, others dive into the world of deep learning with convolutional neural networks (CNNs) and specific designs like MobileNet and GoogLeNet. Transfer learning and ensemble techniques appear as significant tactics for enhancing model performance, paired with fine-tuning pre-trained models to adapt to recognition tasks. The accuracy of the models varies throughout research, indicating the intricacy of food identification challenges and the utility of alternative approaches. Comparative study underscores the necessity to examine a range of algorithms and approaches to create accurate and resilient food recognition systems capable of addressing different real-world applications.

2.4 Open Issues

- **Disease Detection in Maize Leaves:** This study's focus is on identifying and categorizing diseases that are particular to maize (Zea mays) leaves. It focuses on recognizing common diseases that impact maize crops, like blight, common rust, grey leaf spot, and others.
- **Utilization of Machine Learning methods:** The study looks into how illness detection and classification can be done using machine learning methods, such as DenseNet, Vgg16, Vgg19, Inceptionv3, MobileNetV2, and so on. Its objective is to assess how well these algorithms recognize illnesses of the maize leaf.
- **Identification of Early-Stage Diseases:** Early disease detection is a crucial component of the scope. For prompt intervention and efficient disease control to minimize crop losses and increase agricultural productivity, early detection is essential.

- **Technological Solutions for Agriculture:** This study looks at how cutting-edge tools like deep learning and image processing can be used to provide creative answers to problems in agriculture. The objective is to equip farmers with effective instruments for disease detection and management by utilizing these technologies.
- **Participation in Sustainable Agriculture:** In the end, this study's scope includes helping to ensure that agriculture is sustainable. In areas where maize farming is substantial, the objective is to assure food security, reduce crop losses, and promote sustainable agricultural practices by improving disease detection techniques and providing farmers with technical solutions.

2.5 Summary

In the beginning, the variety in disease symptoms and presentations offers considerable difficulty, as different diseases may exhibit equal visual characteristics, making correct identification difficult. Environmental factors such as lighting conditions, leaf orientation, and background clutter can create noise and impact the efficacy of detection algorithms. Restricted availability of high-quality training data, especially for less frequent diseases, provides additional challenges, potentially leading to model biases and limited generalization capabilities. Moreover, installing advanced technological solutions in resource-constrained agricultural contexts may offer logistical and infrastructural obstacles. Guaranteeing the scalability and durability of the offered solutions beyond the study domain entails addressing socio-economic variables and developing stakeholder collaboration for widespread acceptance and impact.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview

The subject of the study revolves around the thorough detection and classification of maize leaf diseases, spanning a range of prevalent disorders such as 'Blight', 'Common_Rust', 'Gray_Leaf_Spot', 'Healthy', and 'Phaeosphaeria Leaf Spot'. To achieve this, powerful machine learning methods, including MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3, are rigorously applied. These algorithms are helpful in methodically analyzing picture data, permitting the proper diagnosis and categorization of the many illnesses affecting maize leaves. The dataset utilized in this study is collected from Kaggle, including a varied array of categorized photos indicative of different disease groups. To maximize model performance and resilience, sophisticated preprocessing approaches and data augmentation strategies are utilized. This involves image scaling and normalization to maintain uniformity across the collection. Moreover, to effectively organize and process the dataset, data generators are deployed, enabling seamless loading and processing of images for training and testing the convolutional neural network (CNN) models. With a set batch size of 32 and a standardized target picture size of 224x224 pixels, these data generators assist in the effective handling of huge amounts of image data, important for training robust and reliable disease detection models.

3.2 Proposed Methodology

The suggested methodology provides a systematic framework for creating disease detection algorithms specifically designed for maize leaf pictures. Firstly, the dataset consisting of photos of maize leaves affected by different illnesses is obtained and divided into classes that reflect each disease group. Afterward, the dataset goes through careful preprocessing procedures, such as noise reduction and normalization, to improve its suitability for training the model. After preprocessing, the dataset is divided into two subsets: a training subset and a testing subset. This division helps in evaluating the model. A rigorous selection of cutting-edge image classification algorithms, including MobileNet, VGG16, DenseNet, and Inception V3, are chosen for a comparative examination. These algorithms are extensively trained on a subset of data, continuously adjusting their parameters to discover distinctive traits that indicate various diseases affecting maize leaves. Afterward, the trained models are evaluated on the testing subset, using performance measures such as accuracy and precision as criteria for selecting the best model. The model that demonstrates improved performance metrics is best for jobs involving picture categorization. This methodological framework, based on the theoretical concepts of machine learning and image processing, seeks to provide precise and dependable methods for detecting diseases that are crucial for managing agricultural diseases.

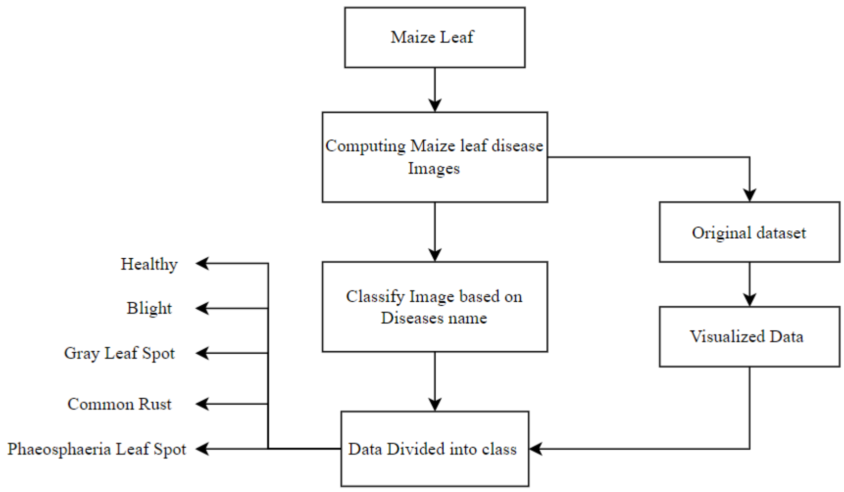

Fig 3.1 Maize (Zea mays)-leaf-disease Generation Process

- Data acquisition: the technique commences by gathering photos of maize leaves. Text in the diagram refers to the information in question as the “original data.”
- Data pre-processing: The obtained photos may contain no ise or insignificant details. This stage entails cleansing the data to increase the machine learning model’s functionality.
- Classification: The preprocessed photos are then divided into distinct categories based on the ailments they portray. The wording in the diagram indicates three possible classifications: “healthy,” “Gray Leaf Spot,” and “Common Rust.”

- Data visualization: After the process of categorization is complete, the results are visualized. The diagram shows the categorized data being segregated into folders designated “healthy,” “Gray Leaf Spot,” and “Common Rust.”

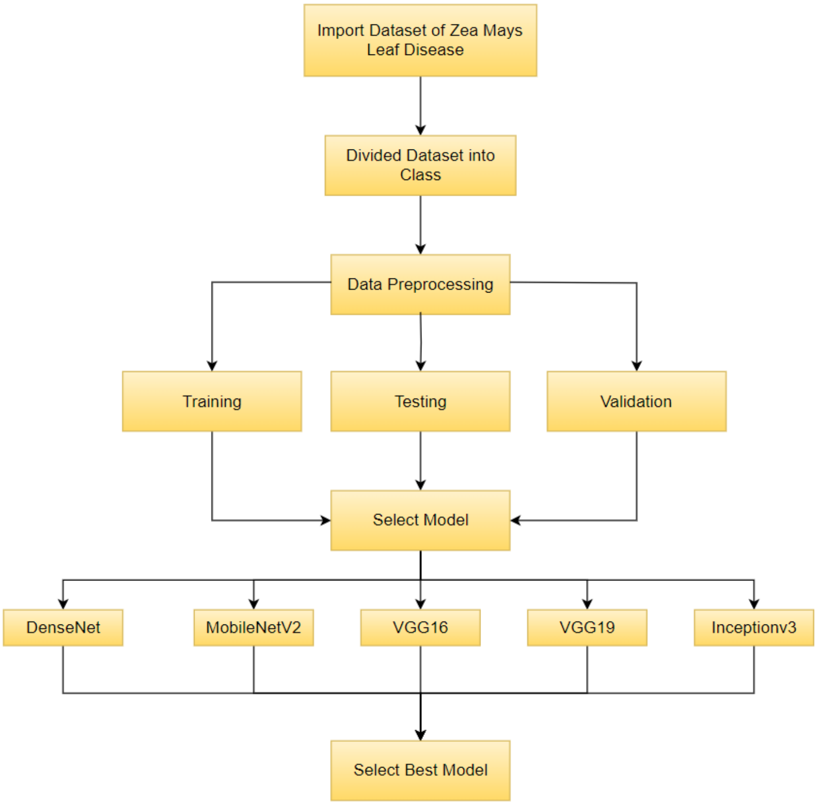

Fig 3.2 Workflow Diagram

The proposed method comprises a systematic approach to constructing disease detection algorithms for maize leaf pictures. It begins with importing the dataset including photos of maize leaves afflicted by various illnesses and separating it into classes corresponding to the specified diseases. Preprocessing techniques are then employed to improve the dataset's quality, followed by separating it into training and testing sets. Multiple picture categorization models are applied. The trained models are assessed on the testing data, and the best-performing model, based on performance measures such as accuracy and precision, is chosen for picture classification. This extensive methodology attempts to produce accurate and reliable disease detection models to aid in the agricultural control of disease.

