Development and Evaluation of a Fine-Tuned EfficientNet-B0 Model for Maize Disease Detection

Kayombo Sakachiva
kayombosakachiva84@gmail.com

ZCAS University
Jackson Phiri
University of Zambia
Mayumbo Nyirenda
University of Zambia

Research Article

Keywords: Maize disease detection, EfficientNet-B0, Deep learning, Transfer learning, Convolutional Neural Networks, Plant disease classification, Artificial Intelligence

Posted Date: September 2nd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10619639/v1

Additional Declarations: No competing interests reported.

Development and Evaluation of a Fine-Tuned EfficientNet-B0 Model for Maize Disease Detection

Kayombo Sakachiva: School of Computing, Technology and Applied Sciences, ZCAS University, Lusaka, Zambia. Email: kayombosakachiva84@gmail.com. Jackson Phiri: Department of Computer Science, University of Zambia, Lusaka, Zambia Email: jackson.phiri@cs.unza.zm. Mayumbo Nyirenda: Department of Computer Science, University of Zambia, Lusaka, Zambia. Email: mayumbo@gmail.com

"Corresponding author: Kayombo Sakachiva"

ABSTRACT

Maize is the staple crop for millions of people in Sub-Saharan Africa, particularly for Zambia. Unfortunately, maize crops are exposed to several serious threats due to their susceptibility to foliar diseases like Maize Rust, Leaf Blight, Leaf Spot, Maize Streak Virus, and Maize Lethal Necrosis that may lead to great yield losses. Conventional methods of crop disease identification consist of field surveys that are not only subjective but also difficult to conduct for smallholder farmers.

This paper presents the design and evaluation of a highly optimized version of the EfficientNet-B0 Convolutional Neural Network for the automatic detection of maize leaf diseases using maize leaf images obtained from real-world scenarios. The proposed model utilized the concept of transfer learning with ImageNet pre-trained weights and was trained on the Mendeley Maize Crop Disease (Leaf) Dataset which consists of 30,120 images in nine maize disease classes.

The developed fine-tuned EfficientNet-B0 yielded 97.57% classification accuracy, macro precision of 97.61%, macro recall of 97.64%, and macro F1-score of 97.61%. From these results, it is evident that transfer learning and fine-tuning greatly boost maize disease classification accuracy while ensuring high computational efficiency. This study makes a significant contribution to precision agriculture as it offers an accurate and computationally efficient AI-based maize disease classification model, which could help smallholder farmers in early maize disease classification.

Keywords: Maize disease detection, EfficientNet-B0, Deep learning, Transfer learning, Convolutional Neural Networks, Plant disease classification, Artificial Intelligence

CHAPTER ONE

1.1 Introduction

Maize (Zea mays L.) also called corn is a key cereal crop in the world, being one of the top three crops whose annual production amounts to more than 1.2 billion tons. It acts as an essential source of food, feed, and material for industries. In sub-Saharan Africa (SSA), maize is the main staple crop that is used to secure food for millions of small scale farmers. while contributing significantly to household incomes, rural economies, and national GDP [1], [2].

The maize crop is considered to be the most significant crop in Zambia due to the fact that maize occupies above 65 percent of total land used for farming. It is very important for feeding people in Zambia, and it also functions as a vital cash crop in the economy of Zambia [3]. Cereals like maize which form breakfast meals constitute more than 30 percent of total energy consumed in more than 20 African nations, maize production is widespread in eastern and southern Africa [4].

Figure 1 below shows a detailed representation of cereals produced in the different countries in Africa using three different panels. Panel A (Bar Chart) shows the yield of cereals in 100g/ha for the selected African countries, and from the graph, it is evident that Mauritius, Egypt, and South Africa have the highest yields, whereas Zambia has medium yield compared to others. Panel B (Donut/Pie Chart) shows the percentage contribution of the most productive cereal producers in terms of volume in millions of tons. Ethiopia comes first with 31.6%, Nigeria second with 30.3%, Egypt third with 23.9%, South Africa fourth with 18.7%, and other countries such as Mali, Tanzania, Sudan, Niger, Burkina Faso, and Ghana with smaller percentages. Panel C (Map of Africa) shows the area harvested in hectares for cereals, where Nigeria takes the lead in having the largest cultivation area (darkest) [4].

