Unveiling Agricultural Insights: Leveraging Deep Learning for Enhanced Diagnostic Accuracy in Maize Disease Detection with Explainable Artificial Intelligence

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A thesis submitted to the Department of Computer Science and Engineering
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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

Agriculture is the backbone of a country's economy and food production. Crop diseases are a major cause of economic crises and low agricultural production. The maize crop, which is one of the largest crop in the world [2], is affected by various diseases that reduce its yield and quality. Most farmers face challenges in controlling and detecting crop diseases. Thus, early detection of diseases is essential for farmers to avoid further losses. To overcome this challenge, this thesis focuses on deep learning techniques such as EfficientNetV2B2, ResNet50, InceptionV3, VGG16, and Xception for maize crop disease detection. It uses maize crop images from the Nelson Mandela African Institution of Science and Technology and Tanzania Agricultural Research Institute. While all the models achieved promising results, EfficientNetV2B2 showed the highest overall accuracy 92%, followed by ResNet50 91%, Xception 89%, VGG16 81%, and InceptionV3 80%. Additionally, for transparent decision-making, XAI (Explainable Artificial Intelligence) techniques have been implemented. Grad-CAM (Gradient Weighted Class Activation Mapping) and Integrated Gradient techniques were integrated with EfficientNetV2B2 to enhance model interpretation.

Keywords: maize diseases direction, transfer learning, Grad-CAM, explainable artificial intelligence, EfficientNetV2B2, ResNet50, InceptionV3, VGG16, and Xception

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Chapter 1

Introduction

1.1 Introduction

Agriculture plays a critical role in maintaining global food security and economic stability [1]. Particularly, crops like maize, also known as corn, have formed the backbone of human diets. Maize has been utilized in numerous ways; as a primary food source, it is consumed directly as corn on the cob which is processed into products like cornmeal, flour, tortillas and various snacks including popcorn and corn chips. It also serves as a key ingredient in sweeteners such as high-fructose corn syrup and cornstarch, which are widely used in processed foods and beverages. In agriculture, maize is a crucial component of livestock feed, providing essential nutrients to cattle, poultry, and pigs. Industrially, maize is transformed into biofuels like ethanol which play a significant role in renewable energy, and into biodegradable plastics used in packaging, making it a remarkably versatile crop [14].

On the other hand, maize production faces so many challenges including different diseases, such as Northern Leaf Blight, Common Rust, Gray Leaf Spot, Maize Lethal Necrosis (MLN), and Maize Streak Virus (MSV). These diseases cause distinct visual symptoms on maize leaves, including chlorotic lesions, necrotic spots, and pustules. Hence, accurate and timely diagnosis of the crop disease is important for ensuring food security and maximizing crop yield. Traditional methods for disease detection require expert and field assessment which is time consuming, not accurate in some cases and also not accessible for the small farmer holders.

Furthermore, the dataset used in this paper contains 17,277 images in 3 different classes of Maize Lethal Necrosis (MLN), Maize Streak Virus (MSV) and healthy. Through use of deep learning algorithms, we can analyze the images and identify the pattern associated with different maize diseases. Which can enable us to develop a system capable of identifying and classifying the disease which led to early detection and treatment. The Convolutional Neural Network(CNN) models used in this paper are InceptionV3, ResNet50, EfficientNetV2B2, Xception and VGG16 due to their proven effectiveness. Following, the data was split into training, and validation sets. The models underwent training for performance evaluation, and the results were validated through classification techniques.

Therefore, by incorporating explainable artificial intelligence(XAI) techniques, we can also ensure transparency and insight into the decision-making process of the diagnostic models. This can help farmers and other stakeholders understand the reasoning behind the disease identification.

To sum up, In this thesis, we are working on various deep learning models to classify image data for disease detection which the structure has been illustrated in fig. 1.1 below. Firstly, chapter one will discuss the introduction, aim, and objectives, and problem statement of the study. Subsequently, chapter two provides the summary of the literature review, discussing the work that has been done so far in the field. Chapter three provides the workflow of the research. Chapter four will describe the methodology, including the dataset used in the research paper and data preprocessing. In chapter five will discuss thoroughly about the model performance and accuracy and finally chapter six will explain the Explainable Artificial Intelligence.

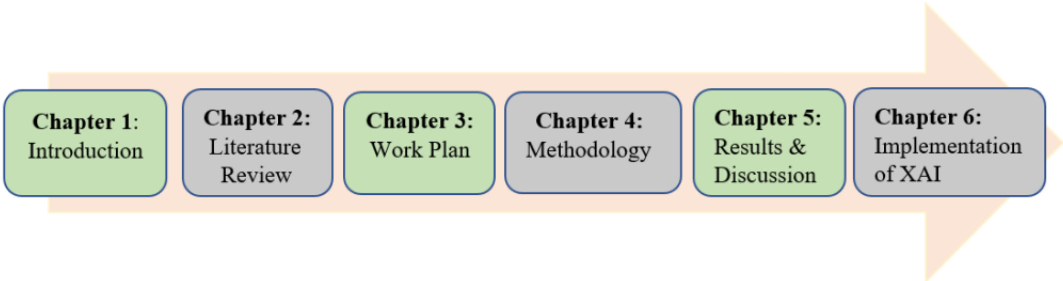

Figure 1.1: Organization of Paper

1.2 Problem Statement

Maize, one of the world's most vital crops, faces a constant threat from diseases, which can drastically reduce crop yields and quality. Diseases have a particularly strong influence on crop yield in places such as Tanzania, where maize agriculture is critical to food security and economic stability. Traditional disease diagnostic methods frequently rely on visual inspection by agricultural professionals, which is time-consuming, subjective, error-prone and sometimes unavailable to smallholder farmers.

Northern Leaf Blight, Common Rust, Gray Leaf Spot, Maize Lethal Necrosis (MLN) and Maize Streak Virus (MSV), etc. all are common Maize diseases. Our study aims to improve diagnostic accuracy using deep learning and Explainable Artificial Intelligence (XAI) methodologies, making predictions more readily identifiable and interpretable by all agricultural stakeholders. This research aspires to give farmers a reliable, accessible, and intelligible diagnostic tool, thereby enhancing maize disease management and agricultural output.

1.3 Aims and Objectives

The main objective of our paper is to develop a reliable and transparent deep learning method for maize diseases detection, incorporating XAI techniques for better interpretation and detection. Our detailed aims and objectives are as follows:

- Finding the best deep learning model timely and accurate classification of maize diseases.
- Focusing on MLN and MSV, to achieve high accuracy in differentiating healthy and diseases maize leaves.
- Using XAI techniques to enhance model interpretation and transparency.
- utilization of EfficientNetV2B2, ResNet50, InceptionV3, VGG16, and Xception on maize diseases classification.
- Implementing XAI methods with the selected high performing model.
- Using XAI to understand the features the model relies on for disease's classification.
- Demonstrating how XAI contributes to building trust in the model's prediction and understanding its decision making process for maize disease classification.

Chapter 2

Related Work

Unlike other crops maize also known as corn, is a versatile crop that can endeavor in different climates. Maize leaf abnormalities can be categorized, identified, and calculated using deep learning and machine learning techniques. This section assess previous studies on identifying corn leaf diseases.

This paper presented by [30]. explored the challenge of accurately identifying and categorizing maize plant leaf diseases, specifically Northern Leaf Blight, Northern Leaf Spot, and GLS (Gray Leaf Spot), in various environmental conditions. Using the CD&S dataset comprising 1,597 images, the study aimed to improve disease classification performance. It proposed MaizeNet, a deep learning model integrating Faster-RCNN with ResNet-50 and spatial-channel attention mechanisms. Through extensive experimentation, MaizeNet achieved a notable accuracy of 97.89%, demonstrating significant improvements in disease spot localization and overall detection accuracy. It effectively distinguished between distinct class of corn leaf disease amidst cluttered backgrounds and lighting variations.

In another study [28], presented a novel mobile system used to detect and classify maize leaf diseases, addressing the pressing issue of agricultural losses attributed to undetected or misclassified diseases, particularly prevalent in regions like Punjab, Pakistan. To confront this challenge, the researchers collected a diverse dataset comprising over two thousand images of maize leaf diseases in several growth stages, weather conditions, and time intervals. By employing deep learning some models used include from YOLOv3-tiny, up-to YOLOv8n, rigorous training and testing procedures were conducted, supplemented by meticulous image preprocessing and annotation techniques. Notably, YOLOv8n came up as the highly effective model, showing superior performance with high precision and mean average precision (mAP) for disease detection and classification, achieving a commendable detection speed of 69.76 FPS. This research underscores the potential of leveraging deep learning for real-time agricultural disease management, advocating for proactive measures to minimize agricultural losses and boost crop yield. Moreover, the study suggests broader applications, advocating for integration with smartphone apps and UAVs to facilitate widespread adoption in agriculture, ultimately aiming to enhance global food security through sustainable crop management practices.

Similarly, another study [35], explored a comprehensive approach to boost the accuracy of corn leaf disease identification through the utilization of advanced technologies. By leveraging Support Vector Machine (SVM) alongside Convolutional Neural Networks such as AlexNet and ResNet50. The study aims to revolutionize disease identification in maize crops, crucial for global food security. Through the collection and preprocessing of a dataset comprising over three thousand corn leaf images from Embu County, Kenya, encompassing three disease categories, the researchers conducted rigorous experimentation and evaluation. The results demonstrate that CNN models, particularly AlexNet, outperformed traditional SVM classifiers, achieving remarkable accuracy rates of 98.3% and 96.6% respectively. This study shows the potential of deep learning techniques in agricultural practices, offering promising avenues for enhancing crop protection measures and contributing to sustainable agriculture worldwide.