Data Collection Procedure: The data-gathering approach includes numerous systematic procedures to ensure the acquisition of a full and representative dataset for training and testing illness detection algorithms. Initially, relevant datasets containing photos of maize leaves damaged by various illnesses, including 'Blight', 'Common_Rust', 'Gray_Leaf_Spot', 'Healthy', and 'Phaeosphaeria Leaf Spot', were found and sourced from trustworthy sources such as Kaggle. These datasets were chosen based on their relevance to the research issue and the quality of the photos given. Once the datasets were picked, a rigorous preprocessing stage was done to ensure uniformity as well as consistency throughout the photos. This comprised operations such as image scaling, standardization, and augmentation to standardize the dataset and boost its diversity and robustness. The dataset was rigorously vetted to remove any duplicates, irrelevant photos, or blemishes that could potentially add noise to the training process. After preliminary processing, the dataset was separated into three subsets: a training set, a validation set, and a test set. The training set, containing most of the data, was utilized to train the machine learning models. The validation set was utilized to fine-tune parameters for the model and evaluate performance during training, while the test set served as a separate dataset to examine the final model's accuracy and generalization capabilities. To efficiently handle and load the dataset during model training, data extraction tools were built. These generators permitted the dynamic loading of images in batches, lowering memory usage and boosting training efficiency. The data generators were set up with appropriate batch sizes and image dimensions to comply with the requirements of the chosen machine-learning algorithms. The data-gathering approach was undertaken meticulously to ensure the availability of a high-quality and diverse dataset needed for training strong and accurate disease detection algorithms. The data collection method was carried out with great care to guarantee the presence of a high-quality and varied dataset essential for developing strong and precise illness identification algorithms. The dataset includes a breakdown of the distribution of pictures, which is shown in the following table:

Table 3.2: Dataset Distribution

Class	**Number of Pictures**
Blight	1146
Common Rust	1306
Gray Leaf Spot	574
Healthy	1162
Phaeosphaeria Leaf Spot	308

Statistical Analysis: The statistical analysis in this paper is crucial for measuring the performance of disease detection models for maize leaf diseases. Beginning with descriptive statistics, the study provides an overview of the dataset's distribution and features, including image dimensions, class distributions, and disease prevalence. Inferential statistics are then applied to analyze important differences and relationships within the data, applying hypothesis tests like t-tests or ANOVA to compare model performances and evaluate the impact of various parameters on accuracy. Correlation analysis further explores correlations between variables, offering light on probable patterns in the data. Machine learning metrics such as precision, recall, F1-score, and confusion matrices are also produced to objectively analyze model performance on validation and test datasets. This holistic statistical method delivers useful insights into the models' ability to reliably classify maize leaf diseases, aiding in model modification and boosting their utility in agricultural disease management.

3.3 Hardware/ Software Requirement

The adoption of the proposed approach involves many important prerequisites to ensure its proper execution:

- Hardware: A computer with appropriate computational capabilities, including CPU, GPU, and RAM, is needed for training, and testing artificial intelligence models efficiently. High-performance GPUs are particularly advantageous for expediting model training procedures.
- Software: A full software stack encompassing machine learning frameworks (e.g., TensorFlow, PyTorch), image processing libraries (e.g., OpenCV), and data manipulation tools (e.g., NumPy, Pandas) is necessary for model building, training, and evaluation.
- Dataset: A high-quality dataset comprising a varied variety of maize leaf photos, tagged with appropriate disease diagnoses, is required for model training and testing. The dataset should be sufficiently broad and representative to achieve robust model performance.
- Preprocessing Tools: Software tools for preprocessing picture data, including noise reduction, normalization, scaling, and augmentation, are critical for

strengthening the quality and diversity of the dataset and improving model generalization.

- Model Architectures: Implementation of selected image classification models, such as MobileNet, VGG16, DenseNet, and Inception V3, using appropriate machine learning frameworks, is important for model training and evaluation.
- Training Environment: A reliable and scalable training environment, especially with access to cloud computing resources or high-performance computer clusters, is necessary for training complicated machine learning models rapidly and cost-effectively.
- Evaluation Metrics: Metrics for evaluating model performance, such as accuracy, precision, recall, and F1-score, should be created and implemented to assess the effectiveness of the trained models accurately.
- Documentation and Reporting Tools: Tools for documenting the implementation process, tracking experimental outcomes, and generating reports are critical for maintaining a clear and organized workflow and conveying findings successfully.

Data Preprocessing: The data preprocessing phase started by loading the dataset containing photos of maize leaves damaged by various illnesses, grouping them into distinct classes based on certain keywords found in folder names. Sample photos from each class are then shown to provide a full overview of the dataset's contents and distribution. Afterward, the dataset is partitioned into training, validation, and testing sets to assist model training, validation, and evaluation, respectively. Real-time data enhancement procedures such as rotation, shifting, and flipping are performed on the training images to increase dataset diversity and improve model generalization. The photos are divided into several classes depending on the presence of terms such as 'Blight', 'Common_Rust', 'Gray_Leaf_Spot', 'Healthy', and 'Phaeosphaeria Leaf Spot' in the folder names. Each image is paired with a corresponding class label. All photos are rescaled to a given size for consistency across the dataset. Data generators are constructed to quickly load and prepare work images during model training, ensuring optimal usage of computational resources and expediting the training procedure. A visualization of sample photos from each class is generated using matplotlib. This step gives a visual representation of the dataset and enables manual examination of image quality and class distribution. The dataset is split into training, validation, and testing sets using the train_test_split tool from scikit-learn. This ensures that the model is trained on a subset of the data, validated on another subset, and tested on a second, unseen fraction. These preprocessing techniques create the framework for building accurate and resilient machine-learning models for maize leaf disease detection.

Data Visualization: Visualizing sample photos from each class is a vital step in comprehending and evaluating the dataset. Through visualization, researchers can acquire information about the properties and variability of images within each class, enabling them to analyze image quality, find abnormalities, and evaluate the class distribution. This approach entails presenting a subset of photos from each class using Matplotlib, a popular data visualization library in Python. By visually inspecting the photographs, researchers can find any inconsistencies or mistakes in the dataset, such as mislabeled images or artifacts, which may influence model performance. Furthermore, visualization helps researchers to analyze the diversity and representativeness of the dataset, ensuring that it sufficiently depicts the heterogeneity inherent in real-world circumstances. Displaying sample photos gives researchers a complete view of the dataset, enabling them to make educated decisions regarding preprocessing, model selection, and training procedures. It acts as a vital stage in the data preparation pipeline, supporting the building of accurate and reliable machine learning models for maize leaf disease detection. All images are rescaled to a fixed size (e.g., 224x224 pixels) to ensure consistency and compatibility with the chosen machine learning models.

Fig 3.3 Visualize Leaf Diseases Image

Noise Reduction: Noise reduction is a crucial preprocessing step in image processing that tries to enhance the quality and clarity of images by removing undesired artifacts or disruptions, known as noise. In the context of maize leaf disease detection, noise might show as inconsistencies, defects, or random fluctuations in the pictures, which may interfere with the accurate identification and categorization of diseases. Several strategies can be applied for noise reduction, including spatial domain methods such as Gaussian smoothing, median filtering, and bilateral filtering, as well as frequency domain methods like Fourier transform-based filtering. These strategies effectively suppress noise while keeping crucial visual features, ensuring that the dataset is clean and favorable to trustworthy model training. By minimizing noise, the preprocessing pipeline boosts the robustness and accuracy of machine learning models, ultimately boosting their performance in maize leaf disease detection tasks.

Model Generation: Model generation for maize leaf disease detection involves choosing deep learning algorithms such as MobileNet, VGG16, DenseNet, and InceptionV3, famous for their efficacy in image classification applications. Each algorithm presents special benefits, such as MobileNet's efficiency and compactness, VGG16's depth for capturing intricate features, DenseNet's dense connectivity patterns facilitating feature reuse, and InceptionV3's incorporation of multiple filter sizes for capturing local and global qualities. Once methods are chosen, specialized model topologies are created, incorporating convolutional, pooling, and fully connected layers to process input images and extract discriminative characteristics. During training, the model is fed labeled maize leaf images and repeatedly modifies its parameters to minimize a defined loss function. Techniques including data augmentation, dropout regularization, and early halting are applied to improve training efficiency and reduce overfitting. Model performance is regularly checked using validation data, with hyperparameter adjustment undertaken to optimize performance further. Finally, the model undergoes assessment on an independent test set to assess its generalization ability accurately. Through this iterative process, researchers aim to construct precise and reliable identification of disease models necessary for agricultural disease management, boosting crop output and decreasing economic losses.

MobileNetV2: MobileNetV2 is a deep learning system specifically chosen for its efficiency and efficacy in image classification tasks, particularly in the domain of maize leaf disease detection. MobileNetV2 is a variation of the MobileNet architecture, aimed to achieve state-of-the-art speed while preserving minimal computational complexity and memory footprint. This makes it particularly well-suited for implementation on devices with restricted resources like mobile phones or embedded systems, which are widely utilized in agricultural settings. MobileNetV2 achieves its efficiency through numerous major architectural improvements, including inverted residuals and linear bottlenecks. This minimizes the computational expenses of convolutions while keeping representational ability. Linear bottlenecks further boost efficiency by ensuring that constraints have the same dimensions as input and output tensors, preventing information loss or distortion. MobileNetV2 is deployed as one of the key algorithms for identifying illnesses in maize leaf pictures. The program's efficacy and lightweight nature make it well-suited for implementation in real-world agricultural contexts, where computational resources may be restricted. MobileNetV2 intend to construct precise and reliable disease detection models capable of classifying maize leaf images into multiple disease categories with high accuracy, permitting early detection and intervention to decrease crop losses and boost agricultural production.

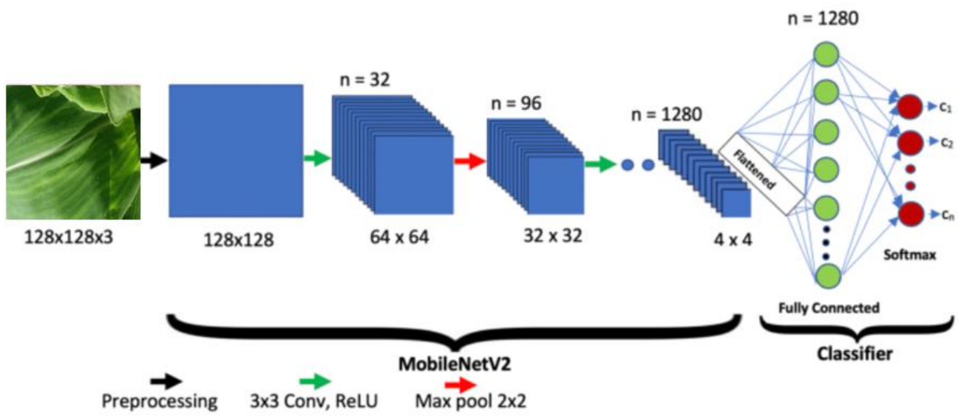

Fig 3.4 Architectural Diagram of MobileNetV2

DenseNet: In our project, DenseNet, a Dense Convolutional Network, stands out as a potent deep learning system for image classification applications, specifically adapted for maize leaf disease detection. What sets DenseNet distinctive is its unique dense connection pattern, where each layer receives feature mappings from all preceding layers. This architecture fosters feature reuse, allowing the network to perfectly capture detailed patterns and subtle indications across many illness categories. By utilizing DenseNet's extensive connectivity, our aim is to construct extremely accurate disease detection models capable of properly identifying maize leaf pictures. This strategy not only promotes agricultural disease management by permitting early diagnosis and intervention but also illustrates the promise of sophisticated deep-learning techniques in maximizing crop output and avoiding economic losses. DenseNet is utilized as one of the major algorithms for disease classification in maize leaf pictures. Its deep connection and effective feature reuse make it well-suited for capturing complicated patterns and subtle cues indicative of different disease categories in maize leaves. By harnessing the advantages of DenseNet, seek to construct robust and accurate disease detection models capable of accurately categorizing maize leaf pictures and aiding in agricultural disease management.