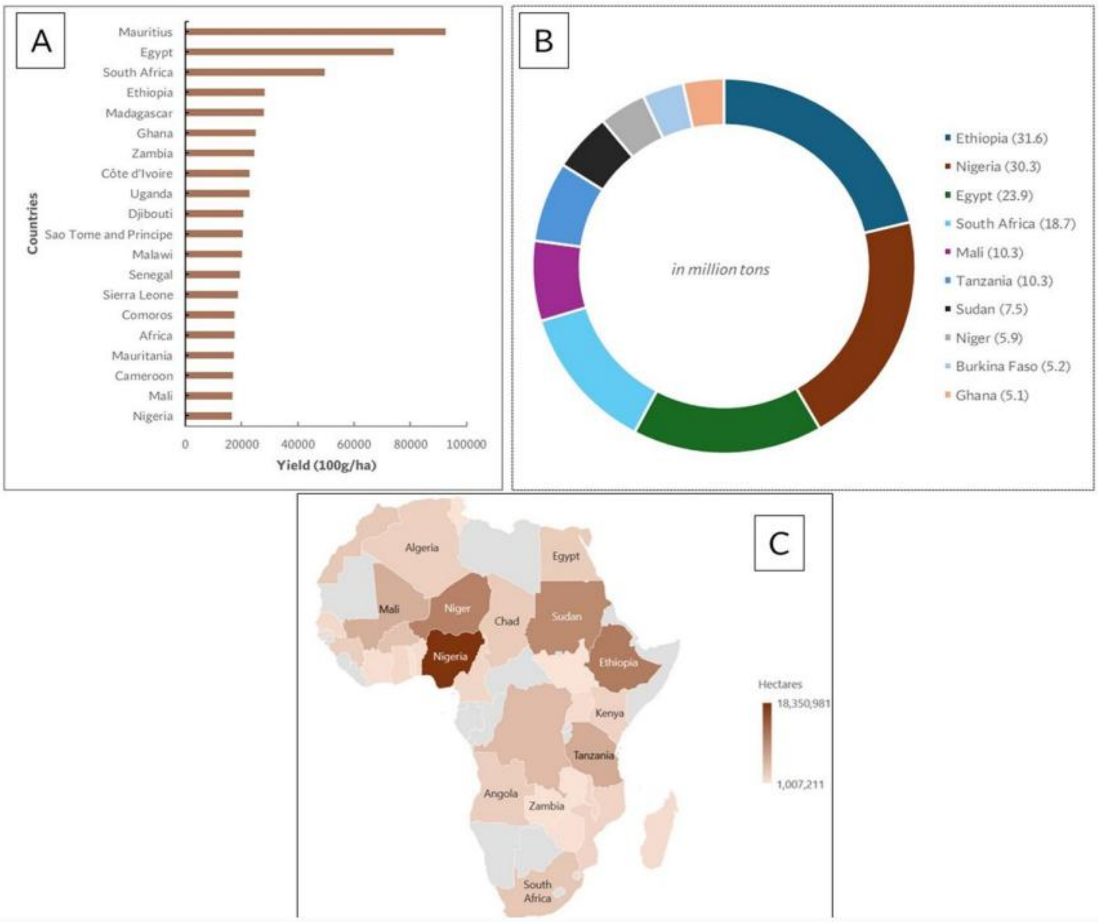


Figure. 1 Top African countries in cereal production per yield (A), production quantity (B) and area harvested (C) Source: [4]

In most cases, Figure 1 serves to demonstrate the control of a few nations in the production of cereals within Africa with an illustration of Zambia as one of the countries contributing to the region's production in Southern Africa. This data serves to stress the relevance of cereals and maize especially for food security purposes in sub-Saharan Africa and gives relevant context for AI-assisted plant disease detection studies [4].

Despite the strategic importance of maize cultivation in the area, this activity is severely constrained by the prevalence of disease, which include, among others, the Northern Leaf Blight (NLB), Gray Leaf Spot (GLS), Common Rust, Southern Rust, and Maize Lethal Necrosis Disease (MLND). Such diseases can cause a loss of up to 30 % to as much as 90 %, based on the severity of the situation. This causes poverty, malnutrition, and economic instability [2], [5]. The manual methods of disease detection, whereby the farmer or agriculture field officer conducts visual inspections are not only time-consuming and subjective but also ineffective [6].

As a result, deep learning algorithms, in particular, Convolutional Neural Network (CNN), have become highly important in automatic plant disease detection using leaf image data due to the ability of CNN to automatically learn hierarchical visual features on a complicated dataset. There are many constraints related to CNN-based system that should be resolved in order to apply CNNs effectively for diagnosing plants in the field [7], [8].

To address these challenges, this research study evaluates the performance of the optimized model of EfficientNet-B0 for the detection of diseases in maize leaves. The proposed model makes use of transfer learning and fine-tuning techniques by taking into account the capabilities of the pre-trained CNN model in extracting features for disease classification. EfficientNet-B0 is a computationally efficient architecture in that the optimized network scaling technique enables the model to represent features more efficiently compared to other CNN models with less number of parameters [9]. Research studies have proved the effectiveness of transfer learning using EfficientNet models for plant disease classification.