In another work [11], the paper addresses the pressing issue of low agricultural productivity due to plant diseases, with a particular focus on maize plants. It emphasizes the significance of early disease detection in mitigating losses for farmers. Employing supervised machine learning models like Naive Bayes, K-Nearest Neighbor, Support Vector Machine, Decision Tree, and Random Forest. The study developed an accurate disease detection and classification models by analyzing high-resolution images of maize leaves and extracting relevant features. The Random Forest classifier emerges as the highly effective model, outperforming others achieving a classification accuracy of 79.23%, underscoring its efficacy in identifying and categorizing maize leaf diseases. With a dataset consisting of 3,823 images categorized into four labels: healthy, common rust, gray leaf spot, and northern leaf blight, the research shows leveraging machine learning algorithms to enhance agricultural practices and sustainability through early disease detection.

Similarly, in [22], focusing on grapes and tomatoes, the VGG16 modeler was used to detect and classify leaf diseases in these crops. They utilize data augmentation techniques, hyperparameter tuning, and model optimization to enhance model performance. This study evaluates the model using different performance metrics, achieving high accuracy rates of 98.40% for grapes and 95.71% for tomatoes. Researchers highlight the importance of early disease detection in agriculture and demonstrate the effectiveness of deep learning techniques in enhancing crop management practices. Through hyperparameter tuning and model optimization, they demonstrate the potential of deep learning to revolutionize agricultural practices and increase food production.

Another work [21], Deep transfer learning, has been used to classify corn disease and healthy plants from leaf images. Using convolutional neural network (CNN) models and a dataset of 3852 images, the researchers achieved an average accuracy of 98.6%, which is a good performance. They used ten public CNN models through transfer learning and evaluated their performance using various metrics. The results emphasize the potential of deep learning to enhance agricultural practices by enabling rapid and accurate disease identification, thereby bringing precision to crop management and food production.
In the paper[19] a method for accurate detection of maize foliar disease in complex environments using LS-RCNN and CENet cascade network is proposed. LS-RCNN

detects corn leaves, and CENet classifies them into four categories. This method uses a two-stage transfer learning strategy for better accuracy and faster training. The results demonstrate higher F1-scores and faster training than other methods. This paper presents the dataset with images of laboratory and natural environments, along with a discussion of data augmentation.

Similarly, another study [34] presents LeafDoc-Net, a strong and lightweight transfer-learning design for precisely identifying leaf diseases over numerous plant species, indeed with constrained image information. The approach combines DenseNet121 and MobileNetV2 models, upgrading them with consideration instruments, world-wide normal pooling layers, extra-dense layers with swish actuation, and batch normalization layers. Assessed on cassava and wheat leaf malady datasets, LeafDoc-Net beats existing models in most of the performance measurements, with potential for further enhancement and expansion in future research.

Existing deep learning methods for corn disease detection often prioritize accuracy over real-time performance, limiting their usefulness in practical settings. To address this, [26] propose a lightweight object detection algorithm based on an improved YOLOv5s model. Their approach incorporates a Faster-C3 module to reduce model complexity, while also enhancing the neck network with CoordConv and a modified CARAFE module to improve semantic information extraction and detection accuracy. Finally, they leverage channel-wise knowledge distillation during training to further enhance accuracy without increasing model size. This method achieves a good balance between accuracy and speed, which made it suitable for real-world corn disease detection applications.

In response to the global spread of maize diseases, a novel classification model using DenseNet201 and an optimized Support Vector Machine (SVM) has been developed to effectively identify maize leaf diseases. In the study [25], leverages the advanced image-classification capabilities of DenseNet201 and Bayesian optimization techniques to improve SVM performance, addressing challenges such as variable lighting and reflections in image analysis. The model was tested on a dataset of 4988 images, categorizing them into four classes: healthy, blight, common rust, and gray leaf spot. Impressively, the proposed model acquired an accuracy of 94.6 percent, significantly outperforming traditional SVM approaches, thereby enhancing agricultural productivity and disease management.

In the study [18], a deep learning approach named WG-MARNet was proposed for identifying maize leaf diseases, that addresses noise, background interference, and low accuracy. WG-MARNet utilizes wavelet threshold-guided bilateral filtering (WT-GBF) to reduce noise and decompose images for improved feature extraction. It then employs a multichannel ResNet architecture with an attenuation factor for optimized multiscale feature fusion and training stability. Finally, the model leverages PRelu and Adabound for enhanced convergence and accuracy. This approach achieved a promising average recognition accuracy of 97.96 percent and a detection time of 0.278 seconds per image, demonstrating its potential for precise maize disease control in fields.

In another recent study [31] underscores the significant impact of deep learning techniques in agriculture, particularly in the realm of weed, pest, and disease detection.The study focused on experimenting with different CNN architectures, including DenseNet201, MobileNet, VGG16, Hyperparameter Search, and InceptionV3. By fine-tuning these models on agricultural image data, it achieved excellent accuracy in detecting the disease. In particular, the DenseNet model with outstanding accuracy of 99.62%, MobileNet performed well with 91.85% accuracy, and VGG16 achieved 78.71% accuracy. Additionally, the study highlighted the data augmentation and feature fusion as critical steps in increasing the models' performance.

Likewise in the research paper by [15], introduced a specialized model, MFaster R-CNN, tailored for detecting corn leaf diseases based on Machine Vision detecting corn leaf diseases in agricultural environments. The model enhances the Faster R-CNN framework by incorporating a batch normalization processing layer and a mixed cost function to improve accuracy and convergence speed. The study used a dataset of 697 images showing different maize diseases taken in various weather conditions. Results showed that MFaster R-CNN performed better than other models in detecting these diseases. Showcasing its potential for practical applications in agricultural disease control.

Another study, by [17], introduces a smart way to detect diseases in maize leaves using a special computer model called MFF-CNN. This model is designed to tackle common challenges in disease detection, like changes in lighting, complex backgrounds, and unclear target areas. The MFF-CNN model outperforms other methods in detecting maize leaf diseases quickly and accurately. The study's experiments prove that the MFF-CNN model works well in spotting maize leaf diseases, even in tricky situations like overlapping areas and sparse targets. This method not only improves detection accuracy but also speeds up the process, making it a useful tool for diagnosing maize leaf diseases and potentially other plant diseases.

In the paper [32], explored the significant impact of biotic stresses, such as fungal, bacterial, and viral pathogens, on maize yield and emphasized the importance of identifying resistant genes to develop disease-resistant cultivars. Their study employs both machine learning and deep learning techniques to classify gene expressions in maize under normal and stress conditions. The machine learning algorithms used include Support Vector Machine, Naive Bayes, Decision Tree,K-Nearest Neighbor, and Ensemble, while a Bi-directional Long Short Term Memory (BiLSTM) network with a Recurrent Neural Network architecture is introduced for deeper gene classification. To boost algorithm feature selection, performance was conducted using the Relief feature selection algorithm. The findings highlighted the superior performance of BiLSTM compared with other algorithms. Crucially, several genes, including (S)-beta-macrocarpene synthase, zealexin A1 synthase, and others, were identified as differentially upregulated under biotic stress, marking them as key targets for enhancing maize resistance to pathogens.

Another study conducted by [24] involved the comprehensive analysis of Convolutional Neural Networks such as MobileNetV2 and Xception modules for detection of plant disease. Among the CNN architecture employed, MobileNetV2 displayed great efficiency suitable for mobile devices while Xception being an extension of the Inception module has improved extraction capabilities as its feature. The research paper presents an ensemble module. This ensemble module combines the strengths of Xception and MobileNetV2 to improve the performance of plant disease detection. The ensemble approach is referred to as LEMOXINET. The ensemble model was able to achieve great results with 99.10% accuracy.

In the study [27] conducted research where they did a comprehensive and comparative analysis of the various deep-learning modules to predict cotton diseases. By utilizing fine-tuning Transfer Learning algorithms, the Xception module achieved the highest accuracy of 99.70% among all the modules used. The researchers selected the Xception module for their web-based application for Cotton disease prediction, which will assist farmers in early diagnosis of cotton disease, increasing cotton production.

Another research paper is by [29]. The paper studied methods of disease classification by using the triCNN architectures including Inception, Xception, and DenseNet169. The paper provides some overviews of the triCNN architectures with the aid of visual images. The paper presents some computerized methodologies for the detection of groundnut disease by using the ensemble method. To get an accurate disease prediction, the researchers used a fusion approach, i.e., combining the triCNN architectures. An accuracy of 98.46% performance was obtained when their proposed framework was applied to the groundnut leaf datasets.

In the paper [33] conducted research using machine learning-based automated disease detection to accurately detect disease. By combining EfficientNetB0 and MobileNetV2 on PlantVilageatasets with about 54,305 images, the accuracy of disease prediction was improved by 99.77%. This model shows a more dependable automated detection system for disease detection.