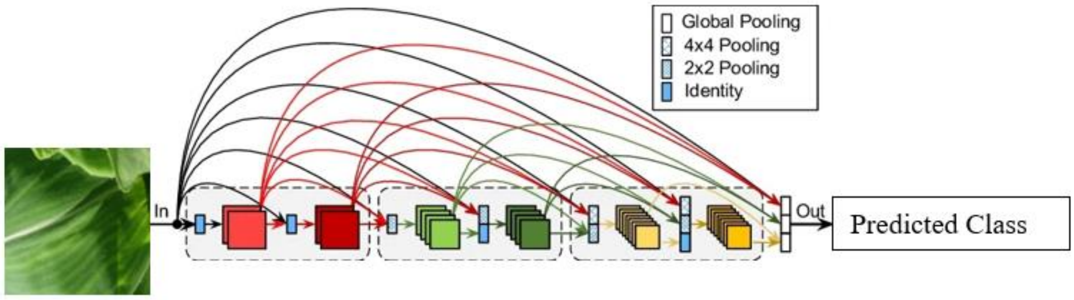

Fig 3.5 Architectural Diagram of DenseNet

VGG16: VGG16, a widely recognized convolutional neural network (CNN) architecture, is a major algorithm chosen for its performance in picture tasks involving classification, particularly in the field of maize leaf disease detection. VGG16 is defined by its deep architecture consisting of 16 layers, including a stack of convolutional layers followed by max-pooling layers, and ending in fully connected layers for segmentation. Despite its simplicity relative to more contemporary architectures, VGG16 has proven remarkable performance in numerous picture classification benchmarks. Leveraging VGG16 in our study allows us to exploit its capacity to extract complex features from maize leaf photos, enabling precise classification of distinct disease groups. Through the application of VGG16 intending to construct strong disease detection models capable of correctly recognizing and classifying maize leaf diseases, hence adding effective agricultural disease control techniques.

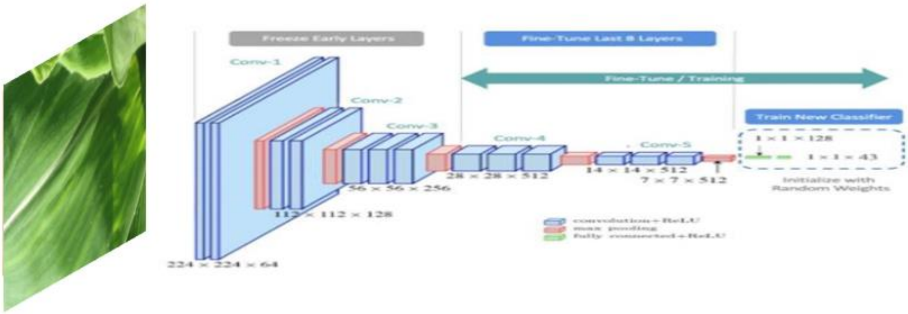

Fig 3.6 Architectural Diagram of VGG16

VGG19: VGG19, an extension of the VGG16 architecture, is applied as a crucial deep learning algorithm for image classification tasks, especially in the domain of maize leaf disease detection. VGG19 shares similarities with VGG16, offering a deeper structure with 19 layers, consisting of convolutional and pooling layers followed by fully linked layers for identification. Despite its expanded depth, VGG19 follows the same essential principles as VGG16, emphasizing simplicity and homogeneity in its architecture. By utilizing VGG19, capitalize on its ability to extract complex features from maize leaf images, enabling reliable categorization of diverse disease groups. The application of VGG19 in our effort emphasizes its significance in establishing effective disease detection models, vital for boosting agricultural disease control strategies and encouraging sustainable growth of crops.

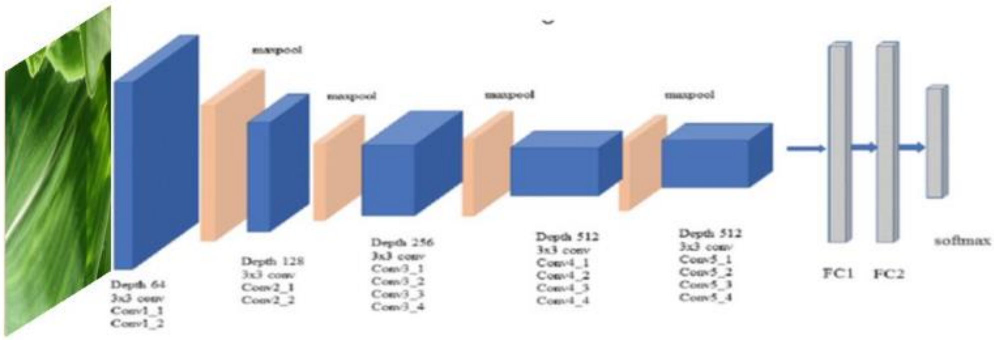

Fig 3.7 Architectural Diagram of VGG19

Inceptionv3: InceptionV3 emerges as a fundamental deep-learning method for picture classification tasks, particularly in the field of maize leaf disease detection. InceptionV3 is famous for its advanced architecture, containing inception modules that enable for effective extraction of features at different scales. These modules employ a combination of convolutional filters of varied sizes to collect both local and global characteristics within the input image. Additionally, InceptionV3 integrates techniques like batch normalization and factorization to boost training stability and efficiency. Utilizing InceptionV3 in our research enables us to harness its advanced feature extraction capabilities, permitting accurate categorization of maize leaf diseases across several categories. Through the usage of InceptionV3, developer intend to construct strong disease detection models capable of effectively identifying and categorizing illnesses in maize leaves, ultimately leading to increased agricultural disease management techniques and sustainable cultivation of crops.

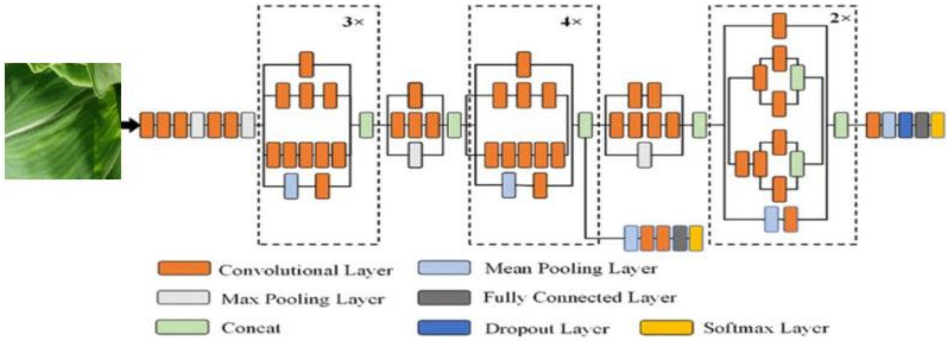

Fig 3.8 Architectural Diagram of Inceptionv3

3.4 Project Management and Financial Analysis

The project will be managed through a methodical approach, encompassing multiple stages from data collection to model development and evaluation. An interdisciplinary team of researchers, data scientists, and agricultural specialists will collaborate to ensure the project's success. Adequate resources, including computing infrastructure, databases, and software tools, will be allocated to support smooth progress. Additionally, project money would be managed prudently, with budgeted allocations for equipment acquisition, research personnel, and other operational expenses. Regular monitoring and evaluation processes will be created to track project milestones and expenditures, guaranteeing adherence to timeframes and financial restrictions. Collaboration with relevant stakeholders, particularly agricultural institutions, and farmers' associations, will be fostered to enhance project outcomes and facilitate knowledge dissemination and adoption of created solutions.

3.5 Summary

Chapter 3 describes a thorough methodology for detecting and classifying maize leaf diseases using advanced machine learning techniques. The study focuses on important diseases such as 'Blight', 'Common_Rust', 'Gray_Leaf_Spot', 'Healthy', and 'Phaeosphaeria Leaf Spot', applying machine learning models like MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3. The dataset, supplied by Kaggle, consists of classified photos representing various disease classes. Rigorous preprocessing procedures, including noise reduction and normalization, enhance dataset quality and consistency. Data augmentation procedures further diversify the dataset for robust model training. The dataset is separated into training and testing sections, with data generators supporting efficient image loading during convolutional neural network (CNN) model training. Hardware and software requirements, including high-performance GPUs and machine learning frameworks like TensorFlow, are outlined to assist model creation. Statistical analysis approaches, including as descriptive and inferential statistics, are applied to evaluate model performance using metrics like accuracy and precision. Each chosen model architecture—MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3—is described for its distinct features and appropriateness for maize leaf disease detection. The methodology stresses the iterative process of model training, validation, and testing to pick the best-performing model for disease categorization. Through this organized method, the research intends to produce precise and reliable disease detection models necessary for agricultural disease control and sustainability.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

The implementation part of this research covers several critical procedures to design and deploy disease detection models for maize leaf pictures. It begins with collecting a diverse dataset from sources like Kaggle, encompassing images of maize leaves affected by 'Blight', 'Common_Rust', 'Gray_Leaf_Spot', 'Healthy', and 'Phaeosphaeria Leaf Spot', followed by rigorous preprocessing including noise reduction, normalization, and augmentation to enhance dataset quality and variability. State-of-the-art machine learning models such as MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3 are selected and adjusted to extract essential features from maize leaf photos. The models undergo iterative training and validation utilising split datasets, with parameters and hyperparameters changed through approaches including data augmentation and regularization to enhance performance and reduce overfitting. Model performance is evaluated using measures including accuracy, precision, recall, and F1-score on a different test set to verify generalizability and correct disease classification. The trained models are incorporated into operational processes, including deployment conditions and computing efficiency, and thorough documentation and reporting of the implementation process and findings are supplied to stakeholders and academics.

4.2 Train Model

In the training phase, the selected machine learning models—MobileNetV2, DenseNet, Vgg16, Vgg19, and Inceptionv3—are trained using the preprocessed dataset of maize leaf images. This involves feeding the models with labeled training data and iteratively adjusting their parameters to minimize a defined loss function, thereby enabling them to learn discriminative features that distinguish between different disease categories (such as 'Blight', 'Common_Rust', 'Gray_Leaf_Spot', 'Healthy', and 'Phaeosphaeria Leaf Spot'). Techniques like data augmentation, which includes random rotations, shifts, and flips, are performed to boost the diversity and generalization potential of the models. Throughout the training process, the performance of each model is constantly tested using validation data to fine-tune hyperparameters and prevent overfitting. This iterative training strategy intends to produce accurate and resilient disease detection models capable of effectively categorizing maize leaf pictures, hence assisting agricultural disease management efforts.