In addition to proposing the model, the study provides an analytical evaluation of various existing CNN models for maize disease detection.

1.2 Background and Motivation

Apart from all the problems discussed above, the cultivation of maize crops in the sub-Saharan part of Africa is also under severe competition from the foliar diseases described above. For instance, the prevalence of Maize Lethal Necrosis Disease (MLND) disease has led to economic losses which have been evaluated at up to $180 million in the regions affected. This is highly harmful especially for the small-scale farmers who operate in poor environments [5].

Though CNN models, which have been trained by utilizing benchmarking data sets like PlantVillage, have achieved remarkable accuracy rates (above 95% in many cases) in laboratory settings by adopting architectures like ResNet, EfficientNet, and VGG [6], [10], it has been shown recently that Transfer Learning with pre-trained models like EfficientNet-B0 is able to improve plant diseases classification [10], [9]. EfficientNet-B0 has been chosen to be used in this project due to its good trade-off between classification accuracy and computational speed, which makes it a perfect fit for the application to agricultural data as well as lightweight deployment in the future. The proposed model has been tested on an independent testing dataset as well as prediction simulation.

The motivation for this research arises from the gap between the highly accurate deep learning algorithm developed for maize disease prediction under experimental conditions and the insufficient research done on the possibility of implementing the same into mobile based decision making systems that can work in constrained environments like Zambia. This research tries to fill in the gap by developing a lightweight deep learning algorithm and showing its ability to infer through mobile deployment simulation using unseen test images.

1.3 Problem Statement

The introduction of deep learning methods has played an important role in enhancing automated disease recognition in plants due to high classification accuracy as compared to the conventional methods for diagnosing the diseases in plants. The recent research papers indicate that models such as EfficientNet, ResNet, and others can provide superior results as compared to other algorithms in terms of classifying diseases in maize and other crops [11], [12]. Nevertheless, many research papers are concentrated on classification accuracy and do not address the issue of computing resources and practical implementation.

Despite the success shown by deep learning algorithms, they cannot be easily applied to resource-constrained agriculture settings because of the need to implement efficient algorithms that can run on mobile phones and edge computing devices. Most complex deep learning algorithms such as CNNs need high computational power and memory storage, which makes them unsuitable for affordable agricultural decision support systems based on mobile technology [12], [13]. Moreover, researchers have identified the need to develop efficient models that achieve high classification performance has been emphasized [11], [14].

Furthermore, there is a lack of consideration of factors like model efficiency, reproducibility, and usability among others in the majority of currently available approaches, although much attention is being paid to accuracy. There seems to be a mismatch between highly performing deep learning models being researched in laboratories and their practical applications.

That is why this study will address these problems by developing and testing a fine-tuned EfficientNet-B0 model for maize disease detection. The suggested solution uses the methods of transfer learning and fine-tuning. In addition, the proposed solution will be compared to currently existing CNN models, and the deployment feasibility will be tested using mobile prediction simulation.

1.3 Research Objectives

1. To develop and implement a fine-tuned EfficientNet-B0 deep learning model for the automatic classification of maize leaf diseases using maize leaf images.
2. To evaluate the performance of the proposed fine-tuned EfficientNet-B0 model using standard evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis, and compare its performance with existing CNN-based models.
3. To analyse the prediction capability of the proposed EfficientNet-B0 model using unseen test images through image-based simulation to assess its suitability for future mobile-based maize disease detection applications.
4. To evaluate the computational efficiency of the proposed model, including model size and inference performance, to determine its suitability for lightweight deployment in resource-constrained agricultural environments.

1.4 Research Questions

This study seeks to answer the following research questions:

1. How can a fine-tuned EfficientNet-B0 deep learning model be developed for automatic classification of maize leaf diseases using image-based analysis?
2. How does the proposed fine-tuned EfficientNet-B0 model perform in maize disease classification based on accuracy, precision, recall, F1-score, and confusion matrix analysis compared with existing CNN-based approaches?
3. How effectively can the proposed EfficientNet-B0 model classify unseen maize leaf images, and what confidence levels can be achieved during prediction simulation?
4. What is the computational efficiency and deployment potential of the fine-tuned EfficientNet-B0 model for future mobile-based maize disease detection applications in resource-constrained environments?