Table 2.1: Summary Table For Selected Papers

Reference	**Year**	**Proposed**	**Findings**	**Accuracy**
[30]	2023	MaizeNet: Recognition of Corn Leaf Diseases using Deep Learning Approach	Showed significant improvements in disease spot localization and successfully distinguished various types of disease lesions amidst crowded backgrounds and lighting variations.	MaizeNet showed notable accuracy of 97.89%

Table continued from previous page

Reference	**Year**	**Proposed**	**Findings**	**Accuracy**
[28]	2023	using deep learning and a mobile-based system for corn leaf disease detection and classification	The research shows the effectiveness of YOLOv8n and the potential for real-time agricultural disease management.	N\A
[35]	2023	The use Support Vector Machine and Convolutional Neural Networks AlexNet and ResNet50 for Identification of corn Leaf Diseases	They combined AlexNet and ResNet50 to identify maize leaf diseases accurately.The study shows that AlexNet outperform traditional SVM classifiers.	Achieved remarkable accuracy rates of 98.3%
[11]	2020	Using Machine Learning Algorithms in corn Leaf Disease Detection and Classification	The study emphasizing the importance of early detection and potential of timely disease identification for farmers. They employed techniques like Naive Bayes and Random Forest.	79.23%

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Reference	Year	Proposed	Findings	Accuracy
[22]	2021	Using VGG CNN for multi-crop leaf disease classification	Leaf diseases detection using deep learning. improve model performance by data augmentation and VGG model tuning.	98%
[21]	2022	Using deep transfer learning for maize diseases Classification	Utilized deep transfer learning for maize diseases classification. Explained deep learning's potential in agriculture. Improves crop management and food production.	98%
[19]	2022	Maize Disease Identification using Cascade Networks & Two-Stage Transfer Learning	Introduces LS-RCNN and CENet for maize disease classification. Two-stage transfer learning boosts accuracy and training speed. Achieves high F1-scores. Includes dataset and discusses data augmentation.	99.70%

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Reference	Year	Proposed	Findings	Accuracy
[34]	2024	A robust and light-weight transfer learning-based architecture for accurate detection of leaf diseases across multiple plants using less amount of images	Outperforms existing models in accuracy, precision, recall, and AUC metrics on cassava and wheat leaf disease datasets. Emphasizes data augmentation and preprocessing, utilizes Grad-CAM++ for performance analysis, and shows promising results for generic leaf disease detection.	98%
[26]	2023	Efficient Model for Detecting Maize Leaf Disease using Knowledge Distillation	Improved the YOLOv5s model for detecting maize diseases by incorporating a Faster-C3 module, enhancing it with CoordConv and a revised CARAFE module, and utilizing channel-wise knowledge distillation.	Obtained an mAP(0.5) accuracy of 3.8% higher than the baseline YOLOv5s model.

Table continued from previous page

Reference	Year	Proposed	Findings	Accuracy
[25]	2023	Identification of maize diseases based on improved support vector machines using DenseNet201's deep features	Developed a classifier that incorporates DenseNet201 and SVM, improved with Bayesian optimization. This model effectively tackled imaging issues, such as lighting contrast changes.	94.6 %
[18]	2023	Maize leaf disease identification based on WG-MARNet	Used machine learning and deep learning techniques, including a Bi-directional Long Short Term Memory (BiLSTM) network, to identify maize genes that respond to biotic stress.	%
[31]	2023	Crop Yield Improvement with Weeds, Pest and Disease Detection	The study highlighted the importance of data augmentation and feature fusion in getting better performance of each model. The models used in the study were the DenseNet, MobileNet, and VGG16.	DenseNet with 99.62% accuracy, MobileNet with 91.85% accuracy, and VGG16 achieved 78.71% accuracy.

Table continued from previous page

Reference	Year	Proposed	Findings	Accuracy
[15]	2023	MFaster R-CNN for Maize Leaf Diseases Detection Based on Machine Vision	The specialized model introduced in the paper, MFaster R-CNN performed better than all other models in detecting diseases which has performed on a dataset containing 697 images.	97.18%
[17]	2022	One-Stage Disease Detection Method for Maize Leaf Based on Multi-Scale Feature Fusion	Comparative analysis of different CNN models, where MFF-CNN outperformed well even in handling overlapping and sparse targets. It can handle effectively challenges like changes in lighting, complex backgrounds, and unclear target areas that make it a feasible solution even for other plants disease detection.	N\A

Table continued from previous page

Reference	Year	Proposed	Findings	Accuracy
[32]	2023	Integrated transcriptomic meta-analysis and comparative artificial intelligence models in maize under biotic stress	Used a variety of machine and deep learning techniques, including a Bi-directional Long Short Term Memory (BiLSTM) network, to identify gene expressions in response to stress. BiLSTM demonstrated greater efficacy in identifying important genes such as (S)-beta-macrocarpene synthase, which are prospective targets for enhancing maize disease resistance.	92.86%
[24]	2022	LEMOXINET: Lite ensemble MobileNetV2 and Xception models to predict plant disease	Combine two CNN modules, MobileNetV2 and Xception to form an ensemble module called LEMOXINET with an accuracy of 99.10%.	99.10%

Table continued from previous page

Reference	Year	Proposed	Findings	Accuracy
[27]	2023	A deep learning module for Cotton disease prediction using fine-tuning with a smart web application	Xception module is selected for the cotton disease prediction web application due to its high accuracy among all the Transfer Learning modules.	99.70%
[29]	2023	Ensemble of CNN models for classification of groundnut plant leaf disease detection.	An accuracy of 98.46% was achieved from the combination of the tri-CNN architecture (Inception, Xception, and DenseNet169) in groundnut plant leaf disease detection.	98.46%
[33]	2023	Ensemble of deep learning models for multi-plant disease classification and smart farming	Combination of EfficientNetB0 and MobileNetV2 to improve plant disease classification accuracy.	99.77%

In summary, from the above discussion, it is distinctly noticed that most of the research in this field is classification and detection and most classification tasks are based on corn leaf disease classification and detection. However, there are some diseases which have not been analyzed. For instance, Maize Lethal Necrosis (MLN) disease classification, Moreover some research was focused on different crop disease detection as depicted in Table 2.3. Furthermore, minor works based on maize leaf disease detection using deep learning have been done, maize disease detection using explainable artificial intelligence should be more prominent. In this digital era agriculture should not be left behind with the use of technology therefore creation of a detection tool for farmers in Africa and the rest of the world especially in Tanzania who mostly face those diseases is essential.

Table 2.3: Comparison of Different Papers With Our Paper

Paper	**Maize Disease Analysis**	**MLN**	**MSV**	**Dataset used**	**ML & DL**	**XAI**
[34]	×	×	×	×	✓	✓
[35]	✓	✓	✓	∼	✓	×
[22]	×	×	×	✓	✓	×
[15]	✓	×	×	×	✓	×
[21], [19]	✓	×	×	∼	✓	×
[30], [28], [11]	✓	×	×	∼	✓	×
Our paper	✓	✓	✓	✓	✓	✓

✓ Covered ∼ Partially Covered × Not Covered
Dataset Image used < 1000: ×; Dataset image used ≥ 1000 and < 5000: ∼

Chapter 3

Methodology

As shown in the figure below 3.1 the first phase of our methodology involves image collection and preparation where both healthy and diseased samples are taken, specifically targeting MLN and MSV. The data preparation for this stage needs a careful selection of the data as well as data pre-processing like resizing and normalization to prepare a good dataset for deep learning model training. The stages of the diseases must be clearly labeled and categorized to guarantee that the settings under which the diagnostic computational methods will work are accurately depicted by the dataset

In the next phase, a number of advanced deep learning models including ResNet50, InceptionV3, VGG16, Xception, and EfficientNetV2B2 are used to train and test. This process includes splitting the data into an 80:The data was split into the training set, which constituted 80% of the data, and the testing set that comprised the remaining 20% of the data, and used image augmentation to improve the model's ability to generalize. Every model is subjected to performance testing based on various measures such as accuracy, precision, recall, and F1-score. Also, Explainable Artificial Intelligence (XAI) techniques are incorporated to make the models' decision-making processes interpretable and comprehensible, thus helping farmers and other agricultural workers put their trust in the models and use themeffortlessly.

The last stage involves deploying the identified best performing model into a more practical and easily applicable diagnostic tool for real world agricultural conditions. The tool is a field-tested tool to confirm its efficacy and feasibility to the end-users who will be utilizing it. These are done in form of changes and improvements based on the results of these tests to come up with a more accurate and user-friendly tool that can help in the improvement of disease management for Maize crops, therefore increasing yield and in turn food security especially in regions such as Tanzania.

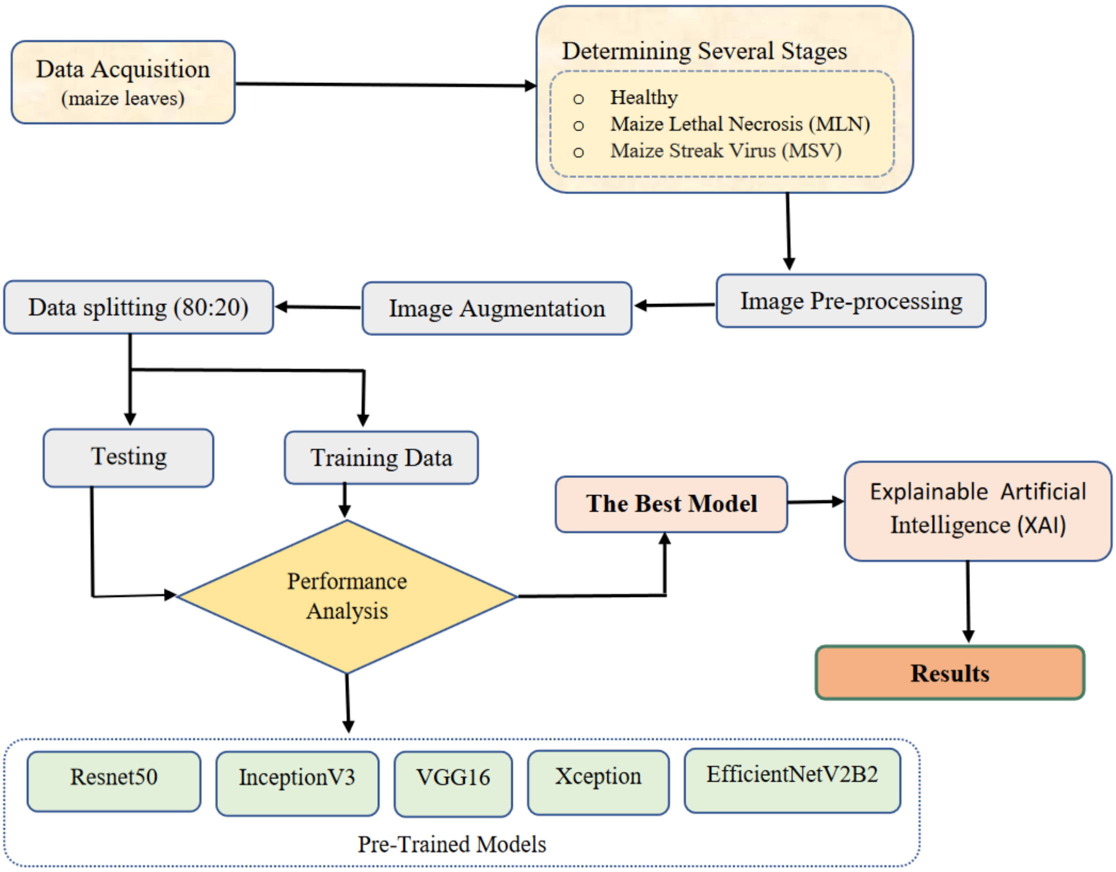


Figure 3.1: Workflow

3.1 Data Collection

The data collection process involved acquiring maize leaf images from farmers' gardens in Tanzania using the AdSurv mobile application installed on Samsung phones.

