Maize Leaf Disease Identification Using Deep Learning Techniques: A Case Study in Bangladesh

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This Report Presented in Partial Fulfillment of the Requirements for
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APPROVAL

This Thesis titled **"Maize Leaf Disease Identification Using Deep learning Techniques: A Case Study in Bangladesh"**, submitted by **Nusrat Jahan**, ID No: **241-25-007** 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 M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13-09-2025.

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DECLARATION

I hereby declare that this research has been done by me under the supervision of Ms. Nazmun Nessa Moon, Associate Professor, Department of CSE, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

This paper presents research on the deep learning methods and how the methods can be used in detecting three of the common corns on the leaves. A dataset was collected containing more than 4,000 actual pictures of contaminated and wholesome curvy leaves of corn. The CNN, MobileNetV2, VGG16, VGG19 and InceptionV3 deep learning models were trained and tested on this dataset. The CNN model attained an accuracy of 83%, followed by MobileNetV2 97%, VGG16 87%, VGG19 85% and InceptionV3 96%. These results indicate that CNN-based models can be an effective and reliable method to identify diseases that potentially are threatening maize farmers in Bangladesh and promote agricultural resilience at a scale and cost-effective approach. This study shows that modern technology has the ability to redefine agriculture. With the provision of more accurate, fast and cost-effective disease detection, such models of mobile deep learning, as MobileNetV2 and InceptionV3, provide practical tools that could be used by farmers in the field. In terms of mobile or edge deployment, MobileNetV2 in particular will provide a feasible means of real-time disease detection that can be applied using smartphones by farmers. It was converted to TensorFlow Lite format and then successfully deployed in a mobile application.

Keywords: Maize leaf disease detection, Convolutional Neural Networks, Deep learning, Agricultural technology Bangladesh, Image classification.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Farm production is the mainstay of the Bangladesh economy as millions of people rely on agricultural production as their source of livelihood. Nevertheless, the corn yields in the Bangladesh country remains below the global average level due to diseases that destroy leaves, decrease quality and crop outputs. Farmers and researchers have been using visual inspection in the identification of these diseases traditionally. However, this method is slow, need labor-related and usually unreliable. To break this challenge, researchers are looking to more advanced methods in deep learning so that corn leaf diseases can be detected automatically and accurately. Experiments with alternative deep learning models have recently proving successful. MobileNetv2 received the best accuracy of 97% and InceptionV3 came in close second with 96%. VGG16 and VGG19 were 87 and 85 percent accurate, respectively, whereas basic CNN model was 83 percent on accuracy. These results demonstrate that lightweight and high-accuracy models such as MobileNetV2 and InceptionV3 are especially suitable to this task, where efficiency is used to evaluate the accuracy. To farmers of Bangladesh, the development is particularly valuable. It will ensure early and confident diagnosis of corn leaf diseases, which will allow them to make specific decisions, prevent the further spread of the disease, and rationalize scarce resources. The outcome is crops that are healthier, increased yields and more environmentally friendly farming. There are three types of the worst corn leaf diseases that are considered in the present study namely Uria Injury, Stewart wilt, and Leaf blight. Both are a serious threat to yield and therefore early detection is crucial in safeguarding one of the premier crops in a country.

This study shows that modern technology has the ability to redefine agriculture. With the provision of more accurate, fast and cost-effective disease detection, such models of mobile deep learning, as MobileNetV2 and InceptionV3, provide practical tools that could be used by farmers in the field. This not only enhances production of corn but also provides strength and growth to the agricultural sector of Bangladesh.

1.2 Motivation

Corn is one of the most significant crops in the world and in Bangladesh; it is the second most productive crop which is critical in the economic growth and in food security. Leaf diseases however pose a serious threat to corn production which results in heavy revenue cuts in the hands of those who produce them, as well as creating a risk of food shortages through a combination of the price rise and their fall in quantity. The identification of these diseases at an early stage and reliable is therefore necessary in order to manage the diseases, and intervene at an early age, reduce the use of chemical pesticides and conduct sustainable agricultural practices. Attending to corn leaf diseases in the Bangladesh setting is still a gap in this area of research on plant disease detection. This paper seeks to fill these gaps by formulating effective methods of detecting the diseases that can bolster the disease management strategies, improve productivity, and improve the national food security.

1.3 Research Objectives

The main aim of this work is to develop a fast and consistent deep learning based system to detect corn leaf diseases at the early stage in Bangladesh. The targeted goals are the following:

1. To determine and distinguish between major corn leaf diseases that have a tremendous impact on crop production in Bangladesh.
2. To create and apply deep learning models which are able to detect these diseases at their early stages accurately.
3. To draw analogies and contrast the efficiency, scaling, as well as adaptability of the models to the real-world agricultural landscape.
4. To develop an effective disease detection system that will assist farmers to make decisions in time, minimize crop losses and to embrace sustainable farming.

1.4 Research Questions

- RQ1: Which corn leaf diseases most critically affect crop productivity in Bangladesh, and how can they be effectively identified using image-based analysis?
- RQ2: How can deep learning models be designed and optimized to ensure accurate and efficient detection of corn leaf diseases at an early stage?
- RQ3: What detection framework can be developed to provide practical, scalable, and sustainable solutions for farmers in real-world agricultural settings?

1.5 Expected Output

The main aim of this paper is to implement and test a set of deep learning models; in particular, MobileNetV2, InceptionV3, VGG16, VGG19, and CNN as used to detect and classify diseases affecting the leaves of corn utilizing raw image data. An analysis of these models will compare them to identify the one that will be effective in the achievement of confident disease recognition within the agricultural sector in Bangladesh. There are 3 possible contributions as expected of this work. First, it will create an effective scheme of early detection and classification of corn leaf diseases that can then be used to identify a more effective and earlier process of disease control. Second, it will provide comparative information about the performance of various deep learning architectures, hence contributing to the current studies of agricultural artificial intelligence. By using a mobile application tool that provides real-time disease detection, a user can upload an image of a corn leaf, and the picture can receive accurate feedback. Such system would enable farmers make wise choices, minimize yield losses and promote sustainable farming.

1.6 Project Management and Finance

This paper aims to identify efficient deep-learning models to detect and classify corn leaf diseases. The dataset was obtained with no cost at all since I used the phone camera to collect more than 4,000 images directly in local corn fields in my village. The project will be executed using a clear project plan that will entail data collection, development of the models (MobileNetV2, InceptionV3, VGG16, VGG19, CNN) evaluation, and deployment with milestones to facilitate professional project delivery within the stipulated time. MobileNetV2/InceptionV3 models had the best results because of the RAM restrictions in case multiple models run simultaneously; therefore, I have used a Kaggle Notebook to support the above need.

1.7 Report Layout

In Chapter 1, this chapter presents the introduction to the study and it states the purpose, objectives and the main findings. In Chapter 2, existing literature on corn leaf disease detection is reviewed. Different approaches in the identification of the leaf diseases are presented as well as other methods. In the chapter, the scope of the problem and its importance as well as the difficulties in the field are indicated. In Chapter 3, making use of predecessor studies, the chapter proposes the outstanding challenges and loopholes that must be covered. It explains the model proposed and the way it addresses these issues. All major steps, such as data collection, preparation, and annotation, feature selection, and the algorithms to be used to detect the disease, are covered in the chapter. In Chapter 4, the chapter reports in detail the performance of the proposed models will be discussed. It describes the setup of the experiment, relates the findings of the results and tells how the models fared against corn diseases identification. The fifth chapter will investigate the larger implications of the study and the ways in which it will influence the farmers, the society, and the environmentally friendly agricultural production. The chapter addresses the applicability and relevance of the results of the study. The sixth chapter will discuss the whole research project summary and its key accomplishments. It also states the limitations that were faced during the study and provides suggestions and future research directions.

CHAPTER 2
BACKGROUND

2.1 Preliminaries

Leaf disease detection has been one of the major areas of research. In this section, I shall overview of various previous works that have captured comparable issues, the major classifiers and algorithms they have used and the percentage of accuracy attained by respective works. A review of these works will give me an opportunity to better appreciate the shortcomings and pitfalls of older studies, thereby providing useful knowledge that can inform the design of my own study. There is some basic terminology we need to establish before getting into the mechanism of detecting corn leaf diseases.

- **Corn Leaf Disease**: The term describes the diverse issues that can afflict the leaves of maize plants, either pathogen problems or environment-induced stress. These diseases may impair the capacity of the plant to photosynthesize, restrict the rate of growth, and eventually yield.
- **Uria Injury**: As compared to the infectious diseases, this is one of the forms of damages that arise due to excessive application of urea fertilizer. Because of the excess nitrogen being burned on the leaf surface, it can be easily confused with diseases as spots and streaks are formed.
- **Stewart's Wilt**: A serious bacterial pathogen *Pantoea stewartii*, It also leaves behind long streaks and wilted patches on foliage which in case of detection late may result in overall significant losses in yield.
- **Leaf Blight:** A general description of a variety of fungal or bacterial diseases of corn, including Northern Corn Leaf Blight caused by *Exserohilum turcicum*. These infections normally form long and dead spots on the leaves. Those are some

additional terms and concepts that are relevant to the approach for identifying maize leaf disease.

2.2 Related works

Sharada P. Mohanty, David P. Hughes, Marcel Salathe. Image-Based Plant Disease Detection with Deep Convolutional Neural Networks. Full contributors. Dataset: PlantVillage (complete with many plant species, such as maize classes). Precision: 99.35% on maize subset on PlantVillage.[1] N. Parashar, S. K. Singh, R. Kumar, M. Gupta, et al."Deep neural network improvement of residual-attention based on maize disease classification (MaizeNet) maize leaf dataset (field and controlled images) custom maize leaf dataset. Accuracy: 95.95% [2] Fathimathul Rajeena, A. Suma, K. P. Saranya M. G. Madhuri "EfficientNet-based method of leaf disease diagnosis in corn. A maize dataset that has been customized and PlantVillage comparisons. Accuracy: 98.85%.[3] Z. Ji, X. Li, L. Xin, Y. Bao ICS-ResNet Lightweight Network to Maize Leaf Disease Recognition. Maize dataset field collection,and PlantVillage maize category. Accuracy: 98.87% [4] S. N. Mohanty et al. (MDPI), "High-level deep learning to detect corn leaf disease (hybrid ResNet50+VGG16) Dataset maize images at PlantVillage. Accuracy: 99.56% [5] Zhang et al."Maize Leaf Diseases (MAF-ResNet50) Detection with High Accuracy. PlantVillage + Maize disease images remote sensing dataset. Accuracy: 97.41% [6] P. Theerthagiri, S. Arun Kumar"Deep SqueezeNet model of diagnosis of maize leaf diseases. Dataset: maize classes in PlantVillage (as well as comparisons with AlexNet).Precision:99.44 (SqueezeNet); 99.16 (AlexNet version)[7] H. Zhou, J. Hu, Z. Xu et al., Maize Leaf Disease Recognition on the basis of the improved SNMPF. Maize field image dataset (custom) Accuracy: 98.40%[8] A. H. Ali, M. A. Murad, S. U. Malik et al. An ensemble of deep learning frameworks to classify leaf diseases. Dataset: Mixed (maize and others), real-time testing environment. Accuracy: 93.56%[9] Srivastava et al., "Corn Leaf Disease Identification with Better Accuracy (CEUR-WS). Custom maize image dataset. Precision: CNN/AlexNet model 87.0 percent.[10] Bachhal et al., PRF-SVM integration to maize leaf disease recognition. Dataset: Field dataset on maize. Accuracy: > 93% in trained models.[11] Timilsina et al., "Innovations in the detection of maize leaf diseases. Dataset: Field images and PlantVillage (GLS subset). Precision: 94.1 (PlantVillage) and 55.1 (field images).[12]Subramanian et al., "Pretrained CNNs (ResNet50, Xception, VGG16, InceptionV3) of maize disease. Dataset: Maize large custom image collection. Accuracy: 93% across models[13]. Waheed et al., An optimized DenseNet architecture of corn leaf disease recognition.Dataset: maize images in PlantVillage (compared variants) Accuracy: DenseNet121 98.45%[14] Varayuri, Corn Leaf Disease Prediction with deep learning (thesis/project).Dataset: Custom maize dataset Precision: ANN baseline 65%, deeper models have better precision[15]. Ahadian et al., "Transfer learning and CNNs to classify maize diseases.Dataset: Maize leaf images field and controlled. Accuracy: >90 percent (when using CNN/transfer learning variant)[16]. Ali et al., "Ensemble on PlantVillage (New PlantVillage subset) Dataset: PlantVillage (maize and others) which has been expanded. Accuracy: 99.89% (ensemble)[17]. Tariq M. et al., "Corn leaf disease: VGG16 approach/evaluation.Name: maize subset of PlantVillage. As of 99.92: Healthy class accuracy is up to that, total also quite high. Alpsalaz, Lightweight interpretable CNN to determine maize leaf disease[18]. F. Alpsalaz, J. Hernandez. Dataset: Maize field pictures (custom) Accuracy: State of the art (numeric value in article) was reported [19]. Rahman et al., "Plant leaf disease monitoring system in real-time (maize included). Dataset: Live system assessment, mixed (maize plus others). [20].