1.4 Contributions of the Study

This study makes the following key contributions to the field of AI-augmented plant disease detection:

1. Designing of an efficient EfficientNet-B0 machine learning model for the classification of maize leaves diseases.
2. Performance analysis and comparison of the suggested model with some existing machine learning techniques based on CNNs.
3. Simulation testing for prediction capability of the suggested model through unseen images.
4. Achievement of high classification performance while maintaining computational efficiency.
5. Provision of experimental results as support to the suitability of EfficientNet-B0 as a lightweight technique for automation of maize disease detection.

CHAPTER TWO

2. Literature Review

2.1 Overview of Traditional vs. AI-Based Plant Disease Detection

In conventional ways, plant diseases have been detected through the process of manual scouting in the field conducted by farmers and agricultural experts, in addition to laboratory techniques including PCR, ELISA, and microscopy. Although this approach is regarded as the most accurate one, it is subject to many limitations. First, it is very laborious and time-consuming; secondly, it depends heavily on the expertise of the person carrying out the process; thirdly, it is costly to implement in large plantations and far-off farms. Additionally, it does not work well in detecting diseases in their initial stages, thus making it useless.[1], [2], [15].

The emergence of AI, especially the deep learning approach, has transformed this area significantly. AI techniques offer automated, non-invasive, fast, and scalable diagnostics through the use of images of leaves captured by smart phones. The Convolutional Neural Networks (CNN) technique has been adopted as the core technique because of its capability of extracting hierarchical spatial features from the raw images in an automatic way without manually doing the feature engineering [6], [16]. On one hand, this has decreased reliance on the agricultural experts who are rare, and on the other hand, it facilitates decision making in precision agriculture. However, while AI approaches show enormous potential, their transformation from laboratory success to field deployment remains challenging [17].

2.2 Public Datasets for Plant and Maize Disease Detection

The PlantVillage dataset [18], [19], released in 2016, has been the most dominant benchmark to date, with more than 54,000 images of 38 diseases in 14 types of crops, including some of the diseases that affect maize (Common Rust, Northern Leaf Blight, Gray Leaf Spot, and healthy leaves). It has allowed significant advancements to be made in the field due to achieving reported accuracy rates above 95-99% [6], [20].

PlantVillage has a number of limitations even despite the usefulness. All the images were obtained under laboratory settings and uniform backgrounds, proper lighting, and single leaves, which is not a good representation of field conditions that may include variation in lighting, complicated background, occlusion, different stages of the disease, and co-infection [21], [22], [23]. Experiments reveal a huge decrease in accuracy (>30-40%) on field images using PlantVillage-trained model [24], [25].

In order to solve these problems, the research community has made use of special maize datasets. The examples of such datasets are field-based maize datasets collected in Africa (for example, Mendeley Maize Leaf Disease Dataset), which utilize natural lighting and various backgrounds with maize in Africa [26]. Such datasets represent practical situations better, but tend to be smaller, imbalanced, and less structured.

2.3 Evolution of CNN Architectures in Plant Disease Detection

The development of CNNs for plant diseases started from classical CNNs. Some pioneering research on using CNNs was conducted were AlexNet and GoogLeNet network was used on the PlantVillage dataset and attained an accuracy of more than 99%. The further research used deep CNNs, such as VGG16/19, ResNet50/101, and Inception-v3, which showed outstanding performance [6], [27].

The emphasis then moved on to scalability and efficiency. EfficientNet, MobileNetV2/V3, and DenseNet have been designed to achieve smaller and cheaper models that can be easily deployed on mobile and edge devices used by smallholder farmers [16], [28]. Pre-trained models from ImageNet have become a norm in order to deal with a shortage of agricultural data [28].

EfficientNet-B0, once fine-tuned, has become the most effective architecture in the area of plant diseases detection, since this neural network combines the great performance and low cost effectively. A lot of researches have proven that once fine-tuned, EfficientNet-B0 networks could reach high accuracy rates (95% and above) for plant disease detection tasks while being small enough to be run on mobile devices [9], [29]. Concerning maize diseases detection, it is worth mentioning that fine-tuned EfficientNet-B0 networks have been successful in solving domain shift problems from laboratory to field images [11], [30].

However, despite these developments, domain shift still poses a significant challenge. Models trained on laboratory data often falter in the real world because of noise in the environment, necessitating the need for more robust models [22], [24].

2.4 Fine-Tuned EfficientNet-B0 for Plant Disease Detection

EfficientNet-B0 is one of the models receiving considerable focus in detecting diseases in plants owing to its great trade-off between accuracy and computation efficiency. It incorporates a compound scaling strategy which scales the depth, width, and resolution of the network simultaneously hence achieving high efficiency with lower parameter count than other models like ResNet50 and VGG16 [9], [31].