The dataset was collected by a team of researchers and students from The Nelson Mandela African Institution of Science and Technology and Tanzania Agricultural Research Institute over a period of six months between February 2021 and July 2021. The images were gathered to diagnose MLN and MSV diseases as shown in figure 3.2, aiming to assist farmers in disease diagnosis and improve maize production.

The dataset consists of 17,277 labeled images categorized into Healthy (5542), Maize Lethal Necrosis (5068), and Maize Streak Virus (6667) as depicted by figure 3.3. Each image instance includes the crop status, variety, age, and location (district, sub-county). The data collected is well-labeled and curated, providing an open and accessible maize image dataset for machine learning experiments.

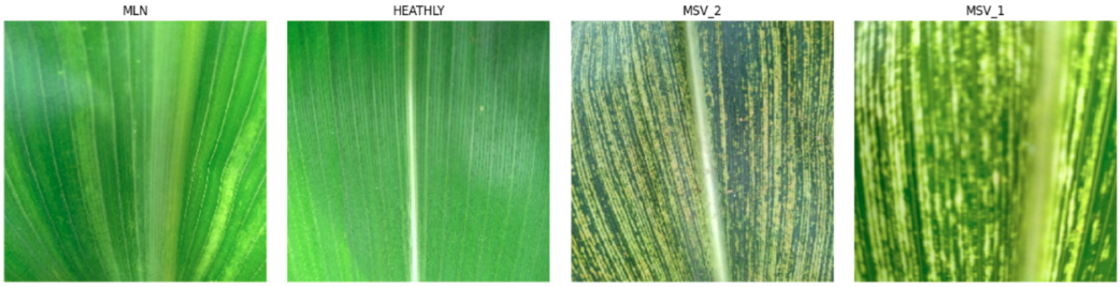


Figure 3.2: Sample images.

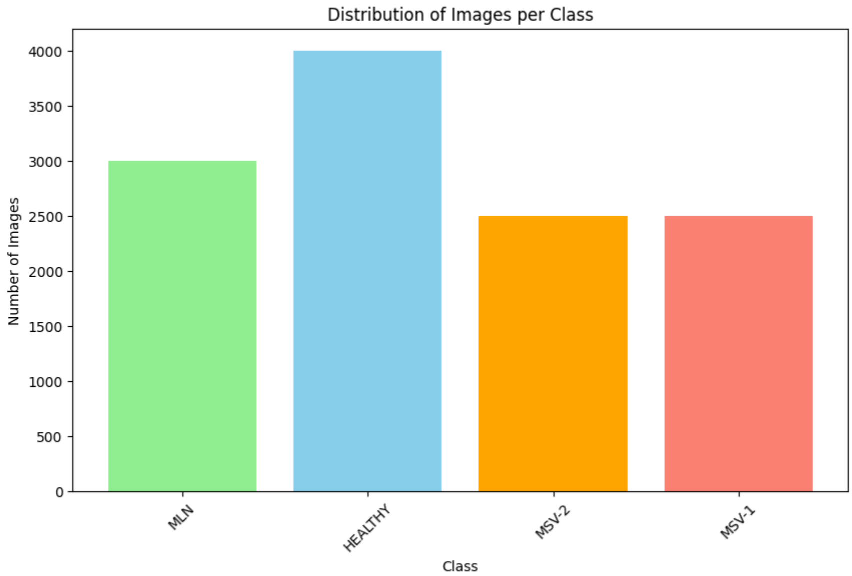


Figure 3.3: Distribution of Images in Each Class.

3.2 Data Preprocessing

Maize image data was collected in Tanzania under the Lacuna Project, Before utilizing it in this research activity, the raw images of the maize leaves were captured using the AdSurv application developed on smart phones, and the images that were identified to be similar were removed from the dataset to maintain cleanliness.

These procedures were very important to ensure that the dataset was curated properly, as similar images can affect training or testing. After that, the images were tagged to the respective class, healthy, Lethal Necrosis, or Streak Virus, to facilitate classification as well as annotation for tasks like computer vision. Further, the images in each class were renamed for easy management of data in the set.

The extensive preparations of the maize image data was done purposely to improve the quality and applicability of the dataset for researchers who are investigating the maize farming and other agricultural activities in Tanzania.

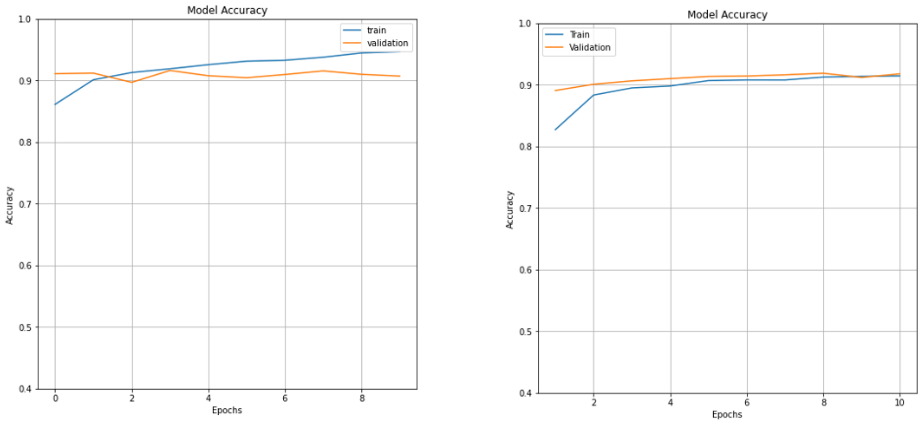
3.3 Data Training

To evaluate the performance of several pre-trained convolutional neural network (CNN) models in classifying maize diseases, we used a dataset of 12,280 images divided into four classes that represent varying states of health and sickness in maize leaves. The CNN models used were EfficientNetV2B2, ResNet50, InceptionV3, VGG16, and Xception, which were selected for their high performance in image categorization tasks.

The training process was conducted for 10 epochs, and the training data sets were divided into batches according to the architecture of the models. This training was done in detail to record training and validation metrics, which are significant for analyzing model performance and ensuring its functionality in cases when it is used on new unknown data. It can be observed that both EfficientNetV2B2 and ResNet50 models had an increasing trend in accuracy throughout the training process, thus indicating successive learning from the provided dataset and good generalization on validation data.

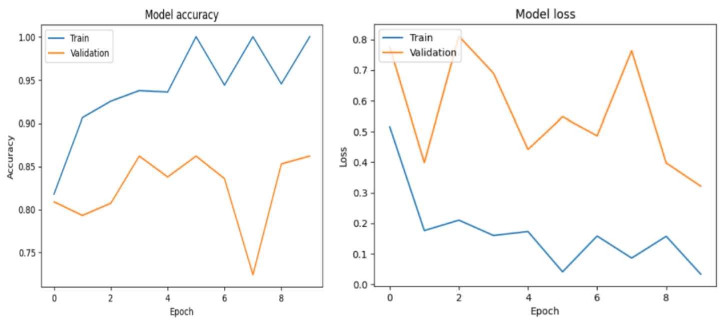
As it can be noted, training accuracy slightly fluctuated during the training phase of InceptionV3; it can be attributed to the model's complex structure that might require more fine-tuning. It can be clearly seen that during the first epochs, VGG16 might have been overfitting since its performance started to decrease, thus, modifications had to be made in learning rates and augmentation techniques. Xception shown high training accuracy and maintained high validation score, thereby showing that it was capable of identifying the intricate pattern of maize diseases.

The graphical representation of training and validation accuracy and loss in the figures 3.4, 3.5, 3.6, and 3.7 revealed more information about each model's learning dynamics. Typically, accuracy increased dramatically as training went, while loss dropped, showing increasing model competency in properly diagnosing maize illnesses. This step was critical for determining the most effective models and identifying those that need further changes. This extensive training phase helped us get closer to our aim of developing a trustworthy and transparent tool for identifying maize illnesses.



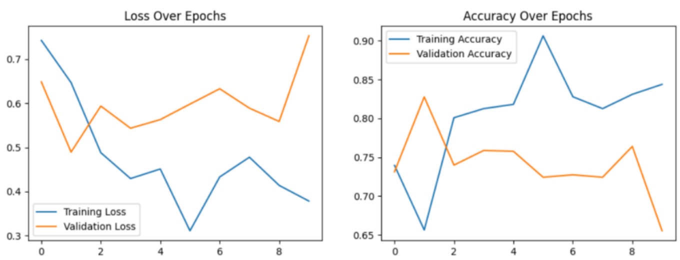
ResNet50 **EfficientNetV2B2**

Figure 3.4: ResNet50 & EfficientV2B2.



Xception

Figure 3.5: Xception.



InceptionV3

Figure 3.6: InceptionV3.