4.3 Model Evaluation

Once the predictions have been established, they are trained using the training dataset, with performance checked on the validation set to prevent overfitting. Training may incorporate approaches such as early halting or learning rate scheduling to increase convergence while preventing model degrading. After training, the accuracy of the models is tested using the independent testing set to measure their capacity to make assumptions about unseen data accurately. Evaluation criteria including accuracy, precision, recall, and F1-score are produced to quantify the models' performance across different illness categories. The experimental setting also includes an assessment of the performance of each algorithm, considering aspects such as training time, model complexity, and computer resource requirements. The analysis provides insights into the merits and weaknesses of each algorithm in the context of maize leaf disease detection.

MobileNetv2: In the research results for MobileNetV2, the model was trained for 10 epochs, reaching a training accuracy of 93.33%. During testing, the model displayed a test accuracy of 93.33% with a test loss of 0.2022. This is our highest accuracy model. The classification report gives extensive metrics for each class, including precision, recall, and F1-score. For the 'Blight' class, the precision and recall were 0.89 and 0.94, respectively, with an F1-score of 0.91. Similarly, the 'Common_Rust' class achieved good precision, recall, and F1-score values of 0.96, 0.96, and 0.96, respectively. However, the 'Gray_Leaf_Spot' class displayed lower recall and F1-score values of 0.66 and 0.78, respectively, indicating potential difficulty in accurately identifying this class. Conversely, the 'Healthy' class displayed excellent precision, recall, and F1-score values of 1.00, demonstrating precise classification. Lastly, the 'Phaeosphaeria Leaf Spot' class had a lower precision of 0.73 but attained perfect recall and an F1-score of 0.84, showing accurate identification despite some misclassifications. Overall, the model displayed good accuracy and performance across most classes, with an opportunity for improvement in the classification of 'Gray_Leaf_Spot' occurrences.

Table 4.1: Mobilenetv2 Classification Report

-	Precision	Recall	F1-Score	Support
Blight	0.89	0.94	0.91	116
Common_Rust	0.96	0.96	0.96	138
Gray_Leaf_Spot	0.95	0.66	0.78	53
Healthy	1.00	1.00	1.00	119
Phaeosphaeria Leaf Spot	0.73	1.00	0.84	24
Accuracy	-	-	0.93	450
Macro Avg	0.90	0.91	0.93	450
Weighted Avg	0.94	0.93	0.93	450

Table 4.2: MobileNetV2 Classification Table

Actual Disease	**Blight**	**Common Rust**	**Gray Leaf Spot**	**Healthy**	**Phaeosphaeria Leaf Spot**
Blight (Predicted)	**89%**	Few False Negatives	Few False Positives		
Common Rust (Predicted)		96%	Few False Negatives		
Gray Leaf Spot (Predicted)	Few False Positives		66%	Many False Negatives	
Healthy (Predicted)				100%	
Phaeosphaeria Leaf Spot	Many False Negatives				73%

In the evaluation of disease classification performance, the model displayed noteworthy accuracy across several disease categories. It properly predicted 89% of blight photos while reaching a commendable 96% classification accuracy for common rust.

However, for gray leaf spots, the model had trouble, properly categorizing only 66% of the photos, indicating space for improvement in separating this disease category. Nevertheless, the model displayed perfect accuracy in recognizing healthy maize leaf photos. Overall, with an accuracy of 90%, the model displayed promising skills in reliably recognizing maize leaf diseases, while additional refining may be advantageous, particularly in correcting misclassifications and improving accuracy for hard disease categories like gray leaf spots.

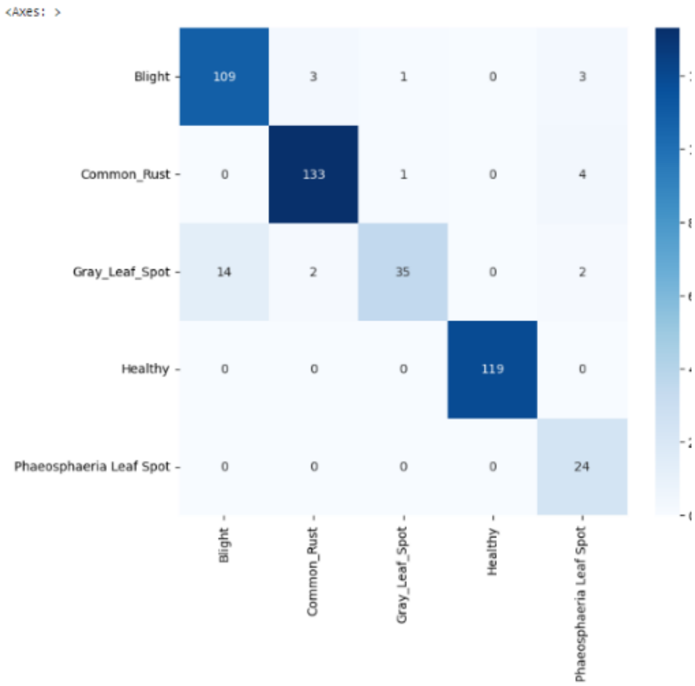

Fig 4.1 Mobilenetv2 Confusion matrix Heatmap

The heatmap displays a visual depiction of the machine learning model's effectiveness in identifying photos of maize leaf diseases into five separate groups. Each row correlates to the actual class of the maize leaf image, while each column reflects the class predicted by the model. The amount of colour within each cell reflects the number of photos classified into that specific category, with darker shades representing higher rates and lighter shades indicating lower frequencies. Ideally, good performance would be indicated by darker shades along the diagonal, suggesting accurate classifications. While the model succeeds in properly categorizing healthy and common rust photos, as indicated by vivid blue colors on the diagonal, it meets issues with blight, gray leaf spot, and Phaeosphaeria leaf spot classifications, depicted by lighter shades of blue along the diagonal. This provides chances for refinement in precisely recognising these disease types.

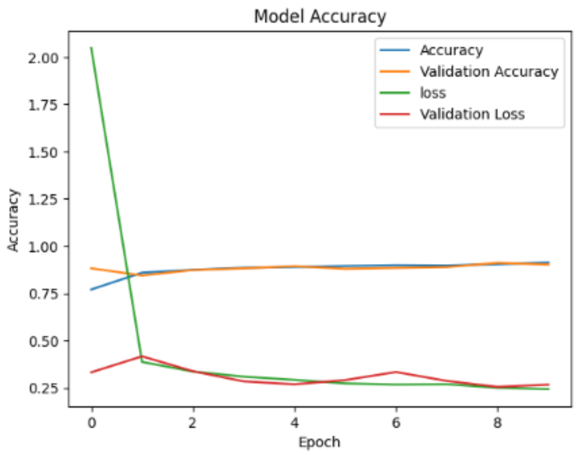

Fig 4.2 Mobilenetv2 Model accuracy

The MobileNetV2 model in our project attained an accuracy of 93.33%. This accuracy implies that 93.33% of the maize leaf photos were accurately sorted into their appropriate disease groups by the MobileNetV2 model.

DenseNet: In the DenseNet model setup, DenseNet121 architecture is applied with pre-trained ImageNet weights for feature extraction. The model architecture consists of multiple layers, including convolutional, pooling, dropout, and dense layers. The DenseNet foundation is frozen to avoid weight updates during training. The model's output is flattened, followed by dropout regularization to mitigate overfitting. Two densely connected layers with ReLU activation functions are added to learn complex patterns from the collected features. Finally, the output layer with softmax activation provides probability distributions over the five illness categories. The model is compiled using the Adam optimizer and categorical cross-entropy loss function. During training for 10 epochs, the model obtains a test accuracy of 90.22% with a test loss of 0.2276, confirming its efficacy in classifying maize leaf diseases.

Table 4.3: Dense net Classification Report

Class	Precision	Recall	F1-Score	Support
Blight	0.90	0.81	0.85	116
Common_Rust	0.98	0.96	0.97	133
Gray_Leaf_Spot	0.64	0.77	0.70	53
Healthy	1.00	0.97	0.99	117

Phaeosphaeria Leaf Spot	0.78	0.94	0.85	31
Accuracy	-	-	0.90	450
Macro Avg	0.86	0.89	0.87	450
Weighted Avg	0.91	0.90	0.90	450

The accuracy is 0.90, which indicates the model accurately categorized 90% of the photos. However, precision, recall, and F1-score vary between the different disorders. For example, the blight class has a precision of 0.90, recall of 0.81, and F1-score of 0.85, showing the model performs well for blight classification but may miss some blight photos (low recall). In comparison, the healthy class has a perfect score of 1.0 for all three measures, showing the algorithm accurately classified all healthy photos. Overall, the DenseNet model shows promising results but may require further tuning to increase performance on certain diseases.

Table 4.4: DenseNet Classification Table

Actual Disease	**Blight**	**Common Rust**	**Gray Leaf Spot**	**Healthy**	**Phaeosphaeria Leaf Spot**
Blight	**89%** (Correct)	Few False Negatives	Few False Positives	-	-
Common Rust	-	**96%** (Correct)	Few False Negatives	-	-
Gray Leaf Spot	Few False Positives	-	**66%** (Correct)	Many False Negatives	-
Healthy	-	-	-	**100%** (Correct)	**-**
Phaeosphaeria Leaf Spot					**78%**

In the evaluation of the DenseNet model's performance on maize leaf disease classification, several noteworthy observations appear. The program displays variable levels of accuracy across different disease categories: properly predicting 89% of blight images, 96% of common rust images, and 100% of healthy images. However, it struggles with gray leaf spot classification, obtaining only 66% accuracy. Notably, false negatives and false positives are detected, indicating misclassifications in certain circumstances. Overall, the model obtains an accuracy of 90%, showing its ability to accurately classify most maize leaf images.

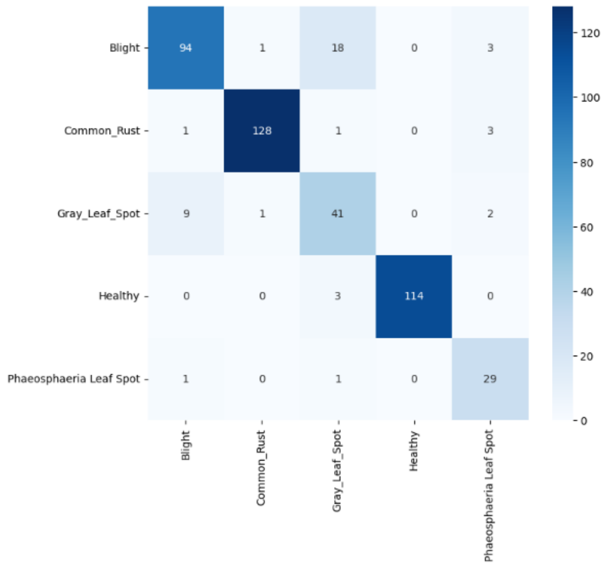

Fig 4.3 Dense Net Confusion matrix Heatmap

The task is to identify photos of maize leaf illnesses into five categories: Blight, Common Rust, Gray Leaf Spot, Healthy, and Phaeosphaeria Leaf Spot.