Table 2.1: Complexity Analysis

No	**First Author**	**Model Applied**	**Accuracy**	**Key Gaps / Limitations**
1	Mohanty et al.(2016)	Deep CNN (custom 32-layer)	99.35%	Controlled dataset; may not generalize well to field conditions

2	Parashar et al.(2025)	MaizeNet (Residual-Attention CNN)	95.95%	Limited dataset size; mostly farm-level images
3	Rajeena et al.(2025)	EfficientNet-B0	98.85%	Mixture of controlled and custom images; potential domain bias
4	Ji et al.(2025)	ICS-ResNet (lightweight ResNet)	98.87%	High performance in controlled settings; field variability not fully addressed
5	Mohanty et al.(2025)	Hybrid ResNet50 + VGG16	99.56%	Overfitting risk due to uniform dataset; limited real-world testing
6	Zhang et al.(2025)	MAF-ResNet50	97.41%	Remote sensing images may not capture leaf-level disease details
7	Theerthagiri et al.(2024)	SqueezeNet (deep lightweight CNN)	99.44%	Dataset is controlled; lacks field image diversity
8	Zhou et al.(2024)	Improved SNMPF CNN	98.40%	Dataset size limited; model may struggle with unseen environmental variations
9	Ali et al.(2024)	Ensemble of CNN architectures	93.56%	Real-time setup; may have inconsistent image quality
10	Srivastava et al.(2024)	CNN / AlexNet	87.0%	Low accuracy; small dataset and less advanced model architecture
11	Bachhal et al.(2024)	PRF-SVM (hybrid ML + DL)	93%	Dataset is limited to specific fields; generalization unclear

12	Timilsina et al.(2025)	CNN baseline (ResNet variants)	94.1%	Large drop in field performance; models not robust to real-world conditions
13	Subramanian et al.(2024)	Transfer Learning (ResNet50, VGG16, InceptionV3, Xception)	93%	Dataset size and diversity not reported; limited evaluation on field data
14	Waheed et al.(2023)	DenseNet121	98.45%	High accuracy in controlled conditions; may fail in practical farming scenarios
15	Varayuri et al.(2022)	ANN (baseline shallow model)	65%	Baseline model; low performance indicates need for advanced methods
16	Ahadian et al.(2024)	Transfer Learning CNNs	90%	Mixed dataset; model may not generalize to large-scale farms
17	Ali et al.(2024)	Ensemble CNN	99.89%	Dataset still controlled; lacks diverse environmental conditions
18	Tariq M. et al.(2024)	VGG16 (fine-tuned)	up to 99.92%	Limited field validation; high accuracy may not reflect real-world performance
19	Alpsalaz et al.(2025)	Lightweight Interpretable CNN	94.97%	Dataset size and details not clear; reproducibility may be limited
20	Rahman et al.(2024)	Custom CNN (real-time)	95.62%	Real-time setup; may have inconsistent image quality

2.3 Research Gap

In the last several years, scientists have achieved impressive results in terms of deep learning and computer vision as an approach to corn leaf disease detection. Very high accuracy has been achieved models like VGG16, ResNet, Mask R-CNN, and MobileNetV2 when they have been tested on different datasets. The few available datasets are however either limited to small in size, gathered in controlled conditions, or restricted to countries and climates. The question arises as to whether these models are capable of performing satisfactorily in unpredictable real-life promptly faced by farmers in such regions as Bangladesh. Recent experiments touched on such directions as federated learning and multi-crop detection. Although effective, such methods are usually computationally demanding and therefore are not convenient to smallholder farmers dependent on inexpensive and simple systems. Most of the works are also limited to one disease or specially prepared applications, which do not show the difficulty of a multi-disease identification in the field. One gap is the absence of a thorough testing of deep learning models on region-specific, real world image datasets. Although certain models demonstrate accuracies up to 99 percent, they perform poorly on noisy, imbalanced and diverse data that are prevalent in small farms. This shows that further investigations have to be conducted to implement and test deep learning techniques on extensive, actual data acquired by the fields of Bangladesh.

2.4 Challenges

Although great strides have been made with ensuring the use of deep learning in the detection of plant diseases, there are still some obstacles to clear before such projects can be widely implemented in actual farming environments:

- Data Limitations The available data are either small or that collected using controlled conditions. In real-world applications, images, in addition to noise, uneven illumination, cluttered backgrounds, and interpenetrating leaves are present and complicate precise detection of disease.

- Adapting to Montgomery. There is a risk that models developed in one area will not work in another due to the differences in temperature, soil, crop type and manifestation of the disease. This renders it difficult to directly apply current approaches in such settings as Bangladesh.
- Detection of Multiple Diseases A lot of research aims at the detection of an individual disease or only the classification of leaves as infected or not. As a matter of fact, a plant may have more than one disease simultaneously meaning that some stronger more flexible models will be necessary to detect multiple diseases within a single plant.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Proposed Methodology

My main aim in undertaking this project is to create a deep learning-based system that would identify some of the diseases inflicting the corn leaf.

This will be important particularly to the Agriculture sector because rapid diagnosis and identification of the disease should enable the farmer to take the necessary measures at the right time before the crops are damaged with ensuing losses in yield.

I performed the project through Kaggle notebook. Kaggle Notebook is a widely used service to perform work on data science and machine learning projects because that activity is convenient and effective. Among the greatest advantages is the fact that it offers free GPUs and TPUs so that anyone can train super deep learning models without the cost of using computers with high computing capabilities.The second advantage is that considerable amounts of open data are presented on Kaggle. Users can access datasets faster now, and by clicking the dataset, they can directly load it to the notebook to experiment with it. This is especially helpful in the area of research where real-life information is required like in the cases of plant disease detection. Kaggle also has numerous machine learning challenges all of which integrate smoothly with Kaggle. That is why it was quite comfortable to me to work in the same environment: build, test and submit the results immediately.The platform also provides an installable package that comprises libraries such as TensorFlow, PyTorch, Keras and NumPy, eradicating setting up problems.One of the greatest unique features of Kaggle is its community. It is easy to share notebooks, learn and collaborate with/through others. A user can access all the notebooks in the cloud, and Kaggle keeps in varied versions so that it can always go back to the early state of an experiment.

The proposed study focuses on practical implementation of deep learning methods in recognition of three diseases that seriously affect corn leaves. To carry the study, a database of more than 4,000 images in real-life field examples of healthy and fire-bitten leaves of corn under field conditions was downloaded.

A machine learning platform, deep learning models which are utilized in this dataset training and testing are Convolutional Neural Networks (CNN), MobileNetV2, VGG16, VGG19, and InceptionV3. The models upon which the custom CNN model has been adapted featured an accuracy of 83%, against the highest scoring MobileNetV2 with 97% accuracy. VGG16 and VGG19 got 87 % and 85 %, respectively, and InceptionV3 was not much different with 96 %.

These results show that CNN-based approaches are quite good at the type of task corn leaf disease classification. Above all, they have potential in the aspect of deep learning to provide accurate and cost-effective and scalable solutions that can help maize growers address the diseases on time and make agriculture more efficient in Bangladesh.

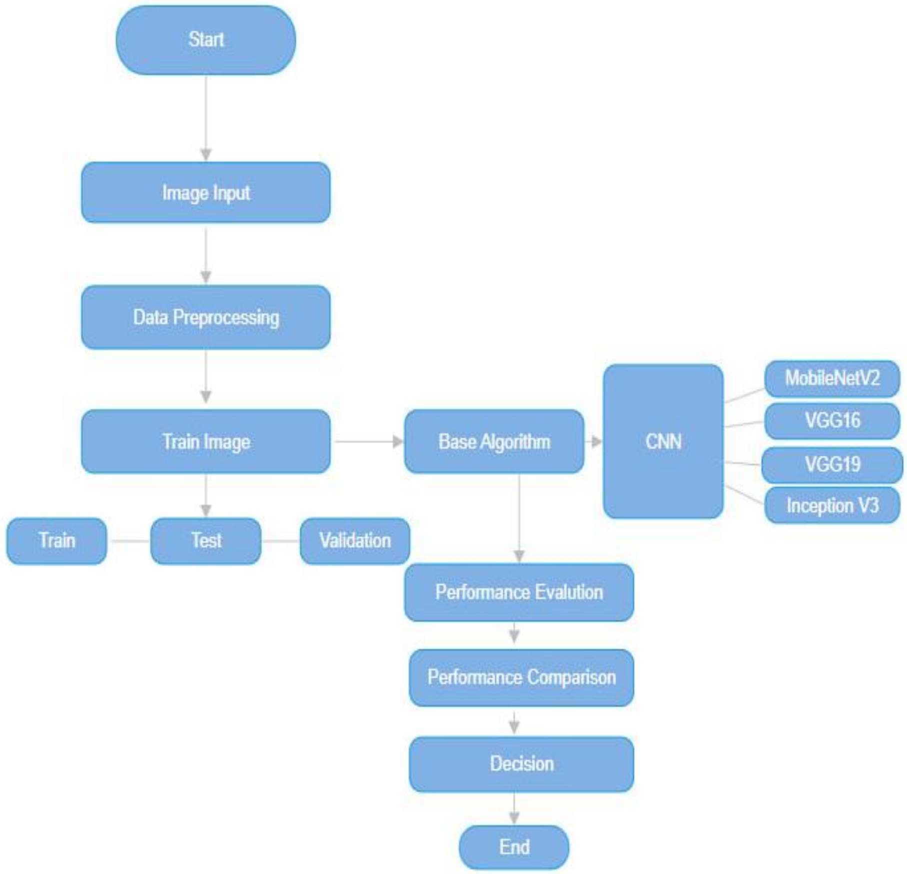

Figure 3.1: Model architecture

The involvement of several approaches of accuracy and reliability is addressed in this work. The data is informed, in which the input data is well pre-processed to eliminate the noise and is refined. Thereafter, the dataset is divided into training, testing, and validating data and is used in the construction of the Model with each serving a different purpose. Strict evaluation methodologies are needed in order to reify effective performance, as such a strategy would enable both an equitable comparison of the performances and an insightful access to the outcomes. It is sought and relied upon the most accurate and effective approach available.

3.2 Data Collection Procedure

To begin this study, I chose to make a phone call to an agricultural officer at the Upazila Agricultural Office in Shibaloy, Manikganj, to help me with my knowledge on corn leaf diseases. My study was founded on a sample data set collected in a farm at Manikganj and facilitated by a permission letter given by the owner of the farmhouse. Some friends helped me in the data collection.