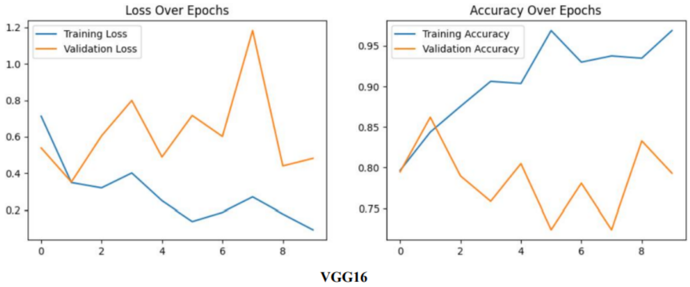


Figure 3.7: VGG16.

3.4 Transfer Learning Models

The concept of transfer learning refers to a machine learning approach that allows a pre-trained model to learn new tasks more effectively. This approach tries to boost the performance by using knowledge from a source domain in a target domain , which is especially helpful during data training when the data is inadequate or outdated. Moreover, it has shown an excellent performance in computer vision, making it particularly useful for applications such as computer-based diagnosis and prediction [16]. Since AlexNet's victory in the ImageNet competition, convolutional neural networks have been widely used in a variety of deep learning problems, frequently involving transfer learning. Where a model trained on a big dataset is modified for a comparable but smaller task, such as utilizing a model learned on a huge image classification dataset to categorize particular images of dogs and cats. Furthermore, the previously trained model's learned characteristics, such as edge and pattern detection, are fine-tuned or reused to boost performance on the task at hand [20]. Therefore, transfer learning as opposed to multitask learning, which learns tasks concurrently, transfers knowledge progressively, making it suited for circumstances that need gradual training and adaptability.

3.4.1 ResNet50

To improve the capacity to train deep networks, adding more convolutional layers by using residual learning is achieved using skip connections which successfully addresses the vanishing gradient problem (figure 3.9) a transfer learning ResNet50 model was constructed. It is a pioneering deep convolutional neural network built by Microsoft Research in 2015. It has 50-layer design where its architecture as depicted in figure 3.8 is separated into four major components: convolutional layers for feature extraction, identification blocks, convolutional blocks for feature modification, and fully connected layers for classification. Furthermore, It was trained on the large-scale ImageNet dataset achieved a remarkable top-5 error rate of 6.71%, which is comparable to human performance. Moreover, It is the favored model for a many image classification applications, including medical image analysis, object identification, and facial recognition, because of its high accuracy, rapid convergence and quick training [5].

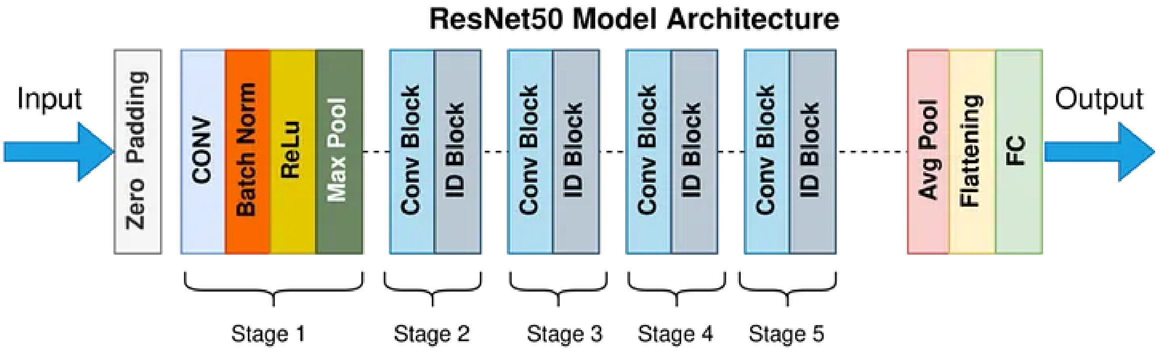


Figure 3.8: ResNet50 Model Architecture [8].

How ResNet50 solved the disappearing gradients problem:

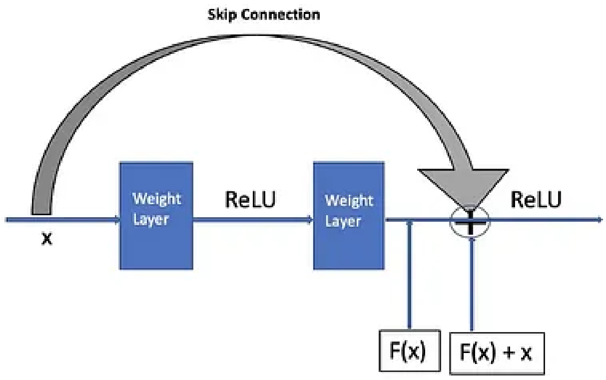


Figure 3.9: Skip Connection [13].

Concluding ResNet50 showed performance of 91% accuracy, an 89 percent F1-score, and a recall of 89 percent in Maize leaf disease identification after using an 80:20 training-to-testing dataset and 10 input data epochs. This demonstrates its versatility and robustness in complicated visual recognition issues.

3.4.2 InceptionV3

InceptionV3 model is used in image identification. This model is a convolutional neural network architecture created by Google researchers in 2015, marks a vast step forward in computer vision. It has been built on the original Inception designs V1 and V2, it is intended to be computationally efficient while maintaining outstanding performance in image categorization applications. To extract features from images, the architecture employs a succession of convolutional, pooling, and inception modules. Furthermore, Inception modules enable the network to learn features at various scales and resolutions by performing numerous simultaneous convolutional operations of varying sizes. Moreover, it has showed world-class performance in a variety of computer vision tasks, including object identification, image classification, and visual question answering. It attained a 21.2 percent top-1 error rate and a 5.6 percent top-5 error rate in the 2012 ImageNet Large Scale Visual Recognition Challenge for single-frame evaluations [6]. Therefore, these performance measurements highlight InceptionV3's remarkable accuracy and efficiency, making it the preferred choice for difficult computer vision applications and cementing its status as the top deep learning architecture. In addition, InceptionV3 obtained a performance of 80% accuracy, an 75 percent F1-score, and a recall of 76 percent in Maize disease identification using an 80:20 training-to-testing dataset. This demonstrates InceptionV3's effectiveness in image classification and detection applications.

3.4.3 VGG16

This is a kind of artificial neural network introduced by K. Simonyan and A. Zisserman of the University of Oxford, It has become a key in the field of computer vision since its release in 2014. This model, which finished second in the ILSVRC 2014 classification challenge [3], is known for its basic yet successful design of 16 layers, comprising convolutional layers with modest 3x3 filters, max-pooling layers, and fully linked layers as shown in figure 3.10. Furthermore, it achieved an outstanding 92.7 percent top-5 test accuracy on the ImageNet dataset, which comprises over 14 million images from 1000 classes [4]. Moreover, by substituting bigger kernel-sized filters with many 3x3 filters, it improves on previous models such as AlexNet, allowing for deeper networks with more parameters. In addition, its design is distinguished by a constant input size of 224x224 RGB images, consistent usage of rectified linear units (ReLU), and the lack of Local Response Normalization (LRN), which reduces computation time and memory consumption. VGG-16 was trained on NVIDIA Titan Black GPUs, which is still an effective technique for large-scale image recognition.

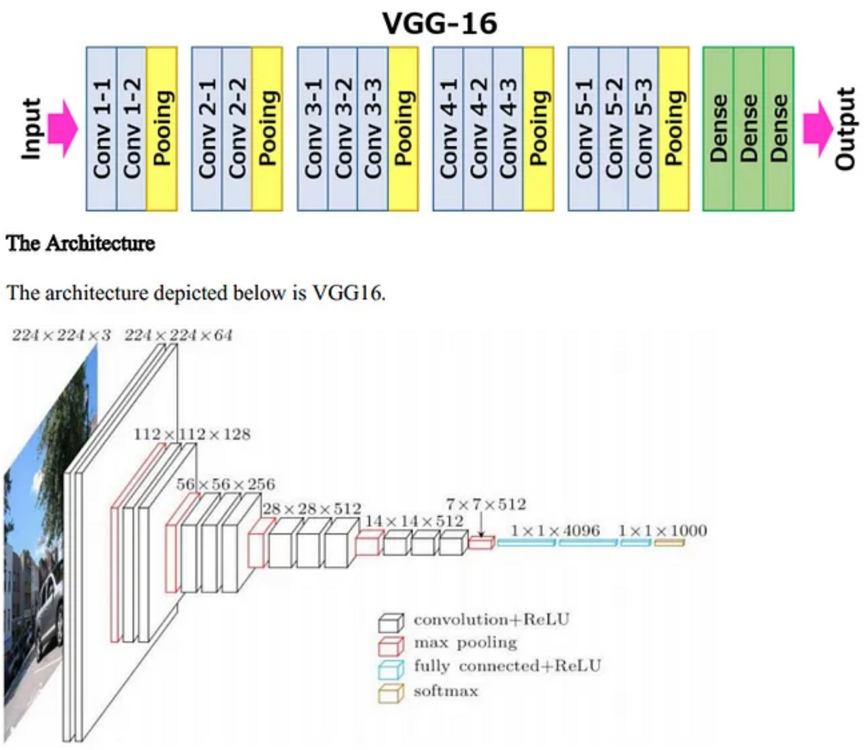
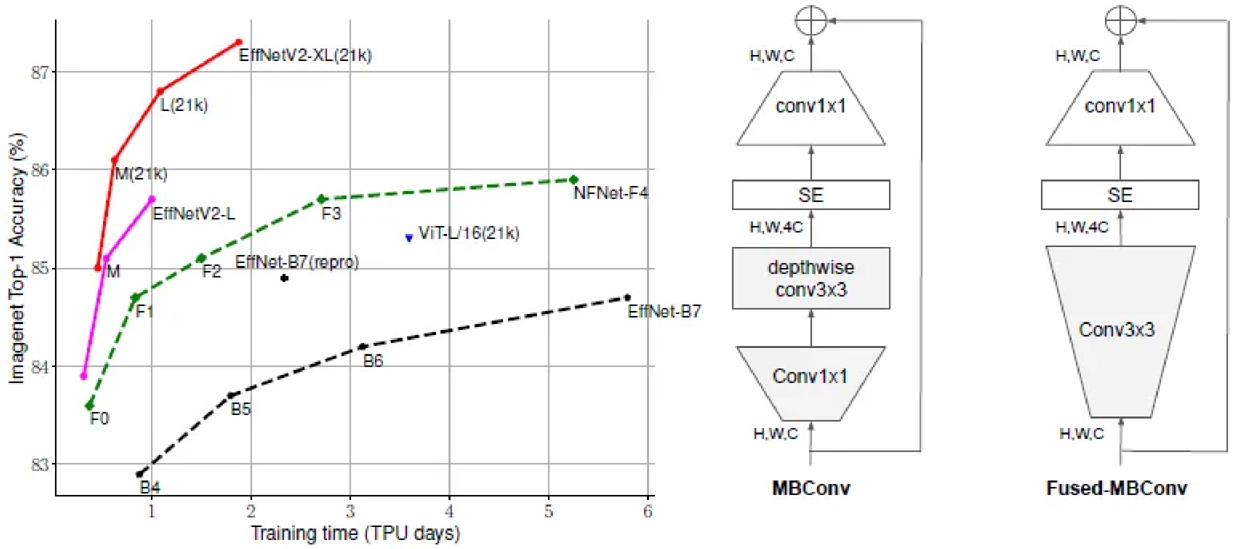


Figure 3.10: VGG16 Architecture [9].