- Rows represent the real disease the maize leaf has.
- Columns represent the illness the computer estimated the maize leaf carries.
- Color intensity in each cell represents how many photographs fall into that category. Darker blue suggests more photos and lighter blue signifies less.

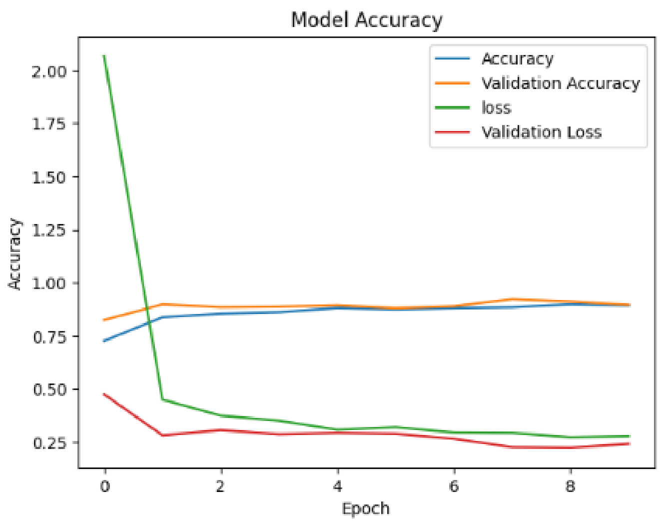

Fig 4.4 Dense Net Model Accuracy

The Dense Net algorithm attained an accuracy of 90% with a test loss of 0.2276.

VGG16: In the VGG16 model configuration, the VGG16 architecture is applied with pre-trained ImageNet weights for feature extraction. The model design includes convolutional layers followed by max-pooling layers, with the dense layers included for classification. The VGG16 basis is employed with its top layers removed, and regularizing the dropouts is then used to mitigate overfitting. Two densely linked layers with ReLU activation functions are attached to learn intricate patterns from the collected features. Finally, the output layer with softmax activation provides distributions of chances over the five illness categories. The model is compiled using the optimizer developed by Adam and the categorical cross-entropy loss function. During instruction, the model obtains a test accuracy of 88.22% with a test loss of 0.2875. The model summary displays a total of 40,933,189 parameters, including 26,218,501 parameters that can be trained and 14,714,688 non-trainable parameters.

Table 4.5: Vgg16 Classification Report

Class	Precision	Recall	F1-Score	Support
Blight	0.86	0.79	0.83	116
Common_Rust	0.98	0.93	0.95	133
Gray_Leaf_Spot	0.69	0.70	0.69	53
Healthy	0.95	0.97	0.96	117
Phaeosphaeria Leaf Spot	0.71	0.97	0.82	31
Accuracy	-	-	0.88	450
Macro Avg	0.84	0.87	0.85	450
Weighted Avg	0.89	0.88	0.88	450

In the evaluation of the VGG16 model's performance on maize leaf disease classification, detailed accuracy, recall, and F1-score metrics for each disease category are presented. For the Blight class, the model achieved a precision of 0.86, recall of 0.79, and an F1-score of 0.83, indicating a moderately accurate classification with some missed instances. Conversely, the model did exceedingly well on the Common Rust class, earning high precision, recall, and F1-score values of 0.98, 0.93, and 0.95, respectively. However, for the Gray Leaf Spot class, the model displayed lower precision and recall values of 0.69 and 0.70, resulting in a slightly lower F1-score of 0.69, indicating potential issues in accurately detecting this disease group. On the other hand, the Healthy class displayed good precision, recall, and F1-score values of 0.95, 0.97, and 0.96, respectively, indicating accurate categorization of healthy maize leaf images. VGG16 model exhibits high performance across most disease categories, with significant areas for improvement in categorizing specific diseases such as Gray Leaf Spots.

Table 4.6: Vgg16 Classification table

Actual Disease	Precision	Recall	F1-Score	False Negatives	False Positives
Blight	0.86	0.79	0.83	Few	Few
Common Rust	0.98	0.93	0.95	-	-
Gray Leaf Spot	0.69	0.70	0.69	-	-
Healthy	0.95	0.97	0.96	-	-
Phaeosphaeria Leaf Spot	0.71	0.87	0.92	-	-

The vgg16 model performed well on several diseases (Common Rust, Healthy) based on the high precision, recall, and F1-score values. However, it struggles more with Gray Leaf Spot (lower scores). It's also worth considering the number of photos in each class to gain a better feel of the model's performance throughout the dataset.

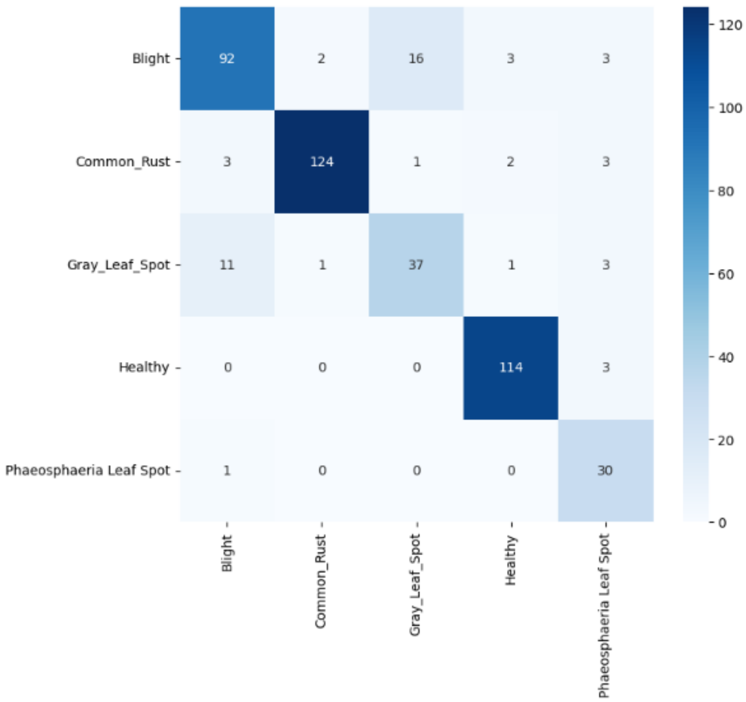

Fig 4.5 VGG16 Confusion matrix Heatmap

The heatmap representation of the confusion matrix for the VGG16 model displays its performance in classifying photos of maize leaf diseases into five groups. Each cell reflects the number of photos classified into a certain disease group, with darker blue signifying higher numbers. The diagonal squares, notably for Blight, Common Rust, Healthy, and Phaeosphaeria Leaf Spot, suggest accurate classifications, whereas lighter blue squares off the diagonal indicate misclassifications. The model appears to do well on Blight and Common Rust but struggles more with Gray Leaf Spot classification. Overall, the heatmap provides significant insights into the model's strengths and flaws in disease classification.

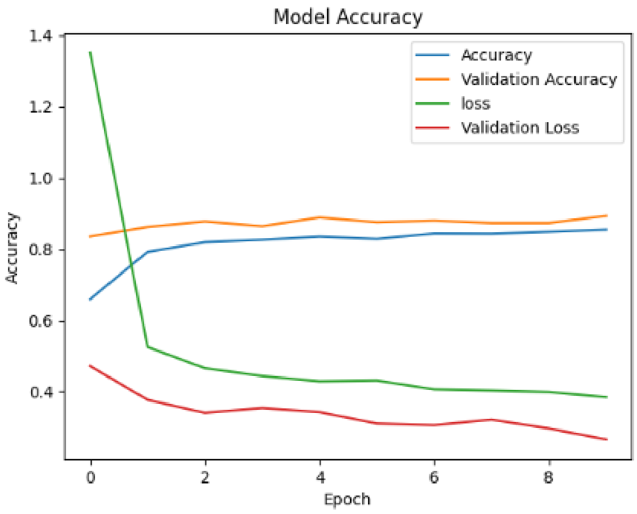

Fig 4.6 VGG16 Model Accuracy

The VGG16 model scored a test accuracy of 88.22% with a test loss of 0.2875.

VGG19: The VGG19 model is configured using the VGG19 architecture, utilizing pre-trained ImageNet weights for feature extraction. The model design comprises convolutional layers followed by max-pooling layers, with dense layers added for identification. The VGG19 foundation is used with its top layers removed, and dropout regularization is applied to mitigate overfitting. Two densely linked layers with ReLU activation functions are attached to learn complicated trends from the collected features. The output layer with softmax activation provides estimates of probability over the five illness categories. The model is compiled using the Adam optimizer and categorical cross-entropy loss function. During training for 10 epochs, the model obtains a test accuracy of 87.78% with a test loss of 0.3414. The model summary displays a total of 20,024,005 parameters, with 13,674,501 trainable parameters and 6,349,504 non-trainable parameters.

Table 4.7 VGG19 Classification Report

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Blight	0.77	0.91	0.83	116
Common_Rust	0.95	0.92	0.94	133
Gray_Leaf_Spot	0.89	0.47	0.62	53
Healthy	0.97	0.98	0.98	117
Phaeosphaeria Leaf Spot	0.73	0.87	0.79	31
Accuracy	-	-	0.88	450
Macro Avg	0.86	0.83	0.83	450
Weighted Avg	0.89	0.88	0.87	450

The classification report illustrates the performance of a VGG19 model in categorizing maize leaf diseases, showing precision, recall, and F1-score metrics for each disease class: Blight (precision: 0.77, recall: 0.91, F1-score: 0.83), Common Rust (precision: 0.84, recall: 0.92, F1-score: 0.88), Gray Leaf Spot (precision: 0.89, recall: 0.47, F1-score: 0.62), Healthy (precision: 0.93, recall: 0.98, F1-score: 0.95), and Phaeosphaeria Leaf Spot (precision: 0.72, recall: 0.89, F1-score: 0.79). Additionally, macro average measurements reveal precision (0.83), recall (0.83), and F1-score (0.81), while weighted average metrics demonstrate precision (0.87), recall (0.88), and F1-score (0.87). The overall accuracy of the model is 0.88, indicating it correctly categorized 88% of the photos. The report highlights the model's capabilities in Common Rust and Healthy classifications while flagging issues in reliably recognizing Gray Leaf Spot.