In total, I gathered over 4,000 pictures of corn leaves which bolstered this study. The information was well organized into four categories, which contain more than 1,000 images. The classes were: Healthy Leaf, Urea Injury, Stewart Wilt and Leaf Blight as the labels. The images were transformed into the .jpg format in order to become homogeneous and conform to the ease of use in training the model.

Besides the formatting, all images were resized and preprocessed so that the input dimensions could be consistent. Further validation of the dataset was done by seeking the opinion of the agricultural officer on the accuracy of labeling. Such structured data served as a good basis to train and test the deep learning model. In addition, equally spaced distribution of images in the four classes aided in reduction of bias and enhanced credibility of classification performance.

Figure 3.2: Sample of dataset

In this data, there are 4249 maize leaf images that are divided into four categories of Healthy Leaf, Leaf Blight, Stewart Wilt and Urea Injury. All the pictures are in JPG format, and their size is unified to 256 × 256 pixels, making their use by a machine learning algorithm convenient. Having a good proportion of healthy and infected leaves, the data is adequate for training and testing deep learning models able to automatically recognize the crop health status.

3.2.1 Statistical Analysis

This collection of photos includes 4249 photos separated as 4 categories. Data in each class are near about 25 percent. To evaluate the model, I divided the data into three (3) sets: the train set, the validation and the test set.

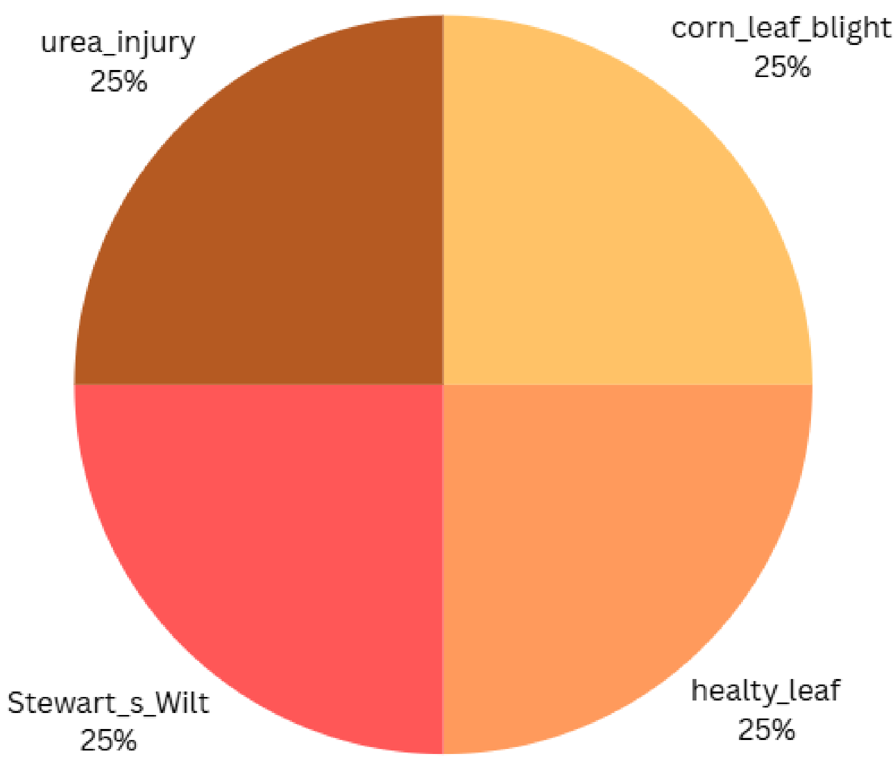

Figure 3.3: Pie chart of total data

3.4 Image Pre-processing

In implementing this project, the pre-processing of the images is the first step of the project that is very important because of the quality of the data that may be involved later in the analytical stage. Enhancement is used to mitigate non-relevant distortions, whilst at the same time highlighting relevant visual features that are of analytical significance to the investigator. It should be noted that the very peculiarities aimed at the process during this step depend on the goals of further analysis. Image pre-processing is a conceptual set of low-level operations that are performed on the raw image data to form the basis of more detailed processing operations. Without this refinement, it is possible that the variability within its dataset would affect the informational content of the images in a negative manner.

The main aim of pre-processing is thus two-fold: to eliminate the extraneous noise and to increase discriminative features important to proper interpretation. A wide variety of methods can be used at this step, such as structural modification, image segmentation and filtering, normalization of pixel intensities, brightness adjustment, Fourier transformations and image restoration procedures.

In this study, the training set of images was uniformly resized to 50 x 50 pixels with the same type of transformations performed on the testing and validation sets. In addition, all datasets were rescaled in order to obtain uniformity across the inputs. To evaluate experimentally, the dataset was divided into 70 percent training, 10 percent testing and 20 percent validation data, thus facilitating both models' optimization and performance evaluation.

3.3.1 Data Augmentation and Train

To enhance the model for robustness and ability to generalize, the pre-processing stage was done in the data augmentation strategies. Refer to data augmentation as follows: Artificially increases the diversity of the training set through a variety of random but realistic transformations of the input imagery. Such an approach will prevent overfitting and will allow the model to be more generalizable to new data. In the present study, the images were reduced in size to a constant value of 224 x 224 pixels and a batch size was set as 16, so that training can be efficient. An ImageDataGenerator was adapted that does normalization as well as augmentation. All images were scaled by one-quarter, which is 1/255, guaranteeing that the values of pixel intensities fell within an acceptable domain.The augmentation pipeline included several transformations:

- Rotation (up to 30°): to simulate variations in orientation.
- Zooming (up to 30%): to account for differences in image scale.
- Width and Height Shifts (20%): to model positional variance within the frame.
- Shearing (20%): to introduce affine distortions for improved invariance.
- Horizontal Flipping: to generate mirrored versions of leaves and account for asymmetry.
- Nearest-neighbor fill mode: to fill missing pixel regions resulting from transformations.

There were directory names that contained labels automatically extracted, and categorical encoding was performed to represent those labels in multi-class format that could be used in classification. This would make each image be mapped to the correct index of the classes thus guaranteeing a clear structure of supervised learning. This methodological framework represents a careful balance of the need to model generalization and the requisite reliability to evaluate the model, a tension that was met by a coherent data augmentation approach followed by a structured train/validation separation.

3.3.2 Class Weight Computation

Class imbalance presents an essential problem when working with real-world datasets in supervised learning tasks, in which there could be negative implications on the level of performance. Those classes that are overrepresented and others that are less represented, a classifier is likely to be biased towards the former, thus lessening its ability to predict the latter. This issue was addressed by class weighting in the model training. The development of the class weights was performed using the sample distribution into the various categories in the training set. Precisely, the compute_class_weight method of the scikit-learn package was employed and the balanced parameter was set. The approach uses weights that are inversely proportional to tentative frequencies of classes so that underrepresented classes are rewarded by large weights and overrepresented classes penalized by small weights. Since this formulation ensures that each class also plays a fairer role to total loss function during training, the imbalance problem is reduced. The computed weights were saved in a-dictionary like format and later incorporated into the training process. Inserting these weights explicitly, the loss function penalized confusion of minority classes more heavily than of the majority classes, which resulted in an improved performance of the classifications under skewed data conditions.

3.3.3 Fine-Tuning

In this study, Fine-tuning was iterative so as to obtain optimal performance. Knowing how to optimise between training efficiency and predictive accuracy was tested on several parameter settings. In a methodological way, systematically improving the network in this way, the model reached a better level of generalization and stability in the application to the task of classifying corn leaf diseases. Fine-tuning offers the additional capability of improving the effectiveness of feature representation. This will include small but selective modulations at various levels of the training pipeline so that the model performance is optimized. Minor alterations can produce overwhelming impacts to computational efficiency, the rate of convergence and resource use which further highlights the overall importance of this step. Since fine-tuning is a critical aspect, the systematic process was repeated several times with different parameter settings in trials. This calibration procedure permitted the search for the optimal parameters and to groom the overall model accuracy. Throughout the mechanism being refined a number of times, the end product became much more accurate and stable in the end.

Table 3.1: Fine Tuning Table for CNN.

Parameter	**Value**
Epoch	50
Optimizer	Adam
Batch size	16
Activation Function	Relu, Softmax

Table 3.2: Fine Tuning Table for MobileNetV2

Parameter	**Value**
Epoch	10

Optimizer	Adam
Batch size	32
Activation Function	Relu, Softmax

Table 3.3: Fine Tuning Table for VGG16

Parameter	**Value**
Epoch	10
Optimizer	Adam
Activation Function	Relu, Softmax

Table 3.4: Fine Tuning Table for VGG19

Parameter	**Value**
Epoch	10
Optimizer	Adam
Activation Function	Relu, Softmax

Table 3.5: Fine Tuning Table for InceptionV3

Parameter	**Value**
Epoch	15

Optimizer	Adam
Batch size	32
Activation Function	Relu, Softmax

3.4 Deep Learning Models

To get satisfactory results of the image classification, many deep learning architectures have been envisioned and substantiated in this paper. The two models have distinctive structural properties and computational trade-offs and are, therefore, appropriate in different aspects of the classification process.

3.4.1. Convolutional Neural Network (CNN)

The modern computer visions are based on CNNs. They employ convolutional stages to learn hierarchies of characteristics on their own, starting with low-degree features such as edge detection and texture and extending to the higher levels of abstract representations. CNNs have especially useful applications in image recognition, since the manual extraction of features is made considerably redundant in favors of the network learning to extract optimal feature representations on its own. A Convolutional Neural Network was custom-designed and coded, with the intention to classify or diagnosing diseases of the corn leaf. The structure is made of a number of convolutional and pooling layers as well as fully connected ones with the goal of automatically extracting hierarchical features in the input images.

3.4.1.1 Model Architecture

The network begins with a convolutional layer of 16 filters, each of size 3×33, combined with ReLU activation and same padding. This is followed by a max-pooling layer, which reduces the image dimensions while keeping the most important features. As the network goes deeper, the number of filters increases to 32 and 64, allowing the model to capture increasingly complex patterns. After these layers, the feature maps are flattened and fed into a fully connected layer with 64 neurons. To prevent overfitting, a dropout layer randomly deactivates half of the neurons during training. Finally, a SoftMax output layer predicts the probability of each disease class.

3.4.1.2 Model Compilation

The model was compiled using the Adam optimizer. categorical cross-entropy as the loss, and accuracy as the performance metric. This configuration enables the model to learn efficiently, at the same time, it yields useful feedback about how well it is performing.

3.4.1.3 Training Strategy

There are two techniques that were used to enhance training. EarlyStopping defines the number of epochs to wait to find a better value after training on the validation dataset (five in this case) and retains the weights with the best validation results. Second, ReduceLROnPlateau autosets a learning rate to a lower value. As soon as the validation loss shows no more improvement, it allows the model to refine its learning process. The network used was trained by a total of 50 epochs using augmented training dataset, and adopting the use of the class weight such that less-represented categories of diseases will not be neglected.

3.4.1.4 Performance Monitoring

The training and validation accuracy and loss bar graphs were used to represent the progress of the model in learning. The plots aid in establishing whether the model is improving with each step, overfitting, or underfitting, and give an idea of the likelihood of their performance at unobserved images. This CNN model combines layered feature extraction, regularization, adaptive learning, and balanced class weighting to provide a reliable classification of corn leaf diseases and a good overall generalization on new data.