In this paper, we used VGG16 to detect corn leaf diseases classification and we obtained a performance of 81 percent accuracy, a 77 percent F1-score, and a recall of 78 percent. After 10 input data epochs utilizing 80:20 training to test data.

3.4.4 EfficientNetV2B2

The EfficientNetV2 model developed by Mingxing Tan and Quoc V. Le is an innovative convolutional neural networks that achieve higher quicker training speeds and parameter efficiency than earlier models. It was created through training-aware neural architecture search and scaling, improves both model size and training speed while including new procedures like Fused-MBConv. This method allows EfficientNetV2 to be up to 6.8 times smaller and much quicker than other models. Furthermore, the design enhances further progressive learning by adaptive increasing regularization in parallel with image size, ensuring accuracy while preventing overfitting [12]. Moreover, it surpassed most current Vision Transformer (ViT) by 2.0% in accuracy and trained 5x-11x quicker with the same computing resources.



(a) Training efficiency.

	EfficientNet (2019)	ResNet-RS (2021)	DeiT/ViT (2021)	EfficientNetV2 (ours)
Top-1 Acc.	84.3%	84.0%	83.1%	83.9%
Parameters	43M	164M	86M	24M

(b) Parameter efficiency.

Figure 3.11: EfficientNetV2 Structures [12], [10].

In this paper, we used EfficientV2B2 in maize disease classification and achieved a performance of 92 percent accuracy, 90 percent f1-score and a recall of 90 percent, after ten input data epochs at an 80:20 training-to-testing ratio. This makes EfficientNetV2 not just a very efficient image classification model, but also a dependable option for real-world applications requiring speedy training and inference.

3.4.5 Xception

Xception model created by François Chollet in 2017 introduces a important step forward in convolutional neural network (CNN) design by using depth-wise separable convolutions, which separate spatial and depth operations to reduce parameters and computational costs while maintaining high computational power. This method enables Xception to surpass InceptionV3, particularly for large-scale image classification tasks. Xception outperfoms InceptionV3 on both ImageNet dataset and on a larger dataset with 350 million images with 17,000 classes, all without increasing the number of parameters [7]. Furthermore, Xception's architecture is made up of entry and exit flows, which are strengthened by ResNet-inspired skip connections, and it uses global depthwise separable convolutions in its final layers to record global context. Additional tactics like data augmentation and batch normalization help to ensure quick training and higher results. Moreover, in our study we employed the Xception Model in Maize disease classification and achieved a performance of 89% accuracy, 86% f1-score, and a recall of 86% utilizing 80:20 training to test data with 10 input data epochs. Therefore, Xception delivers outstanding results, establishing it as a robust and efficient model for a variety of computer vision tasks.

3.5 Proposed Model

In this study we assessed different transfer learning models in maize leaves and classify them as Healthy, Maize Lethal Necrosis (MLN), or Maize Streak Virus (MSV). In our extensive analysis of the dataset, we used models such as ResNet50, EfficientV2B2, Xception, VGG16, and InceptionV3 and the results are shown in figure 3.12. Our evaluation of training outcomes revealed:

- ResNet50 obtained 91% accuracy, with an F1-score and recall of 89%
- InceptionV3 achieved 80% accuracy, an F1-score of 75%, and a recall of 76%
- VGG16 obtained an accuracy of 81%,an F1-score of 77% and a recall of 78%
- Xception acquired an accuracy of 89%, an F1-score of 86% and a recall of 86%

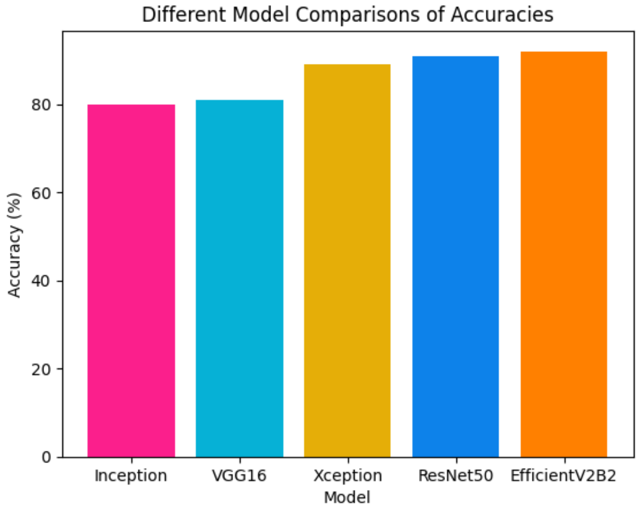


Figure 3.12: Accuracies Comparision

EfficientV2B2 fared better than the others, with an accuracy of 92%, an F1-score of 90%, and a recall of 90%. Given its higher overall performance, we chose EfficientV2B2 as the best model to be used in our study.

Chapter 4

Results and Discussion

This section discusses the key findings of the study, providing comprehensive analysis and results interpretation of the machine learning models used in training the datasets.

4.1 VGG16

Using the VGG16 Model with 10 epochs, 383 batches and a data split ratio of 2:8, with 80% for training and 20% for validation. An accuracy of 81% was obtained. To facilitate clear understanding, a visual representation has been employed. The following confusion matrix(4.1) and table(4.1) highlights the key trends and patterns observed in training the dataset with the VGG16.

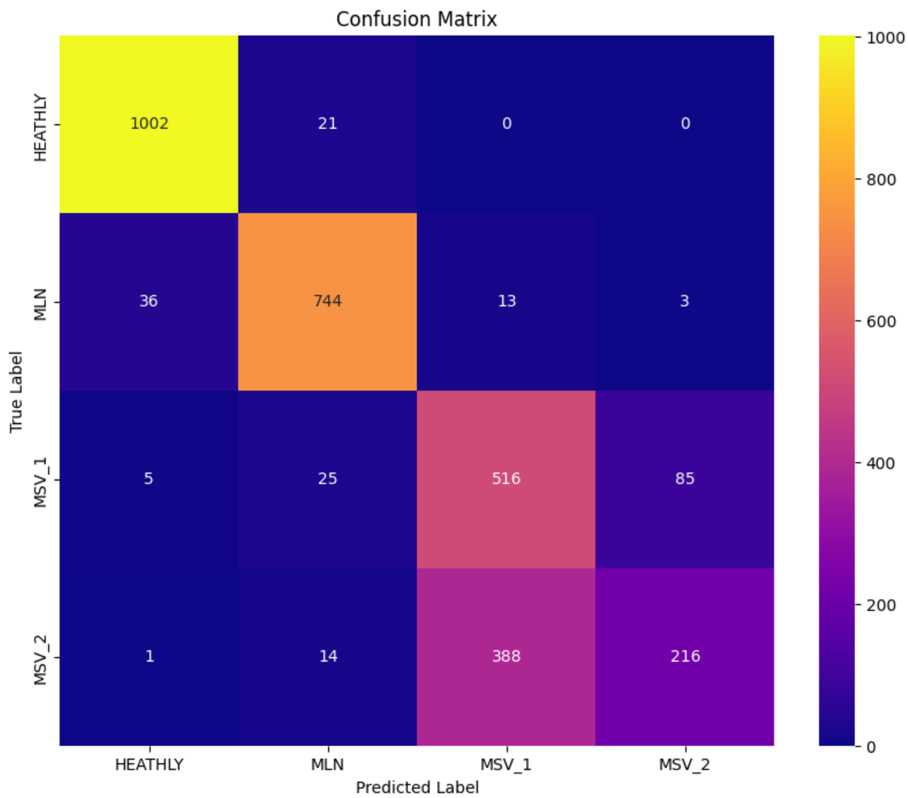


Figure 4.1: VGG16 Model Confusion matrix

Class	precision	recall	f1-score	support
HEALTHY	0.97	0.96	0.97	1023
MLN_1_and_MLN_2	0.91	0.97	0.93	796
MSV_2	0.57	0.82	0.68	631
MSV_1	0.73	0.36	0.48	619
Accuracy			**0.81**	3069
macro avg	0.80	0.78	0.77	3069
weighted avg	0.82	0.81	0.80	3069

Table 4.1: Classification Report(VGG16 Model).