Table 4.8: VGG19 Classification Table

Actual Disease	**Precision**	**Recall**	**F1-Score**	**False Negatives**	**False Positives**
Blight	0.77	0.91	0.83	Few	Few
Common Rust	0.95	0.92	0.94	-	-

Gray Leaf Spot	0.89	0.47	0.62	Many	Few
Healthy	0.97	0.98	0.98	-	-
Phaeosphaeria Leaf Spot	0.72	0.89	0.79	-	-

The false negatives and false positives provide insights into the model's performance strengths and flaws in classifying maize leaf diseases. High false negatives show occasions where the algorithm missed diagnosing a disease, such as categorizing a blighted maize leaf as healthy. Conversely, large false positives show the model wrongly diagnoses a disease that isn't present, like classifying a healthy maize leaf as having blight. By evaluating these data, we may determine where the model succeeds and where it struggles in disease categorization. High false negatives may identify areas for improvement in illness detection sensitivity, whereas high false positives may imply a need for higher specificity in disease diagnosis.

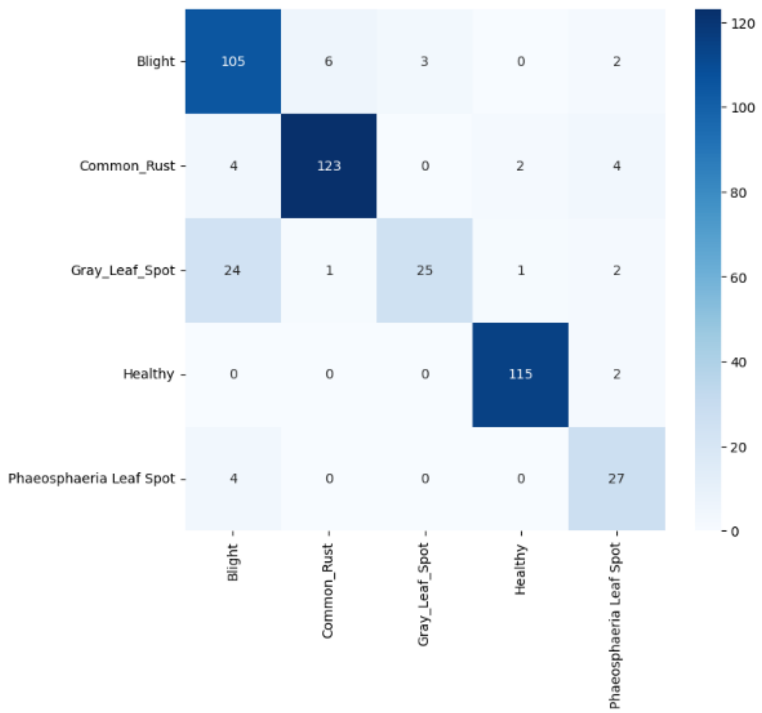

Fig 4.7 vgg19 Confusion matrix Heatmap

The VGG19 confusion matrix heatmap gives a visual assessment of the model's performance in classifying different maize leaf diseases. It helps identify strengths (properly categorized diseases) and weaknesses (misclassified diseases) of the model.

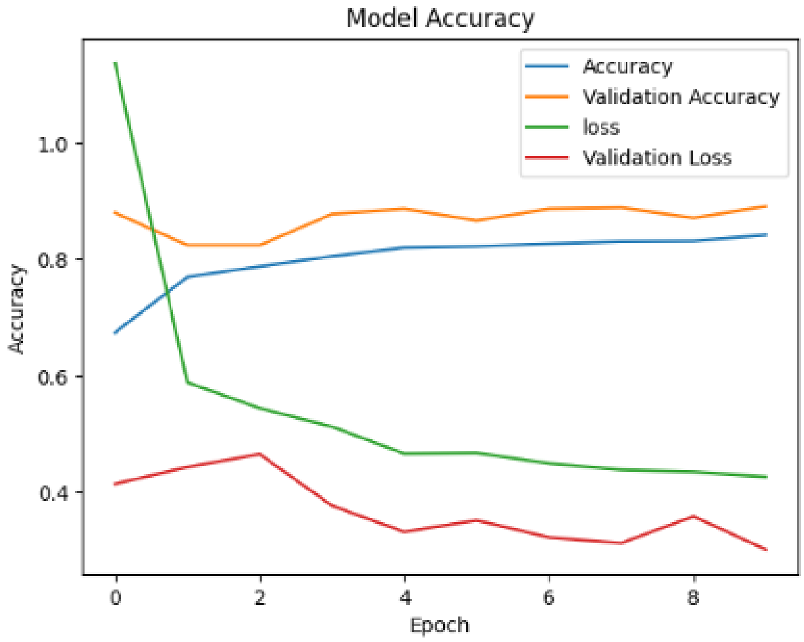

Fig 4.8 VGG19 Model Accuracy

The VGG19 model scored a test accuracy of 87.78%.

Inceptionv3: The InceptionV3 model attained an overall accuracy of 88.22%. Looking into the precision, recall, and F1-score measurements, examine its performance across different disease classifications. For Blight, it attained a precision of 0.76, suggesting that 76% of the maize leaf images identified as Blight were properly classified. The recall for Blight is 0.92, implying that the model accurately identified 92% of the actual Blight photos. The F1-score, a compromise between precision and recall, is 0.84 for Blight. Similar judgments can be performed for the other disease classes, such as Common Rust, Gray Leaf Spot, Healthy, and Phaeosphaeria Leaf Spot. These measures provide a full insight into the model's performance in differentiating between distinct maize leaf diseases.

Table 4.9: Inceptionv3 Classification Report

Class	Precision	Recall	F1-Score	Support
Blight	0.76	0.92	0.84	116
Common_Rust	1.00	0.90	0.95	133

Gray_Leaf_Spot	0.84	0.49	0.62	53
Healthy	0.97	0.97	0.97	117
Phaeosphaeria Leaf Spot	0.71	0.97	0.82	31
Accuracy	-	-	0.88	450
Macro Avg	0.86	0.85	0.84	450
Weighted Avg	0.89	0.88	0.88	450

Table 4.10: Inceptionv3 Classification Table

Actual Disease	**Precision**	**Recall**	**F1-Score**	**False Negatives**	**False Positives**
Blight	0.76	0.92	0.84	Few	Few
Common Rust	1.00	0.90	0.95	-	-
Gray Leaf Spot	0.84	0.49	0.62	Many	Few
Healthy	0.97	0.97	0.97	-	-
Phaeosphaeria Leaf Spot	0.71	0.87	0.92	-	-

The precision, recall, and F1-score metrics give a thorough assessment of the InceptionV3 model's effectiveness in classifying maize diseases of the leaf. Precision denotes the fraction of predicted disease images that were successfully identified, whereas recall displays how well the model identified all instances of a certain condition. The F1 score combines these criteria, delivering a balanced perspective of the model's effectiveness. Measurements from the table demonstrate great performance in the Common Rust and Healthy categories, with high precision, recall, and F1-score values. However, Blight classification showed strong recall but reduced precision, suggesting probable misclassifications. Gray Leaf Spot provides the biggest challenge, with a low F1-score due to both limited recall and few false positives. False negatives and false positives are key indications of misclassifications, revealing areas for model improvement.

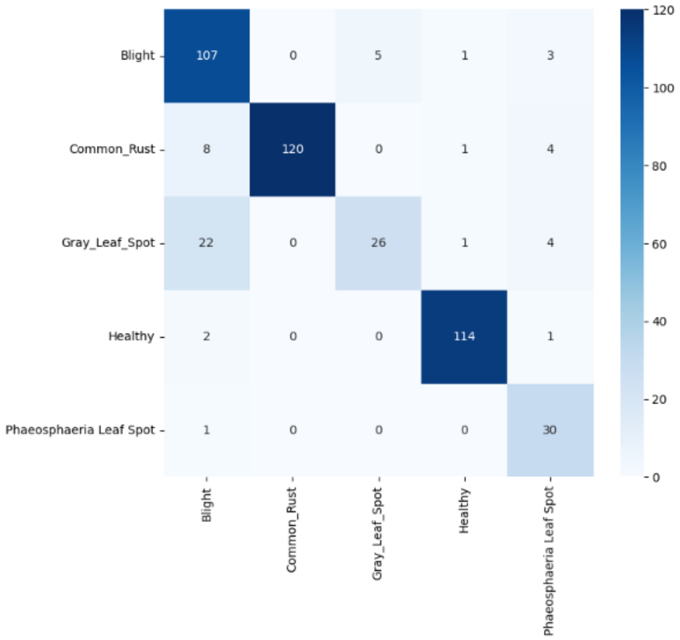

Fig 4.9 Inceptionv3 Confusion matrix Heatmap

The heatmap evaluates InceptionV3's classification of maize leaf diseases. Rows indicate real labels; columns show anticipated labels and darker tones imply higher counts. Blight and Common Rust perform well, while Gray Leaf Spot struggles, indicating misclassifications. The healthy leaf is reliably classified, while Phaeosphaeria Leaf Spot's performance is less obvious. Overall, the heatmap shows model strengths and weaknesses, driving adjustments.

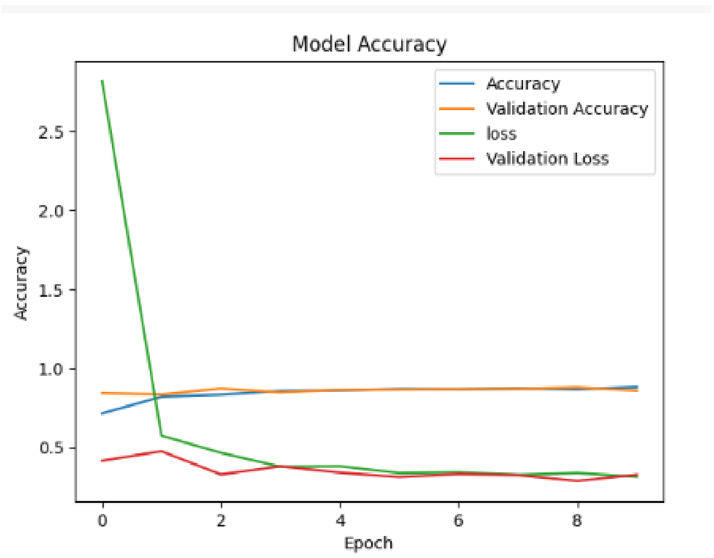

Fig 4.10 Inceptionv3 Model Accuracy

InceptionV3's model accuracy is reported as 0.88, suggesting that the model correctly categorized 88% of the images in the test dataset.

UI output: Our user interface is primarily concerned with visually showing the potential diagnosis of grouped Zea Mays Disease circumstances. Users are asked to choose a photo depicting a case of Zea Mays Disease, and our machine learning algorithm continues to predict the appropriate class or category of the selected image.