A number of studies have confirmed the efficacy of the transfer learning approach in the implementation of EfficientNet architectures for agricultural images classification. The use of EfficientNet results in improved trade-off between the model accuracy and efficiency, since EfficientNet is capable of providing high-level accuracy through simplification of the model structure, which is why it can be used for resource-limited hardware [9]. Recent studies of classification of plant diseases have proven that fine-tuned versions of EfficientNet models are able to provide comparable accuracy levels for agricultural data sets in comparison with other types of convolutional neural networks but with less number of parameters [32].

The use of pre-trained weights from ImageNet has become commonplace, thus leading to quick convergence and generalization despite small-sized datasets for agriculture. However, there are still issues that require addressing in terms of robustness to real-world conditions in the field like changes in light and backgrounds as well as varying stages of disease. Such issues show the need for evaluation of the proposed model in small-scale farms, especially those in sub-Saharan Africa.

2.5 Specific Studies on Maize Disease Detection

There has been an increasing amount of research conducted pertaining to maize disease detection in recent years. A number of research papers have studied various deep learning models for classifying maize leaf diseases [33].

Mehdipour [22] Proposed a lightweight hybrid CNN-Vision Transformer (ViT) model for maize leaf diseases classification. The proposed model was able to achieve a good level of classification accuracy, with a lower number of parameters compared to other state-of-the-art lightweight models.

Gülmez [6] has performed an extensive literature review on the use of CNN in detection of maize disease and brought forth many breakthroughs in deep learning algorithms. This study has shown that CNN algorithms have delivered impressive classification results; however, problems still exist in the areas of model generalization, variety of data set, and practical application.

As mentioned by Ma [34], They carried out research on CNN-based methods using transfer learning for classifying maize leaf diseases. The results revealed that pre-trained deep learning models enhance feature extraction and classification accuracy, especially where there is confusion in recognizing similar symptoms of the diseases. This study has shown the success of using transfer learning and has provided the reason for considering EfficientNet-B0 for detecting maize diseases.

Some other researchers also suggested advanced architectures. MaizeNet was developed by Z. Li [35] which is a deep residual neural network structure, designed to classify diseases on maize leaves. The MaizeNet architecture showed high capability in recognizing complex disease patterns and enhanced image classification capability of maize leaf images.

Recent systematic reviews have further stressed on the advancements made in the field of machine learning/deep learning techniques for detecting diseases in maize plants. This work has shown that the classification performance of CNN-based techniques is quite promising when measured based on some benchmark datasets. However, the importance of further research into the areas of diversity in datasets, computation efficiency, etc. has also been emphasized [17].

In conclusion, the effectiveness of deep learning techniques for disease detection in maize plants is proven by the previous studies. However, the majority of studies focus only on benchmark datasets used for high-classification performance measurement, with relatively limited attention given to lightweight model design, computational efficiency, and simulation of deployment scenarios suitable for resource-constrained agricultural environments.

2.6 Critical Analysis of Strengths, Limitations, and Research Gaps

Strengths:

i. High classification accuracy on benchmark data sets

   Deep learning models have shown high accuracy in classification tasks where many studies have achieved accuracies of more than 95% when tested on benchmark data sets.

ii. Automation and efficiency in disease detection

   By using CNN-based models, the need for human observation of the disease can be done away with since these models help in detecting the features of diseases and classify maize diseases automatically.

iii. Light-weight models development

   Recent research has focused on light-weight model development to reduce computational needs.

Limitations (detailed in Table 1 below).

i. Restricted testing other than benchmark data sets

   Several research papers test their models using a controlled data set, which might not adequately cover the variability that exists in practice when applying agriculture.

ii. Computational needs of advanced architectures

   Even though there are very accurate models, some models require high computational power, making them unsuitable to run on resource-constrained systems.

iii. Restricted research related to deployment optimization

   Most of the research is focused on enhancing the model's accuracy without sufficient analysis of the model size, inference efficiency, and mobile device deployment ability.

iv. Restricted data availability for agriculture

   There is a problem with the availability of diverse geographical data sets, especially in African agricultural settings.

Research Gaps:

i. From the literature review conducted, the following gaps have been identified:
ii. Lack of lightweight and efficient maize disease prediction models for deployment in future.
iii. Evaluation of efficiency of the models along with classification performance is lacking.
iv. There are fewer studies focused on developing reproducible and deployable deep learning approaches for agriculture applications under resource limitations.
v. The potential of deployment of such models has not been demonstrated practically with unseen image predictions.

2.7 Positioning of the Current Work

These gaps call for the development of learning models that not only perform well in terms of their predictive ability but take into consideration their computing abilities as well. Hence, this research designs and implements an optimized EfficientNet-B0 model for detection of maize diseases. This research is useful because it examines a light-weight transfer learning approach, compares its performance with the other CNN models, and analyses its viability for mobile-based applications in the future with the help of prediction simulations on unseen test data. Although the proposed method proves its deployability, testing it on independent field images is something for future research.