4.2 InceptionV3

Employing the Inception Model on the dataset with 10 epochs, 383 batches and a data split ratio of 2:8, with 80% for training and 20% for validation.The model accumulated 80% accuracy. To ensure clarity, the following confusion matrix(4.2) and table(4.2) highlight the key trends and patterns observed in training the dataset with the Inception Model

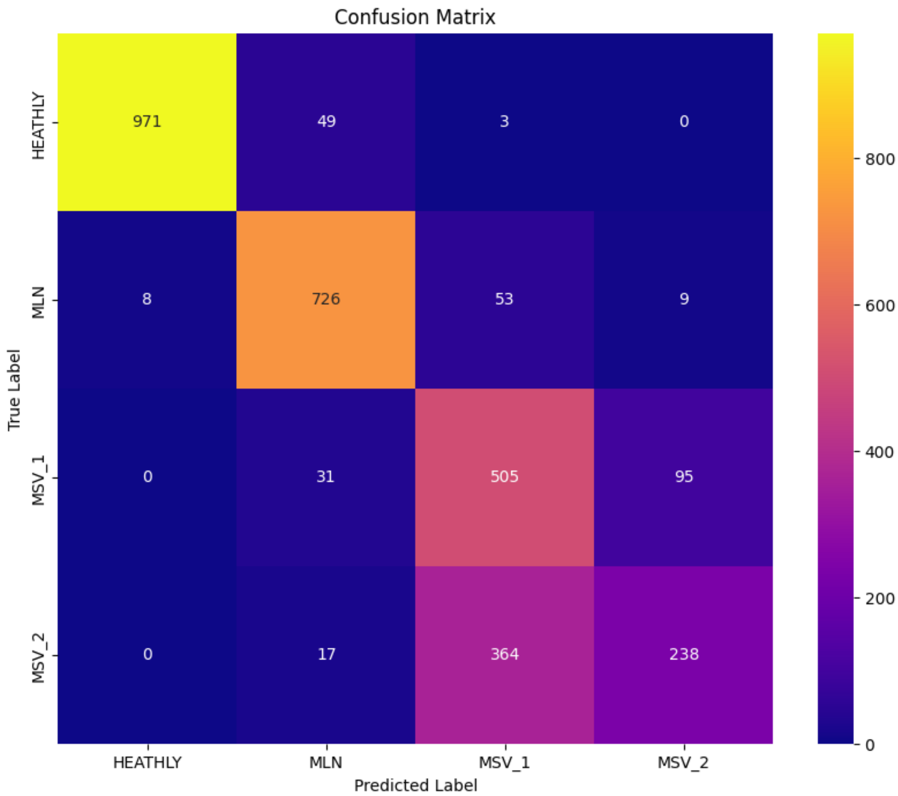


Figure 4.2: Inception Model Confusion matrix

Class	precision	recall	f1-score	support
HEALTHY	0.99	0.95	0.97	1023
MLN_1_and_MLN_2	0.88	0.91	0.90	796
MSV_2	0.55	0.80	0.65	631
MSV_1	0.70	0.38	0.50	619
Accuracy			**0.80**	3069
macro avg	0.78	0.76	0.75	3069
weighted avg	0.81	0.80	0.79	3069

Table 4.2: Classification Report (Inception Model).

4.3 Xception

Training the datasets with Xception Model using 10 epochs, 383 batches and a data split ratio of 2:8, with 80% for training and 20% for validation yielded an accuracy of 89%. To aid understanding, the following confusion matrix(4.3) and table(4.3) highlight the key trends and patterns observed in training the dataset with the Xception model.

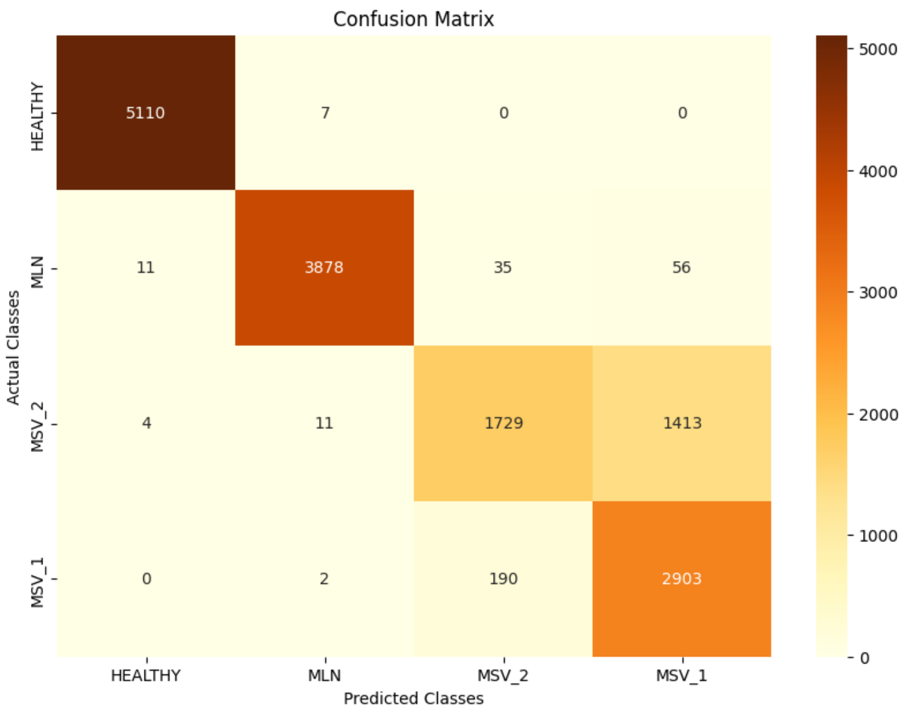


Figure 4.3: Xception Model Confusion matrix

Class	precision	recall	f1-score	support
HEALTHY	1.00	1.00	1.00	1023
MLN_1_and_MLN_2	0.99	0.97	0.98	796
MSV_2	0.88	0.55	0.68	631
MSV_1	0.66	0.94	0.78	619
Accuracy			**0.89**	3069
macro avg	0.89	0.86	0.86	3069
weighted avg	0.91	0.89	0.88	3069

Table 4.3: Classification Report (Xception Model).

4.4 ResNet50

Training the datasets with the ResNet50 Model, 10 epochs, 383 batches and a data split ratio of 2:8 was used, with 80% for training and 20% for validation which yielded an accuracy of 91%. To aid understanding, the following confusion matrix(4.4) and table(4.4) highlight the key trends and patterns observed in training the dataset with the ResNet50 model

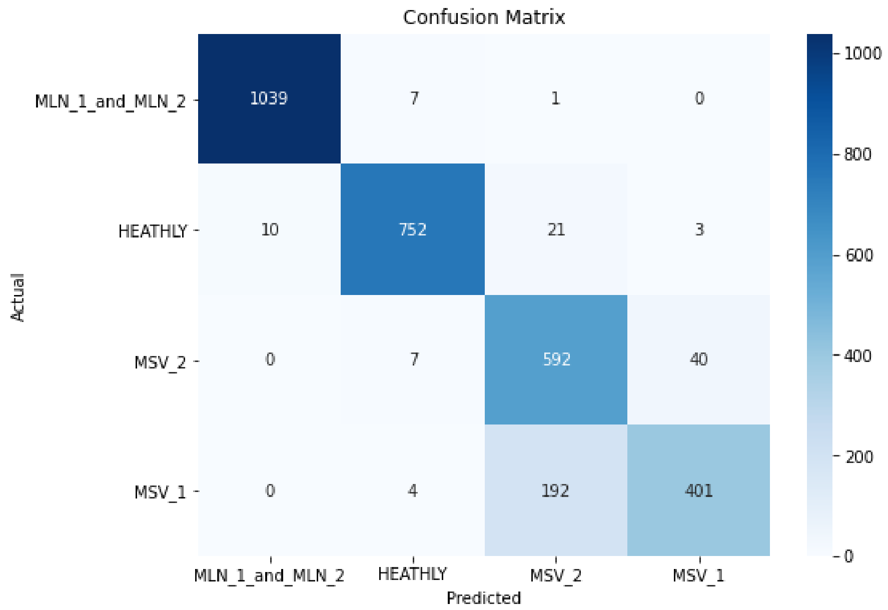


Figure 4.4: ResNet50 Model Confusion matrix

Class	precision	recall	f1-score	support
HEALTHY	0.99	0.99	0.99	1023
MLN_1_and_MLN_2	0.98	0.96	0.97	796
MSV_2	0.73	0.93	0.82	631
MSV_1	0.90	0.67	0.77	619
Accuracy			**0.91**	3069
macro avg	0.90	0.89	0.89	3069
weighted avg	0.92	0.91	0.91	3069

Table 4.4: Classification Report (ResNet50 Model).

4.5 EfficientV2B2

Employing the EfficientNetV2B2 model to the dataset with 10 epochs, 383 batches and a data split ratio of 2:8 was used, with 80% for training and 20% for validation which yielded an accuracy of 91%. To visualize the findings, the following confusion matrix(4.5) and table(4.5) highlight the key trends and patterns observed in training the dataset with the EfficientNetV2B2 model.