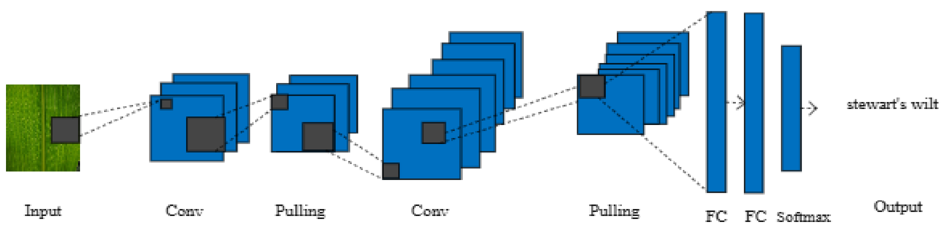

Figure 3.4: Architecture of CNN

3.4.1.5 Convolutional layer

Convolutional layers are the main building blocks of Convolutional Neural Networks (CNN) which are differentiated to the normal neural networks since the latter use standard matrix multiplications. CNNs instead use a specialized operation called convolution, the result of which is an activation map generated by passing an input (typically an image) through a filter or kernel. By means of sliding the same filter through the image, the information that was obtained provides a feature map that facilitating highlighting the location and shape of certain components or features. A major attraction of CNNs is the fact that they can automatically discover an arbitrary number of filters to be learnt during training. Each filter can be adjusted to various patterns or arrangements in the data so that the network creates a wide spectrum of salient features applicable to the classification problem. This results in a representation [hierarchy] of the data with learned filters as training proceeds. After any convolution, a Rectified Linear Unit (ReLU) activation function is employed on the feature maps. This non-linear transformation enables the signaling in the network that involves modeling of complex patterns which are not captured by linear operations. Adding more convolutional layers makes the network deeper so that subsequent layers can combine and modify the input information of earlier receptive fields. The hierarchical organization allows CNNs to be very effective at recognizing complex objects through the step-by-step integration of low-level features such as edges or textures into higher-level patterns such as shapes or objects. Picking out a bicycle in an image can be conceptually described as first identifying the components in an image, namely wheels, frame, pedals and handlebars, before combining them to form a recognizable whole. The same applies to CNNs where kernels are feature detectors that scan across an input image to detect the presence of some pattern. By this convolutional process, the network can learn to recognize progressively more complex structures, and the result is the capability to classify and recognize objects accurately.

3.4.1.6 Pooling layer

Just like convolutional layers, another important component used in the design of Convolutional Neural Networks (CNNs) is a pooling layer. The main objective of the last is to minimize the spatial size of the feature maps whilst maintaining most significant information. This down sampling greatly reduces the computation load and amount of memory consumed in training, and the pooling operation decreases the cost to a very significant extent without compromising performance. Wells are usually grouped into two kinds of pooling performance operations:

- Max Pooling: retrieves the highest score in a given area of the feature map and captures the most influential features.
- Average Pooling: Calculates the average value of an area and this concept creates a better-looking image representation of the features.

The two methods assist in strengthening the model by making it more translationally invariant so that minor variations in position or distortions of input image do not lead to striking changes in the network capacity to ascertain the pattern recognition capabilities.

3.4.1.7 Fully connected layer

The feature extraction is implemented in a Convolutional Neural Network (CNN) where a classification process is executed. In this step, the network switches to categorical prediction rather than learning spatial and structural patterns in an input of images. In the step of feature extraction, Rectified Linear Unit (ReLU) activation following convolution and pooling layers are typically used. ReLU makes the model non-liner, making sure that the complex decision boundaries can be learned by the network instead of being limited to linear transformations. This non-linear transformation increases the ability of the network to identify sophisticated patterns in the data and especially in image classification tasks. As soon as the extracted features are flattened to feed into the FC layers, the networks start the actual classification. In this, the output layer normally uses the softmax activation function. The raw output scores (logits) are then transformed to a probability distribution by application of Softmax normalization so that the probabilities of all classes add to one. Each probability measures the model's confidence that the input was in a particular class. An example is that in a multi-class classification task like the corn leaf disease detection problem, a softmax is used to compute probabilities over all the potential disease categories, and the most probable one is picked out as a prediction. Accordingly, both complex hierarchical features learning and interpretation of these features through classification results are possible by employing convolutional and pooling layers with

ReLU and the final cost layer with softmax activation functions, respectively. This organized process- the feature extraction to a probability-based classification is the basis of CNN in image recognition.

3.4.1.8 Flatten Layer

The final goal is the passage information extracted into a neural network to classify it. Convolutional layers provide a critical process in this by sliding through filters across small portions of the picture and will enable the model to find such characteristics as edges, textures, or contours. In contrast to FC layers, spatial proximity constraints are not imposed. They do not do that, or rather they learn the features that the convolutional layers learn and then they interrelate these features to get unified representation. Effectively FC layers are the interface between the feature extraction phase and the classification phase. The learned trends detected in previous convolutional layers, e.g. lines, curves and color variations, are assembled into further representations. These representations are then flattened into a deterministic two dimensional framework, with each channel adding its own feature map. The fully connected layers are then able to learn complex associations ultimately assigning the image to a specific class with the cross-channel information integration. In more simplistic words, convolutional layers are like experts who are good at differentiating various aspects of the image but leave it to the fully connected layers to conclude the matter by taking all of their conclusions into consideration.

3.4.1.9 Activation Function

Activation functions are an important part of a neural net which makes the decision as to whether a neuron becomes activated or not. It determines how information is passed through the network. They act as mathematical functions to measure the significance of the signals being conveyed by the neurons and also add non-linearity to the model thereby allowing the model to learn complex patterns rather than just a linear relationship.

Among the activation functions used are Sigmoid, Tanh, Softmax and Rectified Linear Unit (ReLU). Of these, the most popular in deep learning systems is ReLU because of its effectiveness and simplicity. By efficiently producing zero when fed a negative value, and by always outputting a positive value when that value is positive, ReLU is much faster to converge, less likely to suffer the vanishing gradient effect, and ultimately more efficiently capable of training a model than older activation functions.

3.4.1.9.1 Softmax

There are different classes and various feature representations to them. The machine then takes the input data and uses it to come out with a bunch of raw scores (logits) of each type. The values are then converted to probabilities through the use of Softmax activation so that the summation of probabilities remains equal to 1. Such a probabilistic interpretation can enable the model to not only make the most probable prediction but also to supply an estimate of confidence on each of those predictions. In the work, the final layer of the CNN was equipped with the Softmax function that allowed the network to differentiate between numerous classes better.

Using higher convolutional layers as maps of probability distributions, the model succeeded to make precise class identifications on the large dataset.

3.4.1.9.2 Relu

A typical example of the activation functions is the Rectified Linear Unit (ReLU), which simply transforms the input value to the same value when the input is positive, and zero otherwise. In comparison to other activation functions (Sigmoid and Tanh, etc.), ReLU is computationally easier and more efficient, and thus is very applicable to more recent deep learning applications.

3.4.2 MobileNetV2

The MobileNetV2 is a lightweight convolutional neural network that is particularly designed to provide significantly efficient image classification and recognition tasks on devices with small computing capabilities including mobile devices and embedded systems. It is an enhanced adaptation of MobileNetV1 and it presents two novel schemes:

- **Inverted Residual Blocks with Linear Bottlenecks:** Rather than using its regular residual connections, MobileNetV2 doubles the dimension of the input, runs it through some depthwise separable convolutions, then reduces the dimension back to the original. The design has the advantage of low computational cost and high representational power
- **Depthwise Separable Convolutions:** Normal convolutions are split in a depthwise convolution (applying the filter to each channel independently) and in a pointwise convolution (mixing the results). This also dramatically reduces parameters and operations versus traditional convolutions.

By using these mechanisms MobileNetV2 produces a good tradeoff between accuracy and efficiency, and the architecture is therefore noted as being highly applicable to real-time applications with memory and speed being important factors.

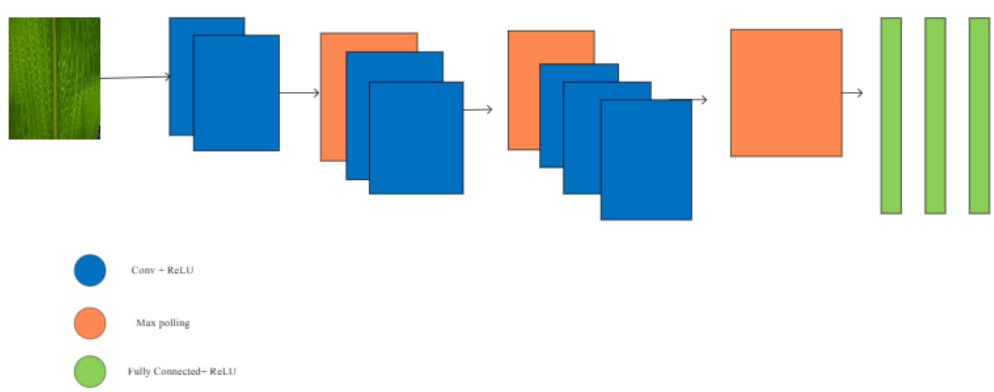

Figure 3.5: Architecture of MobileNetV2

3.4.3 VGG16

VGG16 is a deep convolutional neural net framework by the Visual Geometry Group (VGG) at the University of Oxford. It is considered to be one of the most compelling models in the sphere of computer vision and became widely known after it yielded extraordinary results in the ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) 2014. The architecture is characterized by 16 weight layers (how 13 weight layers will be convolutional and 3 weight layers will be fully connected). Prior art had the convolutional layers using comparatively large sizes of filters (15x15), but all convolutional layers in the CNN use very small filters (3x3). This is achieved by implementing a series of (3x3) convolutions, that allow the network to memorise sophisticated qualities with minimal computational cost. The architecture also consists of the max pooling layers to down-sample followed by the fully connected layers with a Softmax classifier at the end.

Although the reason why VGG16 performed so well belongs to its questionable simplicity and uniform architecture. VGG16 remains highly regarded because it has good feature extraction ability. It continues to be a leading backbone model to transfer learning at a number of computer vision tasks.

3.4.4 VGG19

VGG19 is a longer version of VGG16 which was also created by the Visual Geometry Group (VGG) in the University of Oxford. VGG19 has 19 weight layers (whereas VGG16 has 16 weight layers), 16 convolutional layers, and 3 fully connected layers. The network employs only 3 x 3 convolution filters placed on top of each other, as well as max-pooling layers with the purpose of spatial reduction, and fully connected layers to perform the actual classification. The richer structure of VGG19 enables it to extract more complex and high-resolution features than VGG16. Nevertheless, such an increase in representational ability has the associated negative impact of requiring more computation and training. VGG19 is also rather resource-heavy with around 143 million parameters**.**

3.4.5 InceptionV3

InceptionV3 is a very optimized architecture of the deep convolution neural network and has come forth as an improved version of the Google Net (InceptionV1) and InceptionV2 introduced by Google. It achieved state of the art performance on the ILSVRC (ImageNet Large Scale Visual Recognition Challenge) 2015 and especially large-scale image classification. The key novelty of InceptionV3 is that it applies inception modules in order to capture features of multiple scales in concert. Rather than selecting one kernel size to use in convolution, the Inception modules implement 1×1, 3×3, and 5 x 5 convolutions in parallel, and then concatenate their results. The design allows this model to learn both low-level and high-level features better. To enhance computing speed and efficiency, InceptionV3 people employ such methods like: Factorized convolutions (Converting a 5 popatch 5 convolution to two 3 popatch 3 convolutions, or a 3 popatch 3 to a 1 popatch 3 and a 3 popatch 1convolution.). Auxiliary classifiers, which are defined as intermediary outputs that help fight the vanishing gradients and stabilize training. Label smoothing which decreases overfitting and leads to improved generalization. Regarding their parameters, InceptionV3 is estimated to have about 23 million parameters, making it considerably lighter than both VGG16 and VGG19 but performing better as well (in the ImageNet benchmarks).