Table 1: Summary of Key Gaps in Existing Literature on Maize Disease Detection

Aspect	**Common Approaches in Literature**	**Identified Gaps / Limitations**	**References**
Model Generalization	Evaluation of CNN models using benchmark datasets with controlled image conditions	Limited evaluation using diverse datasets and images representing variations beyond controlled environments	[22], [24], [25], [17]
Computational Efficiency	Use of complex CNN and transformer-based	High computational requirements and limited optimization for resource-	[36], [28]

	architectures with high predictive performance	constrained mobile and edge deployment	
Computational Efficiency	Use of complex CNN and transformer-based architectures with high predictive performance	High computational requirements and limited optimization for resource-constrained mobile and edge deployment	[37], [38], [39]
Real-world Deployment	Lab-focused evaluation	Few studies on SSA smallholder contexts (e.g., Zambia)	[2], [17], [40]
Reproducibility and Accessibility	Development of individual models using specific datasets and experimental settings	Limited availability of standardized datasets, implementation details, and reproducible	[16]
Multimodal & Contextual Data	Image-based disease classification approaches	Limited integration of additional agricultural information such as weather, soil conditions, and sensor data	[40]

CHAPTER THREE

3. Materials and Methods

The current study is based on the use of the experimental research methodology, which contains some aspects of the design science research approach. The methodology requires designing, implementing, and thorough evaluation of the fine-tuned EfficientNet-B0 model for the purpose of maize leaf diseases detection. As illustrated in Figure 2, the proposed methodology starts with the collection and analysis of the Mendeley Maize Disease dataset, then stratified data split, and image processing. The preprocessed images are then employed for training an efficientNet-B0 model that was fine-tuned on pre-trained ImageNet weights. The model uses MBConvs blocks for extracting deep features and a fully-connected Softmax classifier head to classify images in nine classes of maize diseases. The optimization of the model is carried out through Adam optimization and cross-entropy loss. The trained model is evaluated based on the metrics such as accuracy, precision, recall, F1-score, ROC-AUC, specificity, and confusion matrix.