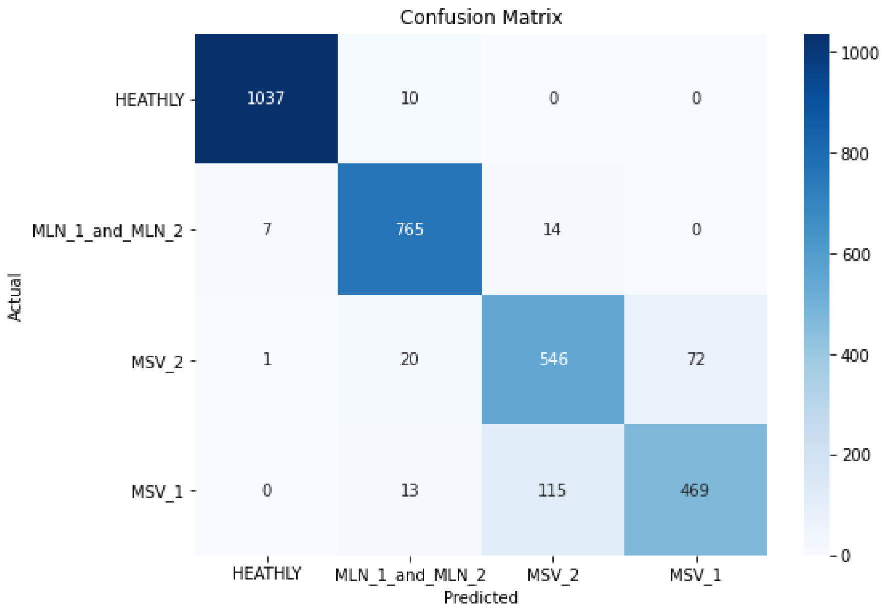


Figure 4.5: EfficientNetV2B2 Model Confusion matrix

Class	precision	recall	f1-score	support
HEALTHY	0.99	0.99	0.99	1023
MLN_1_and_MLN_2	0.95	0.97	0.96	796
MSV_2	0.81	0.85	0.83	631
MSV_1	0.87	0.79	0.82	619
Accuracy			**0.92**	3069
macro avg	0.90	0.90	0.90	3069
weighted avg	0.92	0.92	0.92	3069

Table 4.5: Classification Report (EfficientNetV2B2 Model).

4.6 Classification Summary

Table 4.6: Performance Metrics of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Inception	80	78	75	76
VGG16	81	80	76	77
Xception	89	89	86	86
ResNet50	91	89	89	89
EfficientNetV2B2	**92**	**90**	**90**	**90**

4.7 Comparison Of Module Accuracy

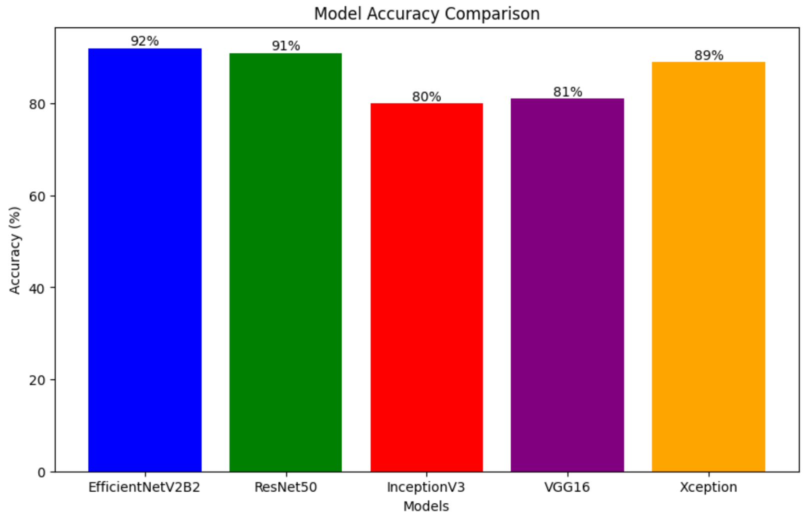


Figure 4.6: Comparison of Model Accuracy

4.8 Discussion

Figure 4.6 compares all the model's accuracies concerning the three types of accuracies, training accuracy, validation accuracy, and test accuracy. For the Xception Model, training accuracy acquired the highest peak of accuracy of about 0.96, with a validation accuracy of around 0.80 and a test accuracy slightly above 0.75, indicating high training accuracy but lower test and validation accuracy.

Additionally, the Inception Model had the lowest training accuracy of about 0.78, making it the lowest among all the models. With a validation accuracy that is approximately below 0.77 and a test accuracy slightly below 0.80, a relative consistency is shown by the model across all datasets, but with the lowest overall accuracy. On the other hand, the training accuracy of the EfficientNetV2B2 model is around 0.90, with validation accuracy a little bit above 0.90 and test accuracy slightly below 0.90. Based on these minimal differences between the three types of accuracy, the EfficientNetV2B2 model showed a balanced performance. Furthermore, the test accuracy of the VGG16 model was about 0.75, the validation accuracy was roughly 0.80, and the accuracy was roughly 0.87. Like the Xception model, VGG16 suggests that there may have been overfitting. Regarding consistent performance, optimal generalization, and possible overfitting,. Both Xception and VGG16 showed potential overfitting, with their training accuracy much higher than the test and validation accuracies. ResNet50 and EfficientNetV2B2 exhibited the best generalization, with all three types of accuracy being close to each other. The measures of the three types of accuracy on our datasets show that training accuracy is the highest, followed by validation accuracy and test accuracy. Inception showed consistent but lower performance across all the datasets. The reason behind the measured results is that the training dataset is used for training the model, for fine-tuning the model, the validation dataset is used; and the test dataset is used to evaluate the generalizability of the model.

Overall, EfficientNetV2B2 has the best-performing model because there is a balanced performance across the training, validation, and testing of the datasets, with very minimal differences exhibiting good generalization compared to the other models. Additionally, EfficientNetV2B2 has a higher accuracy across the different datasets when compared to the accuracy of the other models. The model is dependable for data with constantly fluctuating conditions because of its accuracy level. Moreover, EfficientNetV2B2 shows less overfitting than the other models used, which makes it a highly significant model for real-world applications where the performance of unseen data matters. The effective NetV2b2 performs well in terms of recall and precision, particularly for the health dataset.

Chapter 5

Explainable Artificial Intelligence

Explainable AI is a technique utilized by AI experts to examine deep learning algorithms. It offers the necessary clarity in understanding the intricate operations of the algorithm, explaining the reasons and methods behind it. Grad-CAM utilizes the gradients of a specific target passing through the convolutional network to identify and emphasize areas of the target within the image [23]. For transparent decision-making, XAI (Explainable Artificial Intelligence) techniques have been implemented. Grad-CAM (Gradient Weighted Class Activation Mapping) and Integrated Gradient techniques were integrated with EfficientNetV2B2 to enhance model interpretation. In the below figures 5.1, 5.2, 5.3, 5.4, 5.5, 5.6, 5.7, 5.8, 5.9, 5.10, 5.11, and 5.12 we can see the implementation of Grad-CAM XAI method with our high performing model, EfficientV2B2.

Figure 5.1: Original image Healthy

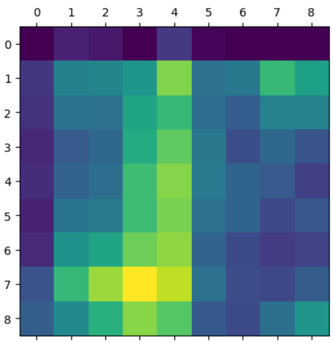


Figure 5.2: Heat Map Healthy

Figure 5.3: Grad-CAM Healthy

Figure 5.4: Original image MLN

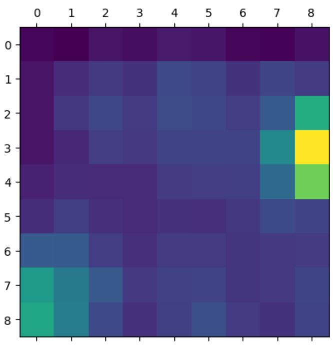


Figure 5.5: Heat Map MLN

Figure 5.6: Grad-CAM MLN

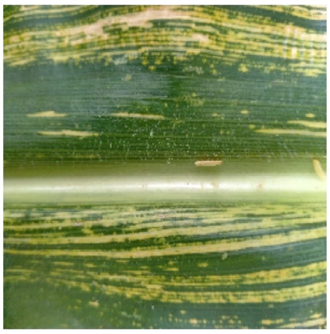


Figure 5.7: Original image MSV1

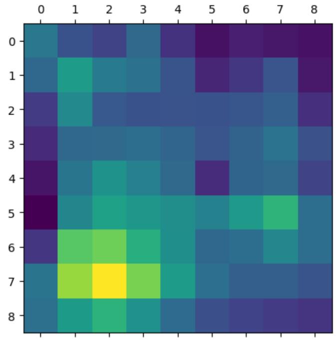


Figure 5.8: Heat Map MSV1

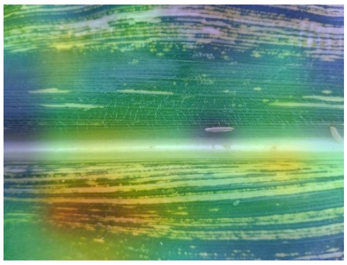


Figure 5.9: Grad-CAM MSV1

Figure 5.10: Original image MSV2

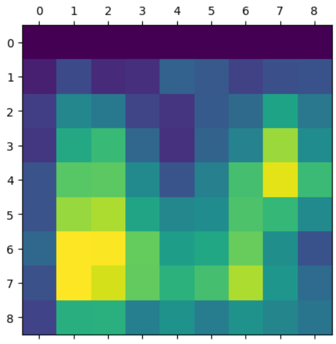


Figure 5.11: Heat Map MSV2

Figure 5.12: Grad-CAM MSV2

Chapter 6

Conclusion and Future Direction

In conclusion, Through the development of deep learning based diagnostic tools together with Explainable Artificial Intelligence, this study aims to address the danger of diseases imposed on maize crops. By evaluating the CNN models and incorporating XAI techniques, we can attain reliable, accessible and interpretable disease detection which would ultimately increase maize agricultural production by improving maize disease detection management. The efficiency of the deep learning techniques in plant disease detection have been proven by various researchers and have made a significant impact on agriculture across the world. With the accumulated knowledge of related works of various researchers altogether with the regimental work plan, EfficentNetV2B2 Model attained the overall best performance out of the five selected Convolutional Neural Network Model. The EfficientNetV2B2 Yielded good results in terms of balanced training, validation and test accuracy with slight differences. Other models like Xception and VGG16 exhibited good performance but EfficientNetV2B2 excelled in areas of fluctuating conditions, making it suitable for real world application where unseen data performances are essential. The ability of EfficientNetV2B2 highlights a great potential to effectively predict maize disease.

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