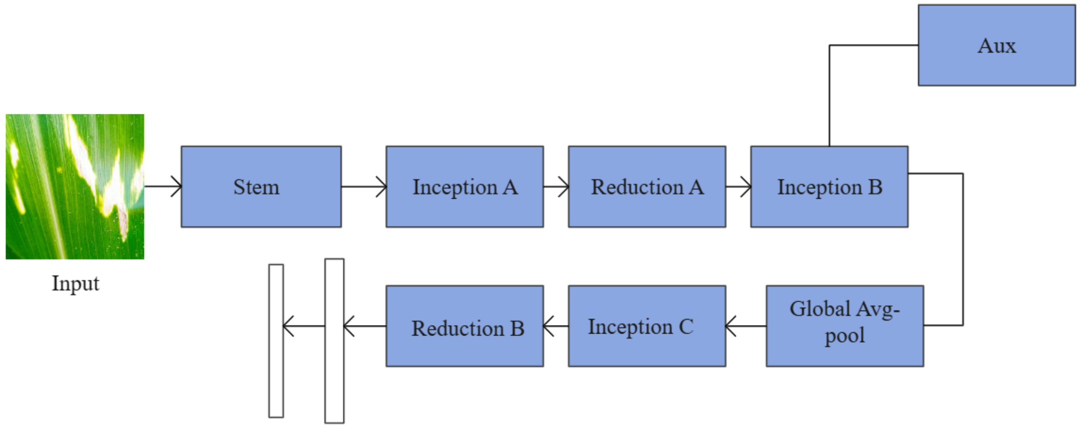

Figure 3.6: Architecture of Inception V3

Its trade-off amid depth, efficiency and precision has helped it become one of the more ubiquitously used architectures in computer vision, notably in corn leaf imaging, object detection and fine-grained recognition where scalable solutions are needed.

The focus of the Inception V3 model is the optimization of the network to result in improved model adaptation.

There is a high efficiency. It is enhanced in terms of network, rather than in processing speed, which is equal to the previous models Inception V1 and V2. Less expensive and it employs auxiliary Classifiers as regularizes.

3.5 Implementation Requirements

The process of conducting this research presupposes the operation of devices with fairly powerful computing resources, especially because of the volume of the data set and the complexity of the training of deep neural networks. The data collection step needs a high-resolution digital camera to capture quality and detailed images of corn leaves so that disease symptoms can be documented with adequate levels of accuracy that can be used in the later stages of analysis. To perform the model development and experimentation stage, it is required that some pieces of hardware and software be used to effectively complete preprocessing, augmentation, and training. At the base, the following are some of the main system specifications required to undertake this research:

- **Operating System:** Windows 7 or higher
- **Memory (RAM):** Minimum 4 GB
- **Storage:** At least 100 GB of available hard disk space
- **Computer processor (CPU): A General modern processor that is sufficient to handle image processing functions.**
- **Graphics Processing Unit (GPU): Highly advisable to use for fastening the computation in deep learning**

Alongside the hardware constraints within a local system one also had to consider cloud-based computing to obtain the required hardware requirements.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

Assessment of this data set was carried out with several performance measures, viz, precision, recall, F1-score and accuracy, which together provide an overall measure of how the proposed architecture fared. These measures are extracted with the confusion matrix, where:

TP (True Positive) is the disease samples that are accurately identified,

FP (False Positive) implies negative samples that are wrongly given a positive disease diagnosis.

False Negative (FN) cri-terion describes the case when the diseased samples are misclassified as healthy.

Detected healthy samples as correct are discussed as TN (True Negative).

The model recorded a best accuracy of about 97 percent which is an indication that the model is stable and reliable in detecting the leaf diseases of corn.

Precision estimates the rating of the model that will identify the positive case carefully without any false alarms. It is called the percentage of true positive predictions divided by total predicted positive cases and given by the formula:

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (1)$$

Recall determines how the model is able to detect the real positive cases. It provides the extent to which the system reduces false negative. On a mathematical note, recall can be written as:

Recall = $\frac{TP}{TP+FN}$ (2)

F1-score gives only one score in which it balances precision and recall. Precision and recall tend to be inversely related, thus the F1-score is used to provide a harmonic mean of both measures so neither is disregarded when gauging model performance.

Accuracy: This value measures the overall accuracy of the model by dividing all the correctly predicted (true and false) with the total number of predictions. It is calculated with the parameters of the confusion matrix as below:

Accuracy = $\frac{TP+TN}{TP+FP+TN+FN}$ (3)

Combined analysis of these metrics leads to the conclusion that not only does the proposed architecture generate a great accuracy rate, but also can maintain a well-balanced and reliable detection of corn leaf diseases.

4.2 Experimental Setup

A representative and well-structured dataset is essential in assessing the performance of models across various domains such as Machine Learning, Deep Learning, Hybrid and transformer-based models such as BERT. In this research, a data set involving more than 4,000 images that is divided into four different categories of corn leaf states was gathered. It is critical to have adequate samples of every class to promote robust training of the models as well as evaluate their accuracy. Once data had been obtained, it was posted to Kaggle Datasets to facilitate its use in Kaggle Notebooks to perform preprocessing, augmentation, and train models. Kaggle offers cloud-based infrastructure with access to GPUs and TPUs, which allows completing computationally resource-intensive operations most effectively without being constrained by the local hardware. The pictures were thoroughly labelled and arranged such that there would be a balance in class representation. Such systematic training and evaluation mean that all models of any domain are tested and trained in the same manner, providing a stronger underpinning of the performance analysis. Also, the reproducibility of the experiment and shareability with other members of the research community are easy because of Kaggle Notebooks.

4.3 Experimental Results & Analysis

The accuracy, precision, recall, and F1-score of the proposed models are evaluated on the performance of the models, as summarized in the confusion matrix are is shown below. Out of these, accuracy shows the general correctness of the model by representing the percentage of accurately predicted cases out of the total number of predictions. Precision measures this accuracy when it comes to the positive cases and does not over-label the negative cases as being positive of equal value is the ability of recall to measure the effectiveness of the model in detecting all the actual positive cases whereby the number of false negatives will be reduced.

Table 4.1: The model's performance results

Model	Accuracy	Precision	Recall	F1-Score
CNN	83%	88%	88%	88%
MobileNetV2	97%	96%	96%	96%
VGG 16	87%	87%	87%	87%
VGG19	85%	85%	85%	85%
Inception V3	96%	96%	96%	96%

As an adequate measure of both precision and recall, in Table 4.1, the model results are shown, the F1 score is often used to balance the effect of false positives and false negative were one or both of them are undesirable.

4.3.1 CNN (Convolutional Neural Network) Model

In this model, I have used the whole gathered data and separated this into three groups, 70 percent training, 20 percent validation and 10 percent test. The images were randomized and resized prior to their processing. The architecture in this model consisted of Convolutional layers, Pooling layers and Fully Connected layers, and ReLU and Softmax functions were adopted as activation functions.

4.3.1.1 Graph of Accuracy and Loss

The visualization demonstrates the behavior of the Convolutional Neural Network (CNN) model both in terms of accuracy values as well as loss values during training and validation across epochs.

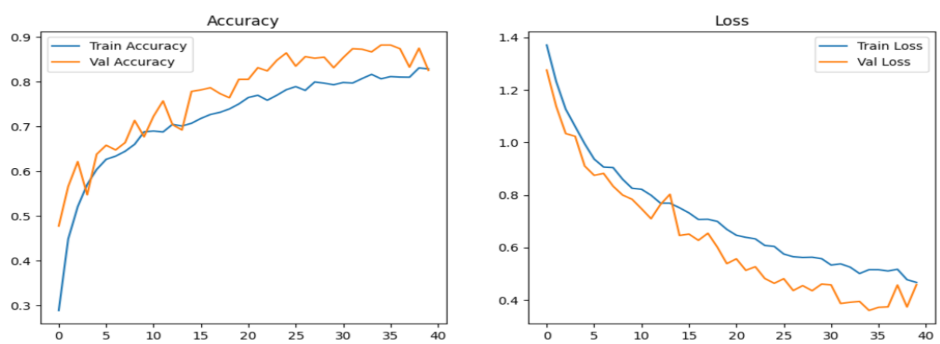

Figure 4.1: Train & validation Accuracy and Loss Graph of CNN

4.3.1.2 Confusion Matrix of CNN

Confusion matrix is made use of when the effectiveness of a classification model is to be evaluated. This matrix provides an explicit overview of the actual and the predictions of the model.

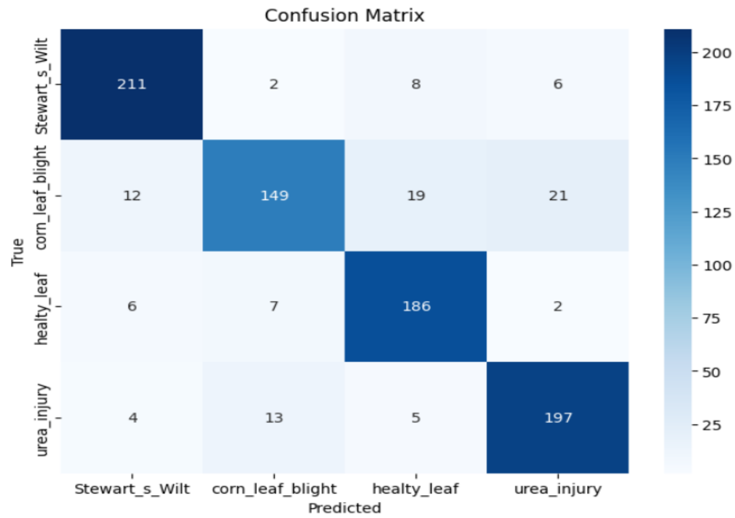

Figure 4.2: Confusion Matrix of CNN

4.3.1.3 Classification Report of CNN

The exact classification model performs well over all classes, but especially on Stewart Wilt (92% precision, 94% recall), which leads to an optimal F1-score of 93%. The performance of Healthy Leaf classification is also good with an F1-score of 89 percent which means that there is a dependable capacity to detect healthy samples. Urea Injury exhibits evenly balanced precision and recall of 88 and thus, the F1-score is equally high. Although Leaf Blight is somewhat less accurate in recall (77) than in its preciseness (87), it is also not a bad F1-score of 82, indicating that some more improvement is possible in identifying all the infected instances.

Table 4.2: CNN model's performance results

Class Name	**Precision**	**Recall**	**F1-Score**
Healthy Leaf	86%	92%	89%
Leaf Blight	87%	77%	82%

Stewart’s Wilt	92%	94%	93%
Urea Injury	88%	88%	88%

4.3.2 MobileNetV2

Besides the tested models described earlier, I also developed the MobileNetV2 model to analyze its efficiency in maize leaf disease identification. The split procedure performed in CNN operation was used to separate the dataset with 70 percent split to training set, 20 percent used in the validation set and 10 percent in the test set. The MobileNetV2 model performed well after training, where a training accuracy of 96.98 was obtained (loss = 0.1021) and a test accuracy of 96.04 (loss = 0.1285) was achieved. These results reveal that the MobileNetV2 model is very efficient at capturing deep features of maize leaf images and it can deliver realistic results on the accuracy of classifications, resulting in a percentage accuracy of 95-96% across the board.

4.3.2.1 Graph of Accuracy and Loss

The visualization demonstrates the behavior of the MobileNetV2 model both in terms of accuracy values as well as loss values during training and validation across epochs.