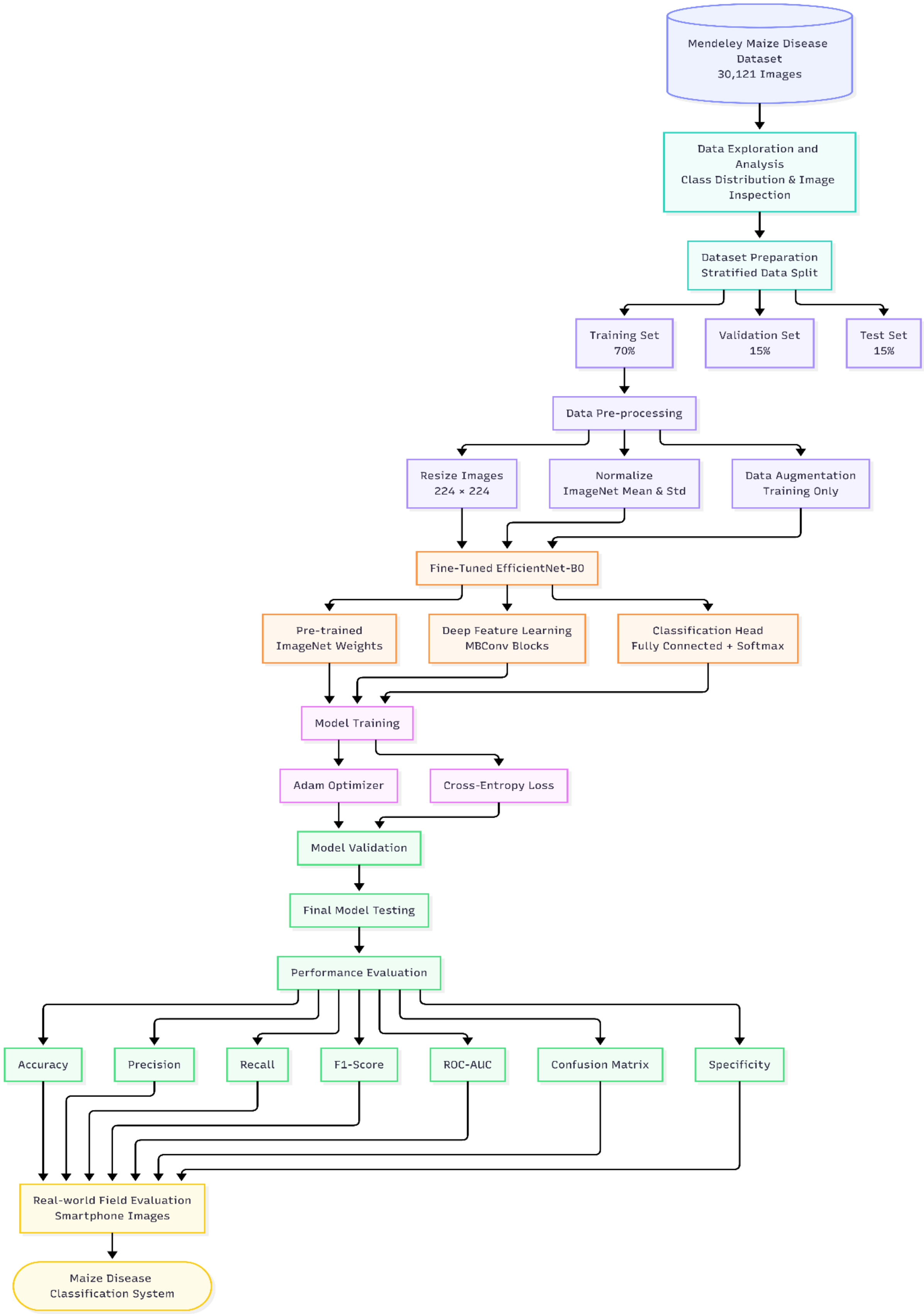


Figure 2: Proposed Methodology Framework for Fine-Tuned EfficientNet-B0-Based Maize Disease Detection

3.1 Dataset

For this study, the Mendeley Maize Crop Disease (Leaf) Dataset [26] was used as the main source for collecting the data. It involves the field collected images from an African setting, which contains eight categories of diseases of maize with varying symptoms, lighting, background, and local varieties of maize grown in sub-Saharan Africa. Using this dataset is a way of ensuring that the model is trained and tested on images that can be found in a real-world smallholder farming setup in countries such as Zambia.

Stratified sampling was used to split the data into three sets; namely training set (70%), validation set (15%), and testing set (15%). Data augmentation techniques such as random rotations, horizontal and vertical flips, changing brightness and contrast levels, and random crop operations were performed on the training set only.

The data set contains images of different kinds of maize leaf taken under natural light with background complexities, as depicted in Figure 3. Some examples of the images include images of healthy maize leaves with vein patterns, images of pests' attack on the leaves (fall armyworm, grasshopper, leaf beetle), and images of diseases such as rust, leaf spot, leaf blight, and streak virus. As depicted in Table 2, the dataset is balanced in terms of classes (i.e., there are thousands of images for each class; for example, Maize leaf blight has 3,376 images, Maize rust has 3,145 images, Maize leaf spot has 3,488 images).