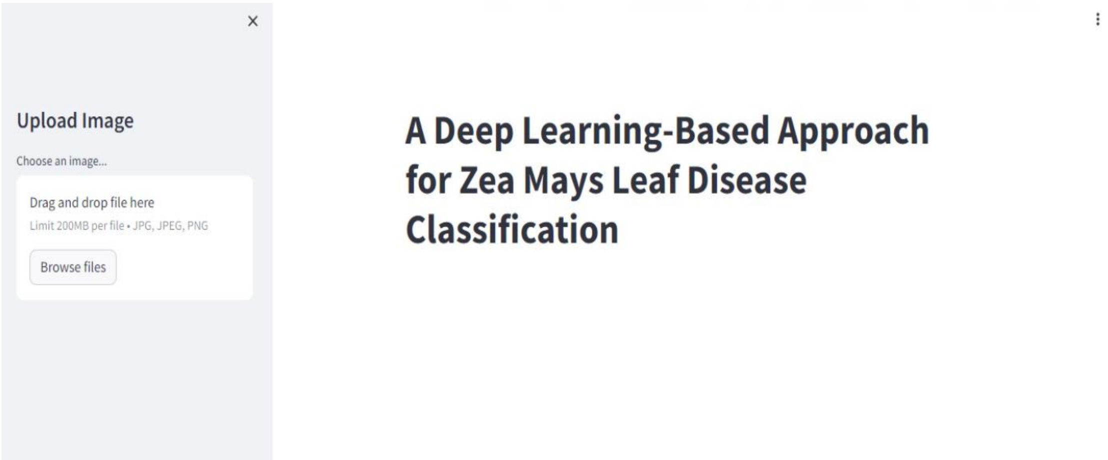

Fig 4.11 Before Prediction

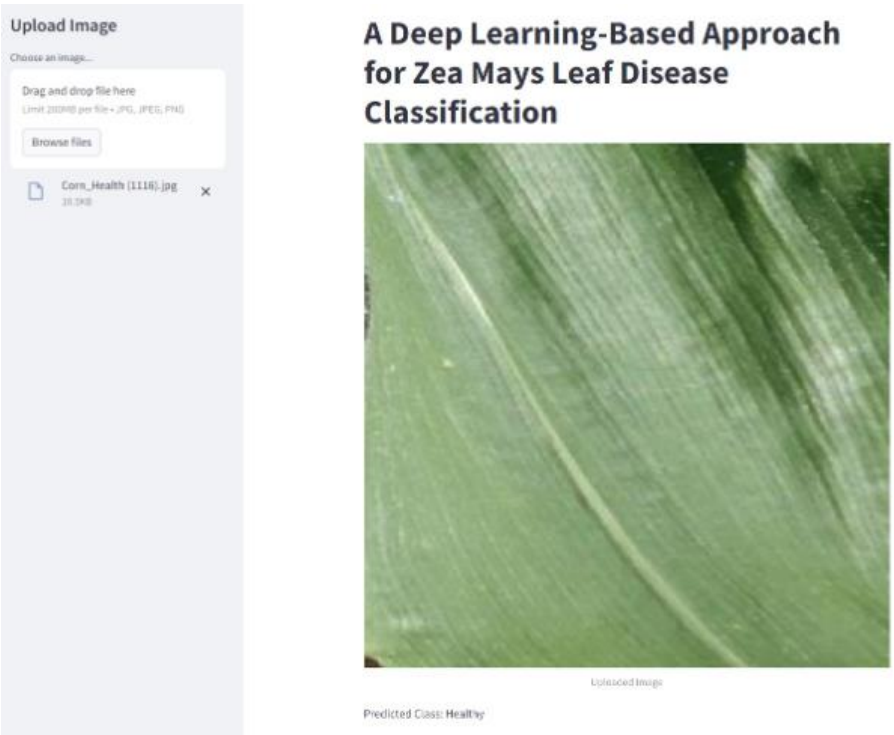

Fig 4.12 After Prediction

4.4 Summary

In the details of our research conclusions, acknowledging the positives and weaknesses revealed during our analysis. Critically assess the aspects contributing to model performance, including data quality, method selection, and parameter adjustment. Discuss potential biases and limits inherent in our study methodology, offering insights into areas for improvement and further exploration. Additionally, explore the larger implications of our findings for the field of agricultural technology, highlighting prospects for innovation and practical applications in crop disease management. Ultimately, our conversation serves to contextualize our results within the greater research environment, encouraging a deeper awareness of the obstacles and opportunities in employing machine learning for agricultural sustainability.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

The results and analysis of our study on maize leaf disease classification using deep learning techniques. This section provides a comprehensive overview of the outcomes obtained from training and evaluating various models, including MobileNetV2, DenseNet, VGG16, VGG19, and InceptionV3, on a dataset containing multiple disease classes such as Blight, Common Rust, Gray Leaf Spot, Healthy, and Phaeosphaeria Leaf Spot. The chapter describes the performance parameters achieved by each model, including accuracy, precision, recall, and F1-score, which are critical for measuring their effectiveness in illness diagnosis. The examination digs into the merits and shortcomings of each algorithm, showing their applicability for particular deployment circumstances and computing restrictions. Through thorough statistical analysis and visual representations, this chapter attempts to provide insights into the efficacy of deep learning technologies in addressing agricultural concerns connected to crop disease control.

5.2 Experimental/ Simulation Result

The results and analysis of our study on maize leaf disease classification using deep learning techniques. This section provides a comprehensive overview of the outcomes obtained from training and evaluating various models, including MobileNetV2, DenseNet, VGG16, VGG19, and InceptionV3, on a dataset containing multiple disease classes such as Blight, Common Rust, Gray Leaf Spot, Healthy, and Phaeosphaeria Leaf Spot. The chapter describes the performance parameters achieved by each model, including accuracy, precision, recall, and F1-score, which are critical for measuring their effectiveness in illness diagnosis. The examination digs into the merits and shortcomings of each algorithm, showing their applicability for particular deployment circumstances and computing restrictions. Through thorough statistical analysis and visual representations, this chapter attempts to provide insights into the efficacy of deep learning technologies in addressing agricultural concerns connected to crop disease control.

5.3 Performance/ Comparative Analysis

In our project, applied a varied collection of algorithm strategies for maize leaf disease classification tasks. These techniques comprised a spectrum of deep learning architectures, each with unique traits and strengths. MobileNetV2 is notable for its lightweight design, enabling efficient inference on mobile and embedded devices without losing accuracy. DenseNet, exploiting dense connections between layers, accurately captured detailed features from input photos. VGG16 and VGG19, conventional designs with different depths, excelled in extracting hierarchical representations, whereas InceptionV3, integrating multi-scale processing with inception modules, adeptly balanced computational efficiency, and classification performance. Through the cumulative use of these algorithm methodologies, obtained robust and accurate maize leaf disease classification, adapting to varied deployment scenarios and performance constraints.

Table 5.3: Comparison Between Different Algorithm Techniques

Algorithm	**Feature**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
MobileNetV2	Lightweight	0.93	0.90	0.91	0.90
DenseNet	Dense	0.90	0.89	0.85	0.87
VGG16	Classic	0.88	0.86	0.81	0.83
VGG19	Deep	0.88	0.88	0.86	0.87
InceptionV3	Multi-Scale	0.88	0.86	0.85	0.84

5.4 Summary

"Results and Analysis," presents a complete review of our study on maize leaf disease categorization using deep learning techniques. We assessed different models including MobileNetV2, DenseNet, VGG16, VGG19, and InceptionV3 on a broad dataset comprising diseases like Blight, Common Rust, Gray Leaf Spot, Healthy, and

Phaeosphaeria Leaf Spot. Detailed performance parameters including as accuracy, precision, recall, and F1-score are painstakingly assessed for each model, vital for measuring their efficacy in illness detection. The chapter discusses the merits and limits of each method, assessing their applicability under various computational restrictions and deployment circumstances. Through rigorous statistical analysis and visual representations, this chapter seeks to provide useful insights into the practical use of deep learning technology for addressing agricultural concerns connected to crop disease management and sustainability.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Our research has a wide-ranging and complex influence on society. Through the utilization of machine learning algorithms, try to make a significant contribution to improving agricultural output and ensuring food security by accurately categorizing maize leaf diseases. Early and precise disease identification can greatly help farmers, especially in areas where maize farming is common. This allows for prompt interventions to reduce crop losses and maximize yield. Moreover, our research shows potential for implementing sustainable agriculture methods by decreasing dependence on chemical pesticides using focused disease management tactics. In addition to the immediate advantages in agriculture, our study highlights the wider possibilities of artificial intelligence in tackling worldwide issues. It emphasizes the significance of interdisciplinary cooperation and technology-based solutions in promoting a more resilient and food-secure future for everyone.

6.2 Impact on Society and Environment

The implementation of machine learning algorithms in classifying maize leaf diseases has profound environmental ramifications. Our approach allows for the early identification and focused treatment of crop diseases, which in turn decreases the necessity for widespread pesticide application. As a result, this approach minimizes the release of chemicals into the environment and lowers soil pollution. This action helps to maintain the health of the soil and the diversity of living organisms in agricultural settings. In addition, our work promotes sustainable agricultural practices by effectively managing crop diseases, thereby optimizing crop output, and reducing the need to encroach on natural habitats for agricultural land expansion. In conclusion, our research not only supports the preservation of the environment but also encourages a more balanced ecological approach to agricultural production, in line with broader initiatives aimed at reaching global sustainability objectives.

6.3 Ethical Aspects

Our research classification of maize leaf diseases using machine learning algorithms raises various ethical considerations that require cautious attention. One significant worry is the potential for biased outcomes, wherein the model may demonstrate discrepancies in performance across different demographic groups or geographic regions. Addressing this entails assuring varied and representative datasets and employing fairness-aware algorithms to prevent prejudice. Moreover, there are privacy problems linked with collecting and analyzing agricultural data, particularly with farmers' personal information and land use habits. It is vital to respect data privacy and security requirements while simultaneously fostering transparency and informed consent in data-gathering operations. Our approach should focus on the equitable distribution of technical advantages, ensuring that smallholder farmers and marginalized groups have access to and can benefit from these breakthroughs. Finally, considering the broader socio-economic repercussions of our study, Here must seek to reduce any potential negative consequences on livelihoods and traditional farming practices, supporting inclusive and sustainable agricultural growth.

6.4 Sustainability Plan

Developing a sustainability plan for our research comprises several essential aspects to ensure long-term beneficial outcomes and reduce environmental and social footprints. Firstly, prioritize the adoption of sustainable agriculture practices promoted by our technology, such as targeted disease management and reduced pesticide consumption, to boost crop health and minimize environmental harm. Try to push for the use of energy from renewable sources in model training and data processing to reduce carbon emissions related to our research efforts. Besides adopt comprehensive data management standards to maintain privacy, confidentiality, and integrity, promoting confidence among stakeholders and defending against any misuse of agricultural data. This development will prioritize constant monitoring and evaluation of our technology's socio-economic and environmental impacts, permitting adaptive management and continuous development in line with shifting sustainability goals and priorities.