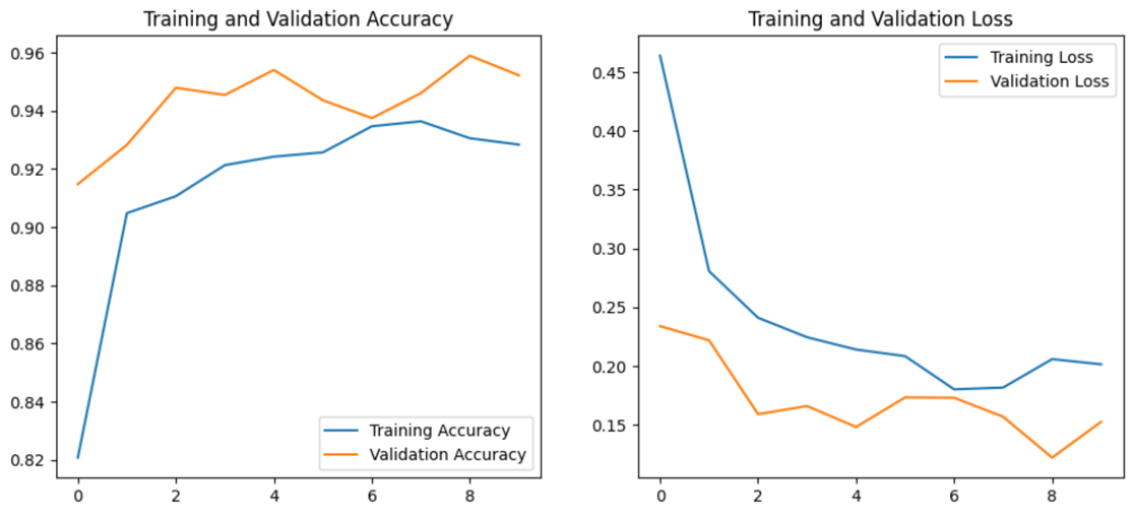

Figure 4.3: Train & validation Accuracy and Loss graph of MobileNetV2

4.3.2.2 Confusion Matrix of MobileNetV2

The result of a classification routine is presented and summarized in Figure 4.4:

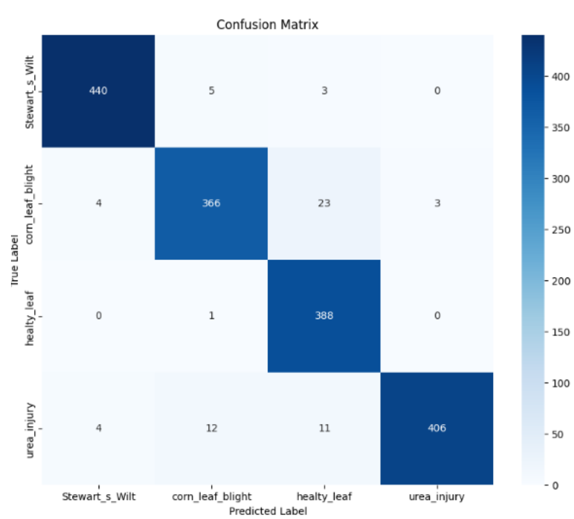

Figure 4.4: Confusion Matrix of MobileNetV2

All the curves are tightly concentrated at the top-left corner, meaning large true positive rates and small false positive rates at all levels.

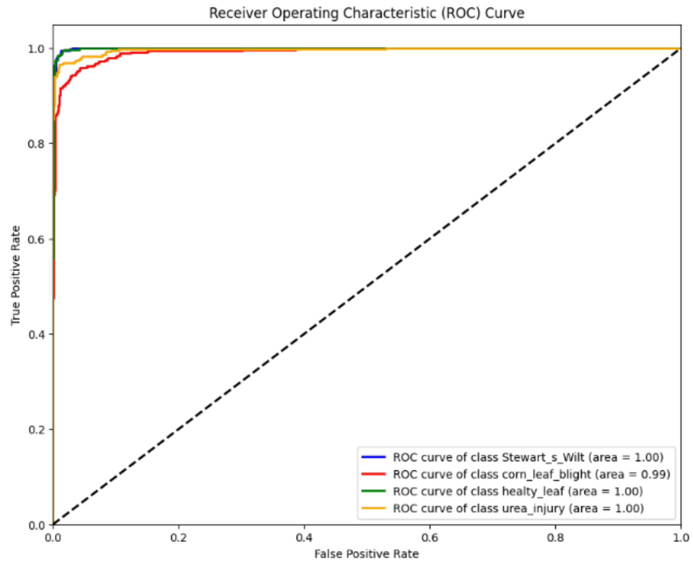

Figure 4.5: ROC Curve of MobileNetV2

4.3.2.3 Classification Report of MobileNetV2

The Performance results of MobileNetV2 model are given below:

Table 4.3: MobileNetV2 model's performance results

Class Name	**Precision**	**Recall**	**F1-Score**
Healthy Leaf	91%	100%	98%
Leaf Blight	95%	92%	94%
Stewart’s Wilt	98%	98%	98%
Urea Injury	99%	94%	96%

4.3.3 VGG16 MODEL

The overall accuracy rate of VGG16 model is 87%, which is a good result showing that the model performs well at correctly classifying the data. The model, however, has had a loss output of 46 percent meaning that there is still an opportunity to optimize the predictions. This indicates that further parameter optimization, use of data augmentation or training can be of help towards minimizing the loss and enhancing the stability as well as generalization of the model.

4.3.3.1 Graph of Accuracy and Loss

Here in this visualization, we have VGG16 model. We are able to view of VGG16 model training, validation accuracy and training, validation loss graph.

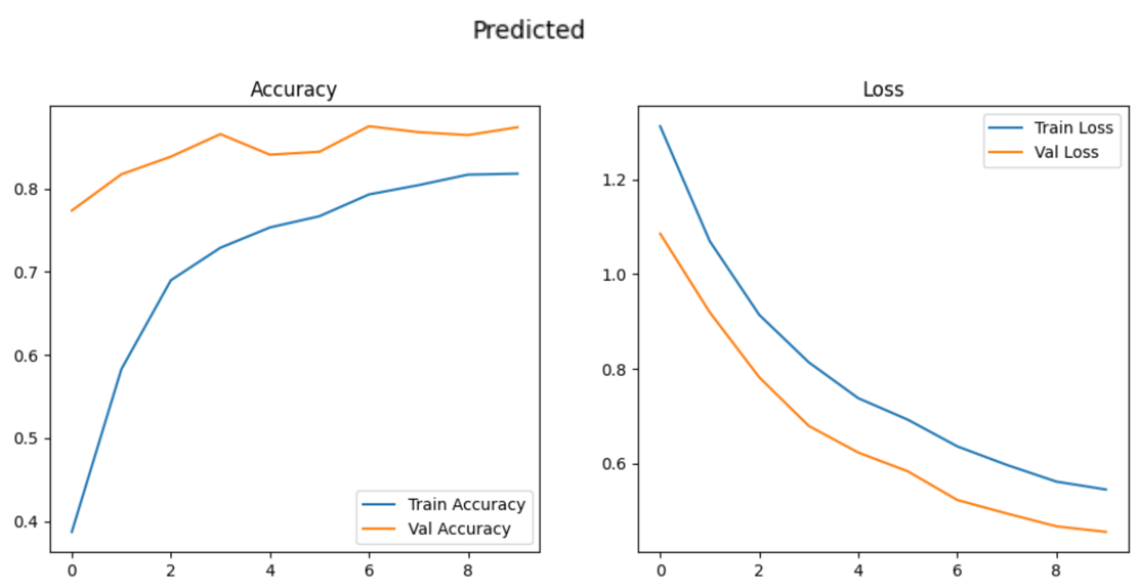

Figure 4.6: Train & validation Accuracy and Loss Graph of VGG16

4.3.3.2 Confusion Matrix of VGG16

The result of a classification routine is presented and summarized in a confusion matrix.

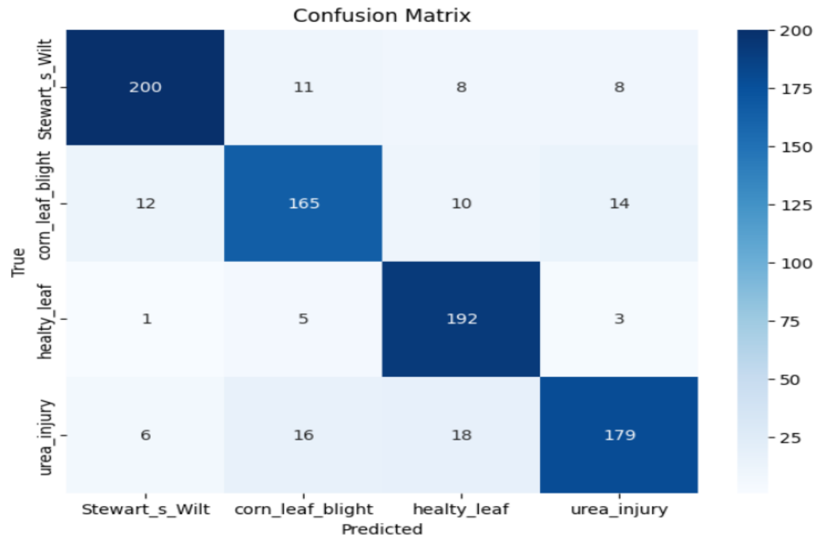

Figure 4.7: Confusion Matrix of VGG16

4.3.3.3 Classification Report of VGG16

The Performance results of VGG16 model are given below:

Table 4.4: VGG16 performance results

Class Name	**Precision**	**Recall**	**F1-Score**
Healthy Leaf	84%	96%	90%
Leaf Blight	84%	82%	83%
Stewart's Wilt	91%	88%	90%
Urea Injury	88%	82%	85%

4.3.4 VGG19 MODEL

Divided Data into 3 parts same as CNN, MobileNetV2, VGG16 and then applied VGG19 model and it gave 85% accuracy.

4.3.4.1 Graph of Accuracy and Loss

In this visualization, we can see graph for VGG19 model training, validation accuracy training and validation loss graph.

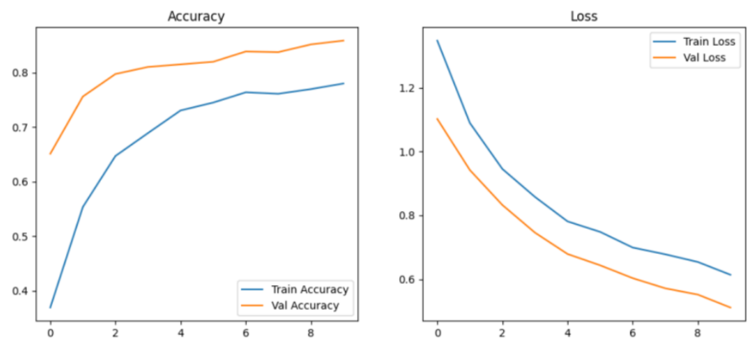

Figure 4.8: Train & validation Accuracy and Loss Graph of VGG19

4.3.4.2 Confusion Matrix of VGG19

The result of a classification routine is presented and summarized in a confusion matrix.

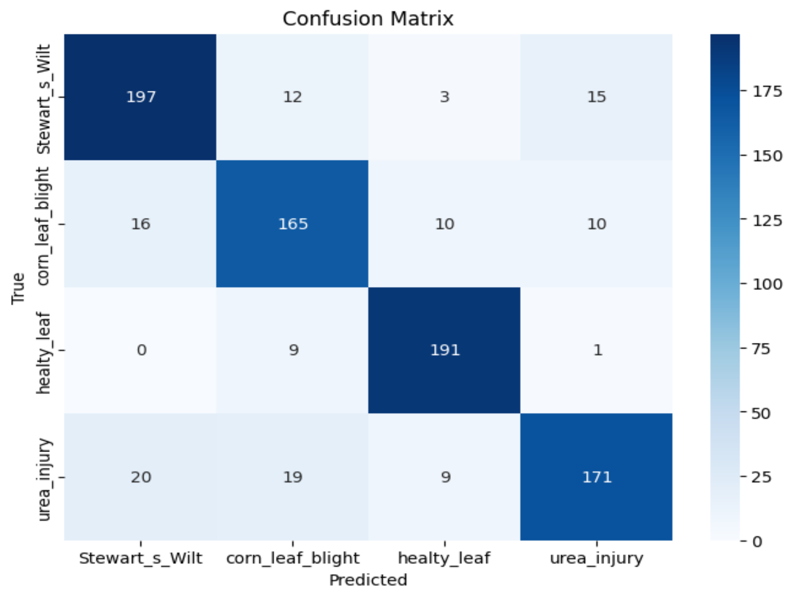

Figure 4.9: Confusion Matrix of VGG19

4.3.4.3 Classification Report of VGG19

The Performance results of VGG19 model are given below:

Table 4.5: VGG19 model's performance results

Class Name	**Precision**	**Recall**	**F1-Score**
Healthy Leaf	90%	95%	92%
Leaf Blight	80%	82%	81%
Stewart's Wilt	85%	87%	86%
Urea Injury	87%	78%	82%

4.3.5 INCEPTION-V3 MODEL

Divided Data into 3 parts same as CNN, MobileNetV2, VGG16, VGG19 and then applied InceptionV3 model and it gave 96% accuracy.

4.3.5.1 Graph of Accuracy and Loss

In this visualization, we can watch InceptionV3 model training, validation accuracy, training, validation loss.

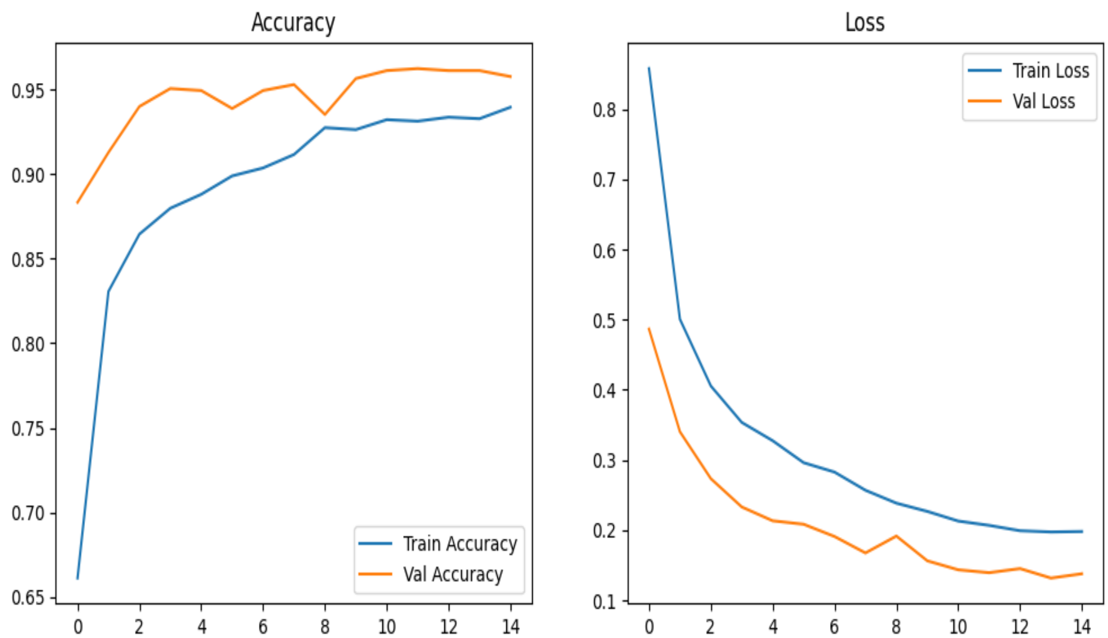

Figure 4.10: Train & validation Accuracy and loss Graph of InceptionV3

4.3.5.2 Confusion Matrix of INCEPTION-V3

The result of a classification routine is presented and summarized in a confusion matrix.

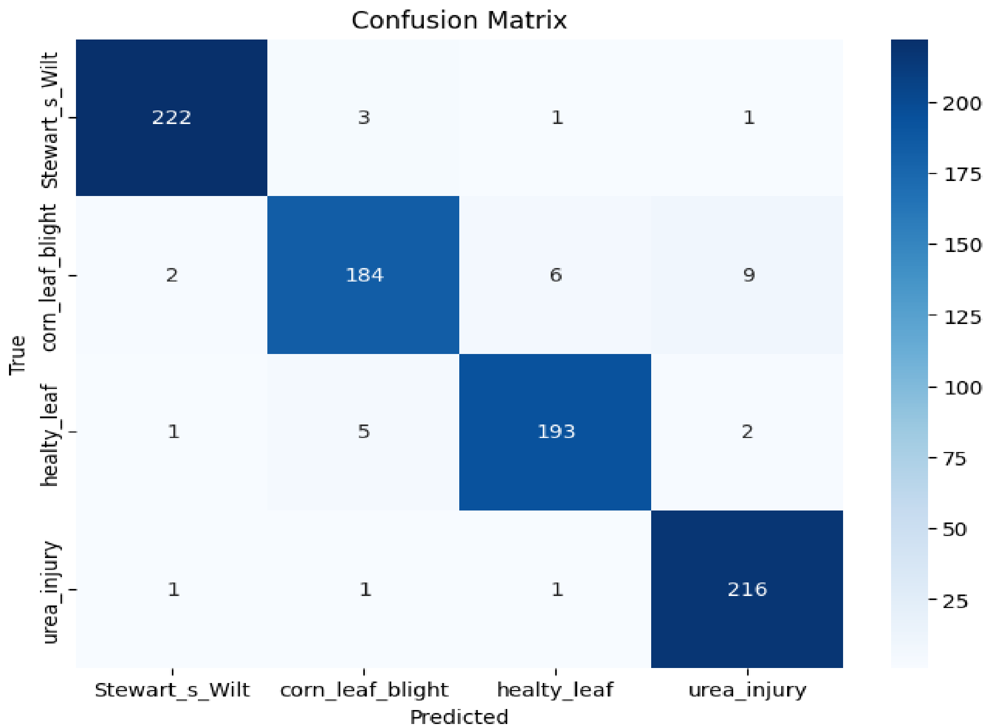

Figure 4.11: Confusion Matrix of InceptionV3

Table 4.6: InceptionV3 model's performance results

Class Name	Precision	Recall	F1-Score
Healthy Leaf	96%	96%	96%
Leaf Blight	95%	92%	93%
Stewart’s Wilt	98%	98%	98%
Urea Injury	95%	99%	97%

4.4 Mobile Application Demonstration and Real-Time Inference

It was classified as the best performing model, Custom MobileNetV2, and was converted to TensorFlow Lite (TFLite) format and then successfully deployed in a mobile application as mentioned in Chapter 3. The present section illustrates the deployment and proof of its efficiency in practice.

4.5 Qualitative Prediction Examples

The abilities of the application were demonstrated using a set of corn leaf images of the test dataset as inputs. The mobile application was able to carry out real-time diagnosis of every picture.

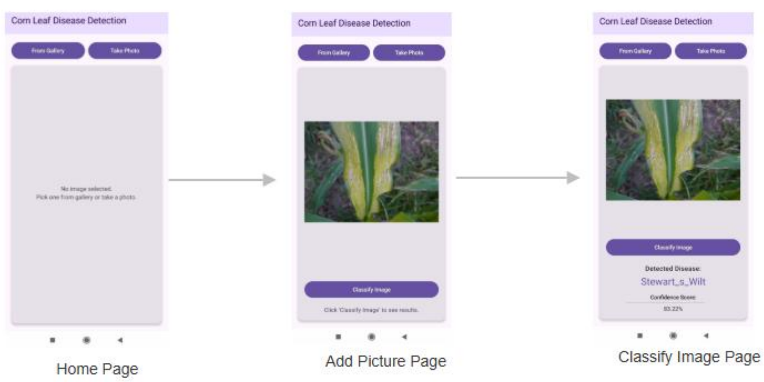

Figure 4.12: Mobile Application Screenshot Showing Corn Leaf Disease

This functionality is graphically demonstrated in Figure 4.12, where a screenshot of the application output in a test image of corn leaf blight is seen. The app was able to automatically diagnose the disease and placed a high confidence score. Figure 4.3 denotes the mobile application screenshot that shows an accurate corn leaf blight prediction response. The figure is a screen snapshot of the user interface of the mobile application. The UI shows the image of a diseased corn leaf, as well as the result of the classification made by the model, which is the identification of the pathogen with a given confidence score, verifying the usefulness of the model on real-life data. The results of this demonstration confirm that the suggested methodology has the potential to be applied as an effective method of deploying high-performance deep learning models on a practical in-device diagnostic tool in agriculture. With the above capability, this system achieves one of the primary goals of the thesis- providing farmers with a convenient and dependable application to use in detection of corn leaf diseases early enough.

4.6 Discussion

The findings of the work prove that deep learning algorithm can effectively classify and detect diseases in maize leaves. MobileNetV2 and InceptionV3 had the best performance with more than 97 and 96 accuracy respectively. The findings indicate that lightweight models like MobileNetV2 can be very efficient, not only with respect to accuracy, but also concerning the computational burden, thus able to fit real-time applications in the field of precision agriculture. By comparison, a CNN specifically trained on the datasheet reached 83% accuracy, which, though indeed lower than the pre-trained architectures, demonstrates the usefulness of transfer learning to enhance classification of agricultural datasets. This is further confirmed by the performance of VGG16 (87%) and VGG19 (85%) that were also outclassed by MobileNetV2 (88%) and InceptionV3 (89%). To the strength of this study is showing that deep learning models could learn disease signs, even the complex ones using leaf images to present a reliable automatized crop disease management tool. Among the implications of the disease classification of this quality and at an early stage, oneself should refer to agriculture, and first of all to those countries that produce maize extensively, such as Bangladesh. Suspected disease in the early stage can directly manage loss of yield and guarantee food security. Yet, the study also has certain limitations. To start with, the size of the dataset utilized in the experiment was not large. Deep learning models are more commonly sensitive to larger and more heterogeneous datasets, and undersized, verified maize disease images could have restricted total generalization. Second, the models attained high accuracies, but in controlled environments: their performance in the real farming settings might be lower because of the changes in the light conditions, presence of background noise or variation in the leaves. Third, research intensive computational involvement was necessary and this may restrict accessibility to farmers and small scale researchers due to the use of high-performance hardware. In spite of these difficulties, the results do support the possibility of deep learning having a revolutionizing effect on contemporary agriculture. In terms of mobile or edge deployment, MobileNetV2 in particular will provide a feasible means of real-time disease detection that can be applied using smartphones by farmers. This is consistent with the larger objective of marketing smart farming that transcends technology integration with conventional farming. Additional work to improve on the size of the dataset in terms of a collaborative effort with other agricultural institutes and test the models in real life settings to determine how well they work under real life situations should be done. Moreover, the combination of deep learning systems with IoT platforms, drones, and sensors may help with the monitoring of the disease and the consequent decision-making in scale.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on society

Early diagnosis of diseases of the corn leaves is critical in ensuring that farmers can take appropriate preventive measures early enough before losses may occur, which means that yields will be maintained at better levels and thus have a more sustainable agricultural ecosystem. The early detection of symptoms will help farmers reduce the development of infections, increase the healthiness of crop growth, and make good use of resources. This is a proactive strategy as, besides protecting the yield potential, it improves the economic resilience of individual farmers as well as the agricultural sector, on a larger scale. Economically, proper detection and management of diseases is a booster in terms of productivity and profitability. Farmers lose fewer crops because of crop failure, and steady yields build income stability. More nutritious and superior crops open avenues to variation in marketing products, giving farmers the chance to sell to high-value markets and to command better prices. This, in turn, promotes more agribusiness growth, since there is stability in production in terms of supply chain continuity and food security. In addition to economic results, capacity-building programs could be developed in farm communities based on the introduction of advanced detection methods.