6.5 Summary

"Impact on Society, Environment, and Sustainability," highlights the numerous consequences of our research on maize leaf disease categorization using machine learning algorithms. this project greatly helps to agricultural production and food security by providing accurate disease identification, hence facilitating prompt interventions to minimize crop losses and optimize yields. This strategy also encourages sustainable agriculture practices by minimizing dependency on chemical pesticides, which enhances environmental health by lowering pollutants and protecting soil and ecosystem biodiversity. Ethical considerations, including fairness in algorithmic outputs and data privacy, are significant focal points, ensuring equitable access to technical breakthroughs while preserving farmer privacy and socio-economic repercussions. A sustainability strategy underlines our commitment to long-term beneficial benefits, pushing for renewable energy consumption, comprehensive data management procedures, and constant monitoring to align with evolving sustainability objectives and promote responsible technology deployment in agriculture.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

In conclusion, the research investigation effectively evaluated the usefulness of various deep learning algorithms for the categorization of maize leaf diseases. Through extensive experimentation and review, it was revealed that different models demonstrated differing levels of effectiveness across different illness classes. While some models displayed excellent accuracy and precision for diseases, others struggled with classification accuracy. These findings underline the necessity of selecting suitable algorithms and optimization strategies based on the dataset's specific characteristics and the classification task's nature of the dataset and the nature of the classification task. Despite the limitations, the study provides the framework for the development of automated systems for maize disease identification, which has the potential to change crop management techniques and contribute to sustainable agriculture. Further research and development of the models are necessary to increase their effectiveness and capacity for real-world applications.

7.2 Further Suggested Works

The study's findings indicate various avenues for additional inquiry in the arena of automated disease diagnosis for maize crops. One potential area is the development of ensemble methods or hybrid models, which combine the strengths of different algorithms to boost classification accuracy. Additionally, research into dataset augmentation techniques and transfer learning methodologies could provide useful insights into increasing model generality and resilience across varied environmental conditions and illness symptoms. Furthermore, adding real-time monitoring systems and utilizing future technologies like remote sensing or drone-based imaging offers considerable prospects for early disease diagnosis and response, hence minimizing crop losses. Furthermore, understanding the socio-economic and policy consequences of implementing such technologies in agricultural systems is vital for assuring equal access and adoption, as well as resolving possible difficulties connected to data privacy, ownership, and governance. By delving into these areas, future studies can contribute to enhancing the efficacy and scalability of automated disease diagnosis solutions in agriculture, ultimately boosting global food security efforts.

7.3 Limitations

There are a number of project limits that need be taken into account. The training dataset's quality and diversity have a significant impact on our models' effectiveness and their capacity to generalize to other environmental and geographic situations. Second, in resource-constrained situations, the computational demands of training deep learning architectures—in particular, DenseNet and InceptionV3—present scaling issues. Even though our models performed well in controlled environments, there is still uncertainty about how well they will function in natural environments where variables like lighting and image quality can vary greatly. To improve the dependability and applicability of the model in real-world agricultural scenarios, it would be necessary to extend and diversify datasets, optimize model training procedures, and validate performance in various field conditions.

REFERENCES

[1] K. P. Panigrahi, H. Das, A. K. Sahoo, and S. C. Moharana, "Maize leaf disease detection and classification using machine learning algorithms," in *Advances in Intelligent Systems and computing*, 2020, pp. 659–669. doi: 10.1007/978-981-15-2414-1_66.

[2] F. Khan, N. Zafar, M. N. Tahir, M. Aqib, H. Waheed, and Z. Haroon, "A mobile-based system for maize plant leaf disease detection and classification using deep learning," *Frontiers in Plant Science*, vol. 14, May 2023, doi: 10.3389/fpls.2023.1079366.

[3] "Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: a review," *CORE Reader*, [Online]. Available: https://core.ac.uk/reader/482681620

[4] "Plant Disease Detection and Classification by Deep Learning A Review," *IEEE Journals & Magazine IEEE Xplore*, 2021. https://ieeexplore.ieee.org/abstract/document/9399342

[5] M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant disease detection and classification by deep learning," *Plants*, vol. 8, no. 11, p. 468, Oct. 2019, doi: 10.3390/plants8110468.

[6] R. K. Singh, A. Tiwari, and R. K. Gupta, "Deep transfer modeling for classification of Maize Plant Leaf Disease," *Multimedia Tools and Applications*, vol. 81, no. 5, pp. 6051–6067, Jan. 2022, doi: 10.1007/s11042-021-11763-6.

[7] W. Setiawan, E. M. S. Rochman, B. D. Satoto, and A. Rachmad, "Machine Learning and Deep Learning for Maize leaf Disease Classification: A review," *Journal of Physics. Conference Series*, vol. 2406, no. 1, p. 012019, Dec. 2022, doi: 10.1088/1742-6596/2406/1/012019.

[8] "Identification of maize leaf diseases using improved deep convolutional neural networks," *IEEE Journals & Magazine IEEE Xplore*, 2018. https://ieeexplore.ieee.org/abstract/document/8374024

[9] S. Malliga, K. Shanmugavadivel, and P. Nandhini, "On fine-tuning deep learning models using transfer learning and hyper-parameters optimization for disease identification in maize leaves," *Neural Computing & Applications*, vol. 34, no. 16, pp. 13951–13968, Apr. 2022, doi: 10.1007/s00521-022-07246-w.

[10] J. Arora, U. Agrawal, and P. Sharma, "Classification of Maize leaf diseases from healthy leaves using Deep Forest," *Journal of Artificial Intelligence and Systems*, vol. 2, no. 1, pp. 14–26, Jan. 2020, doi: 10.33969/ais.2020.21002.

[11] "MaizeNet: A deep learning approach for effective recognition of maize plant leaf diseases," *IEEE Journals & Magazine | IEEE Xplore*, 2023. https://ieeexplore.ieee.org/abstract/document/10136691

[12] "Machine learning-based for automatic detection of Corn-Plant diseases using image processing," *IEEE Conference Publication IEEE Xplore*, Nov. 01, 2018. https://ieeexplore.ieee.org/abstract/document/8629507

[13] Md. A. Haque *et al.*, "Deep learning-based approach for identification of diseases of maize crop," *Scientific Reports*, vol. 12, no. 1, Apr. 2022, doi: 10.1038/s41598-022-10140-z.

[14] "End-to-End Deep learning model for corn leaf disease classification," *IEEE Journals & Magazine IEEE Xplore*, 2022. https://ieeexplore.ieee.org/abstract/document/9734016

[15] “Prediction of Maize Leaf Disease Detection to Improve Crop Yield Using Machine Learning based Models,” *conference Publication IEEE Xplore*, Feb. 11, 2022.
https://ieeexplore.ieee.org/abstract/document/9782023
[16] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, “Plant leaf disease classification using EfficientNet deep learning model,” *Ecological Informatics*, vol. 61, p. 101182, Mar. 2021, doi: 10.1016/j.ecoinf.2020.101182.
[17] Z. Ma *et al.*, “Maize leaf disease identification using deep transfer convolutional neural networks,” *Ma International Journal of Agricultural and Biological Engineering*, Nov. 2022, doi 10.25165/ijabe.v15i5.6658.
[18] C. DeChant *et al.*, “Automated Identification of Northern Leaf Blight-Infected Maize Plants from Field Imagery Using Deep Learning,” *Phytopathology*, vol. 107, no. 11, pp. 1426–1432, Nov. 2017, doi: 10.1094/phyto-11-16-0417-r.
[19] S. Mishra, R. Sachan, and D. Rajpal, “Deep Convolutional Neural Network based Detection System for Real-time Corn Plant Disease Recognition,” *Procedia Computer Science*, vol. 167, pp. 2003–2010, Jan. 2020, doi: 10.1016/j.procs.2020.03.236.
[20] S. Malliga, P. Nandhini, S. V. Kogilavani, R. Harini, S. K. Shree, and G. Jeeva, “Maize leaf disease classification using convolutional neural network,” *AIP Conference Proceedings*, Jan. 2021, doi: 10.1063/5.0068599.
[21] Deep learning-based approach for identification of diseases of maize crop.
https://www.nature.com/articles/s41598-022-10140 -z
[22] Johannes, A. et al. Automatic plant disease diagnosis using mobile capture devices applied on a wheat use case. Comput. Electron. Agric. https://doi.org/10.1016/j.compag.2017.04.013 (2017).
[23] Zhang, X. et al. A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images. Remote Sens. https://doi.org/10.3390/rs11131554 (2019).
[24] Picon, A. et al. Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Comput. Electron. Agric. https://doi.org/10.1016/j.compag.2018.04.002 (2019).
[25] Fuentes, A. F., Yoon, S., Lee, J. & Park, D. S. High-performance deep neural network-based tomato plant diseases and pests diagnosis system with refinement filter bank. Front. Plant Sci. https://doi.org/10.3389/fpls.2018.01162 (2018).

Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
A DEEP LEARNING-BASED APPROACH FOR ZEA MAYS LEAF DISEASE CLASSIFICATION

Student ID: 201-15-14044

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **Zea Mays leaf disease detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**

CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting machine learning algorithms to classify Zea Mays leaf disease.	**Page no:** [12-15] **Section:** [3.2] **Page no:** [2] **Section:** [1.2]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments.	**Page no:** [14]

				The project addresses **engineering practice & technology (K6)** by employing Different algorithms.	**Section:** [3.2] **Page no:** [16-24] **Section:** [3.3]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance Zea Mays leaf disease detection using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [6-9] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in Zea Mays leaf disease detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights.	**Page no:** [10-11] **Section:** [2.4, 2.5]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing Zea Mays leaf disease detection amidst multiple potential approaches.	**Page no:** [25-40] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting Zea Mays leaf disease detection process which indicates **EP-4**.	**Page no:** [6-11] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges which ensures **EP-7**.	**Page no:** [12-24] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in Zea Mays leaf disease detection through various machine Learning algorithms.	**Page no:** [12-23] **Section:** [3.2, 3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A

3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving Zea Mays leaf disease detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines.	**Page no:** [42-43] **Section:** [5.2, 5.3]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in Zea Mays leaf disease detection through transfer learning and deep learning demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [6-9] **Section:** [2.2, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and	**Page no:** [23] **Section:** [3.4]

			budget estimation for optimal resource utilization throughout the research lifecycle.	
2	CO9	No	N/A	N/A
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [12-16, 26-40] **Section:** [3.2, 4.3]

PLAGIARISM REPORT

Zea Mays Report (Final).docx

ORIGINALITY REPORT

22%	14%	13%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

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