Schooling programs are also organized for farmers to give practical skills in identification, monitoring, and how to curb diseases. Such programs enable farmers to diagnose their crops better and thus allow them to adopt a more sustainable and effective approach to crop management by adopting evidence-based preventative measures. Confidence obtained through this knowledge also pushes farmers to accept the modern methods in agriculture, building resilience in the farming industry. In addition, a concerted effort, coupled with interdisciplinary approaches, is needed to curb issues of corn leaf disease. Scientists, experts, agronomists, agronomical extension staff, and farmers must collaborate to reduce the knowledge gaps and encourage the process of transferring best practices. Such collaborations foster shared knowledge, innovation, and collaborative problem-solving, which have the ultimate effect of making disease management approaches more effective. Under this comprehensive model, farming communities can have better access to scientific knowledge by the researchers receiving a more interesting point of view after spending time in the field, and hence, a healthy loop of innovation and utilization is created. To sum it up, early diagnosis and active control of corn leaf diseases can be associated with economic and social advantages. Not only do they help offset losses and increase profitability, but they also constitute capacity building and collaboration, as well as long-term sustainability of the agricultural sector.

5.2 Impact on the environment

In today's world, the ecological and socio-economic importance of trees cannot be overstated. Trees give us one of the most fundamental pillars of our natural environment, providing oxygen, maintaining ecological balance, preserving biodiversity, and supporting agricultural livelihoods. Other than their critical role, it is a deep concern that global forests and tree populations are being depleted at an alarming rate. One of the most pressing contributors to this decline is deforestation, which not only reduces green cover but also increases the effects of climate change and global warming. To counter this crisis, early detection of diseases and infections in trees emerges as a key strategy. It is just as important as preventive healthcare in safeguarding human life. Timely identification of tree diseases allows for the implementation of remedial measures that can restore tree health, prevent large-scale losses, and sustain the productivity of ecosystems. This becomes very significant in agricultural landscapes where trees, crops, and surrounding vegetation form interdependent systems. Preserving tree health ensures the continued availability of fruits, timber, and other plant-based resources while simultaneously enhancing agricultural productivity and food security. From an environmental viewpoint, maintaining healthy tree populations contributes directly to carbon sequestration and the production of fresh oxygen, both of which are crucial in mitigating greenhouse gas emissions that drive global warming. In the extract, investing in the well-being of trees is an investment in the well-being of all life forms on Earth.

5.3 Ethical Aspects

When performing research that involves the work in the field and collecting data in agricultural systems, the ethical principles are of the utmost importance. This process is quite critical to obtain informed consent of all participating farmers. Informed consent makes sure that the participant is completely aware of the purpose, scope and objectives of the research project conducted and on the methods of data or sample collection that will be used in the research project. It is not enough to just ask someone to participate but it is my obligation as a researcher to convey the message in an easy to understand language by avoiding the use of jargon that could result into confusion. This will bring transparency meaning farmers will voluntarily make a good decision on whether to participate.

Additionally, in obtaining the informed consent, the possible benefits of the study including the way the research results could be used to help enhance farming activities and crop health management and sustainability must be highlighted. Meanwhile, the risks that can be caused, however insignificant they are, must be made known to the participants as well as how those risks will be addressed. Through this openness, mutual trust is built between scholars and farming communities, and a partnership, rather than data collection relationship, therefore, prevails. The other very vital ethical consideration is the guarantee of voluntary participation. Farmers should never be made to feel pressured to give data or samples, nor should there be a risk of penalty to them in case they choose to drop out at any stage of the study. This value of respect to autonomy is a pillar in the setting of ethical research principles.

Moreover, it is necessary to focus on the confidentiality of the research process, as well as data protection. Personal or farm-specific data which is collected must be used, stored and disposed of in a responsible manner and solely as it pertains to the study. Specific information should be removed in survey or publication reports to protect the privacy of those surveyed. In addition to the consent of an individual being submitted to the study, the investigators should work within the accepted guidelines of ethical reviews. It is necessary to seek an opinion on the study with a relevant oversight body such as an institutional ethics committee in order to meet standards which have been established in human and community-based studies. This supervision will protect participants and enhance the validity and soundness of the research. Additionally, there is the concept of the ethical considerations exercised in the reporting and sharing of results. Researchers have a duty of presenting results without falsifying or distorting the results and making results accessible to the communities that are involved in the farming practices. The flow of engagement is closed by sharing results with the participants and this empowers the farmers with knowledge that can become the route of guidance in making decisions in agricultural practices. In short, ethical research in agricultural research is not just a formality aspect in scholarly work. They guarantee the consideration of rights and dignity to farmers, and empower the relationship of trust between researchers and communities, as well as a social relevance and sustainability of research results.

5.4 Sustainability Plan

This proposed idea should finally be tested in real-life agriculture settings to evaluate the effectiveness and scalability of the idea. Laboratory tests and controlled trials are beneficial, but the method will have to be taken into the fields by farmers to decide its overall utility and acceptance. By deciding how the system works in the real world of farming through piloting it in various farming communities, researchers can check how it works under different conditions, such as climatic changes, soil quality, and disease prevalence. Of equal merit is the need to communicate continuously with the farmers, agricultural experts, and other stakeholders. Their experience will enable us to make the system more polished, reveal its gaps and limitations, and improve it by incorporating new features that are relevant to actual farming. These successive amendments will not only enhance the usability and accessibility of the system but also render it more suitable for different socio-economic conditions. The other important factor is an increase in data collection. The more farmers and regions donate images and their data in the fields, the wider and richer the underlying database will become. The continuous enrichment of the dataset will mean that the detection model becomes less susceptible, precise, and general over a variety of geographies and crop variants. The bigger and more extensive the dataset, the more effective the system will be in identifying any minute disease patterns and offering confident diagnoses. Corn is one of the crops involved in worldwide crop cultivation, hence providing great potential for the worldwide implementation of such a system. In focus on food security, animal feedstuff, and industrial application, the health of corn crops has a direct bearing on agricultural productivity worldwide and economic stability. Thus, the research could, in the long term, be scaled to a global scope to assist farmers on different continents. In the future, one can envision that such work can be incorporated into a larger worldwide project and gain enormous benefits for those who cannot afford modern diagnostic equipment. A highly connected system across the world, with shared data and cooperative platforms, could enable farmers in one region of the world to take advantage of knowledge produced in another. This is the vision of sustainable agriculture, where technology should enable farmers to reduce losses, increase yields, and ensure food security in the face of an increasing population. In conclusion, although the current work demonstrates a positive result, it is its future scalability, continuous improvement, and real-world deployment that present its potential. A concerted effort, stakeholder cooperation and technology-led advancement of research will transform this study into a system of global agricultural support that will not only conserve corn production but also significantly enhance sustainable agricultural resilience and sustainability across the entire agricultural industry.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

In the present study, I used various deep learning models-CNN, MobileNetV2, VGG16, VGG19 and InceptionV3- to identify diseased leaves in maize and assess how each model performed in distinguishing between various disease classes. The data involved maize leaves, which were already processed and used to perform several operations of image processing and deep learning. The results showed that the customized CNN model displayed an accuracy of 83%, the MobileNetV2 model displayed 97%, VGG16 model displayed 87%, VGG19 model displayed 85%, and the inception V3 model displayed 96 percent accuracy. Such findings demonstrate that the models have solid potential to both classify and identify corn leaf diseases. The results also prove that, deep learning techniques could be effectively used as solutions to detect early disease and make farmers take decision on time, minimizing crop losses. Going forward, studies should consider more advanced technological incorporations in precision agriculture, besides growing what exist already to enhance the ability of models to generalize and enhance the performance of diagnosis. In the process of carrying out this investigation, a number of problems were experienced. Unlike data consisting of text, the data taking an image form needs more complicated and time consuming processing. The computing resources and image processing tools required that, at given times, were high-performance computing systems and dedicated software tools, neither of which was readily available. It was also challenging to collect a sufficient amount of images representing maize leaf diseases considering that verified and high-quality datasets were hard to find, and visits to a set of trusted sources were necessary. Another time-consuming issue was the processing and cleaning of the images that had been obtained to contribute toward the training of the models. Also, optimization of deep learning models to improve the accuracy required long experimentation and analysis. Nevertheless, the limitations notwithstanding, the research shows the huge potential of deep learning in sustaining and adopting technology-based agriculture disease management solutions.

6.2 Conclusions

This paper explores whether deep learning models can be used to detect maize leaf diseases using image data effectively. Using a database of maize leaf images, a number of architectures, including CNN, MobileNetV2, VGG16, VGG19, and InceptionV3, were trained, validated, and compared. The performance shows that MobileNetV2 (97%) and InceptionV3 (96%) were the most successful, but even VGG16 (87%), VGG19 (85%), and the custom-built CNN (83%) achieved high performance. These results demonstrate that deep learning models can indeed learn disease-related characteristics and develop a stable method for automatic diagnosis of maize leaf conditions. The importance of this work lies in its potential for early disease detection, enabling farmers to make informed decisions and reduce losses. Especially in the case of models like MobileNetV2, it is easier to implement some of these more advanced disease detection systems in agricultural communities due to the lightweight nature of the model. However, the research does admit some weaknesses, such as a rather small amount of data and the need to rely on powerful computing resources. An even greater challenge will entail extending the dataset with images that are more diverse and verified, as well as testing the models in practice in the real field, which will help to enhance the robustness and applicability of the models. In conclusion, this study finds deep learning models to have significant potential for improving agricultural productivity by means of automating plant disease detection. As digital farming practices become more refined and merge, the technologies have the potential to provide more sustainable farming and food security, as well as resource-conscious allotment in maize production and elsewhere.

6.3 Implication for Further Study

The outcomes of this research demonstrate the strong potential of deep learning techniques in the field of agricultural disease detection. However, there remain several avenues through which this work can be expanded and refined to maximize its impact.

First, one of the primary future directions involves broadening the scope of disease categories under investigation. In the current study, only a limited number of maize leaf diseases were considered, but real-world agricultural environments often face a wide spectrum of biotic stresses. Expanding the model to recognize additional diseases, including those caused by fungi, bacteria, and viruses, would significantly improve its practical utility and reliability for farmers.

Secondly, dataset enlargement and diversification are crucial for improving model performance. The present dataset, while carefully collected, remains relatively modest in scale. By acquiring a larger and more representative dataset—spanning diverse geographical regions, environmental conditions, and seasonal variations—the model's robustness and generalization ability can be substantially enhanced. Leveraging open-source agricultural image repositories in combination with newly collected data could also facilitate the creation of a global benchmark dataset for maize disease detection.

Another important area for future work is the development of real-time deployment platforms. Implementing the trained models into user-friendly web applications and mobile applications would allow farmers to diagnose crop diseases instantly by uploading images captured through smartphones or field cameras. Such applications could be further integrated with decision-support systems, offering tailored recommendations for disease management, pesticide usage, and preventive actions. In addition to deep learning models such as CNN, MobileNetV2, VGG 16, VGG 19 and InceptionV3, it is worth exploring a wider range of machine learning and hybrid approaches. Algorithms such as Support

Vector Machines (SVM), Random Forests, or Gradient Boosting can be combined with deep learning feature extractors to assess whether.
Lastly, future studies should consider field validation and farmer-centric participatory testing.

While controlled experiments show promising accuracy, real-world environments introduce variations such as lighting conditions, overlapping leaves, or partial occlusions. Conducting on-site validation trials with farmers will ensure that the models remain practical, adaptive, and accessible under realistic agricultural conditions.

In summary, expanding disease categories, enlarging datasets, deploying mobile/web-based tools, experimenting with additional machine learning models, and validating under real-world conditions represent vital next steps. These efforts will not only strengthen the technical rigor of future research but also ensure that such systems can meaningfully transform agricultural practices at both local and global scales.

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