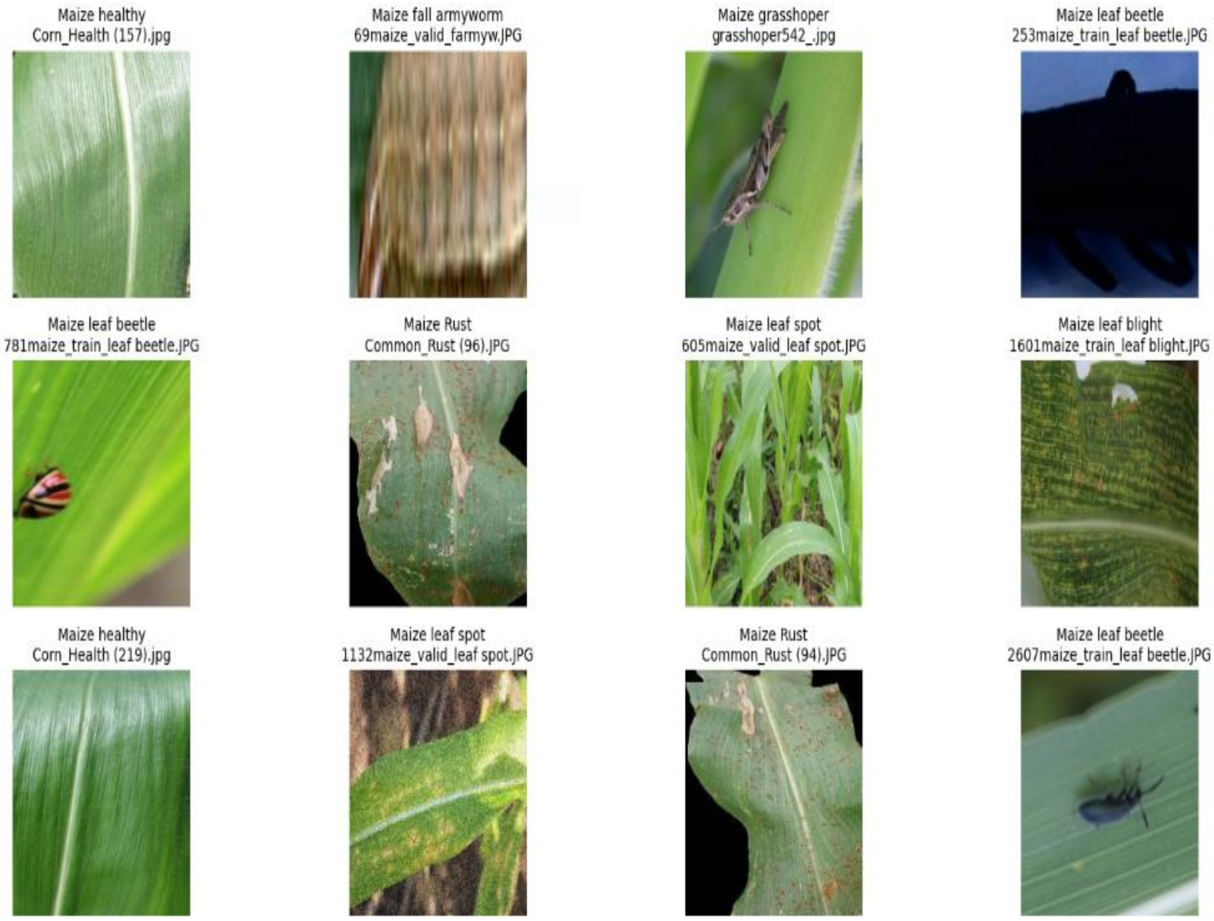


Figure 3. Representative sample images of maize leaf diseases from the dataset used in this study.

Table 2: Distribution of Maize Leaf Disease Classes

Class	Number of Images
Maize Fall Armyworm	2,560
Maize Grasshopper	3,712
Maize Healthy	3,520
Maize Leaf Beetle	3,616
Maize Leaf Blight	3,376
Maize Leaf Spot	3,488
Maize Lethal Necrosis	3,231
Maize Rust	3,145
Maize Streak Virus	3,472
Total	30,120

3.2 Data Pre-processing

Each of the images present in the dataset was resized to 224 × 224 pixels in accordance with the input criteria for the pre-trained CNN backbone (EfficientNet-B0). Normalization was done using the mean ([0.485, 0.456, 0.406]) and standard deviation ([0.229, 0.224, 0.225]) values used for ImageNet. This process is consistent with the weights of the pre-trained model and aids in faster model convergence.

The following data augmentation was used to make the model more robust to real-world image variations, but only on the training set. It comprised of the following transformations:

a) Random rotation (±15 degrees)
b) Flip horizontally and vertically
c) Brightness and contrast adjustment (±20%)
d) Random crop and zoom

The Mendeley Maize Crop Disease (Leaf) Dataset contained a total of 30,120 images. The dataset was divided into three sets as follows:

i. Training set: 21,084 images (70%)
ii. Validation set: 4,518 images (15%)
iii. Test set: 4,519 images (15%)

3.3 Proposed Model Architecture

The architectural design for the proposed model is based on the fine-tuned EfficientNet-B0 model, which is highly efficient and strikes a balance between performance accuracy and efficiency, thus making it appropriate for use in resource-limited environments [9].

As illustrated in Figure 4 below, this model has an architecture comprising of three stages:

Stage 1: Input and Pre-processing

i. Resize the maize leaves' images to 224 x 224 pixels.

ii. Include image normalization based on ImageNet stats, alongside data augmentation through rotation, flipping, change in the brightness and contrast levels, along with random crop and zoom only for the training data.

Stage 2: Feature Extraction

i. The backbone uses the ImageNet pre-trained weights.
ii. The backbone has a stem convolution layer, followed by seven stages of MBConv with different kernel sizes and expansion ratios.
iii. The feature extraction is thus a hierarchical one which extracts both low and high-level features from the input images.

Stage 3: Classifier Head

i. Use Global Average Pooling to downsample spatial dimensions.
ii. Use a dropout layer (with a rate of 0.2) as regularization.
iii. Apply Fully connected Layer along with Softmax activation function to generate multi-class output of nine categories of maize disease.

Transfer learning from pre-trained ImageNet weights was used to fine-tune this model for faster convergence and better results on the mendeley maize leaf dataset.

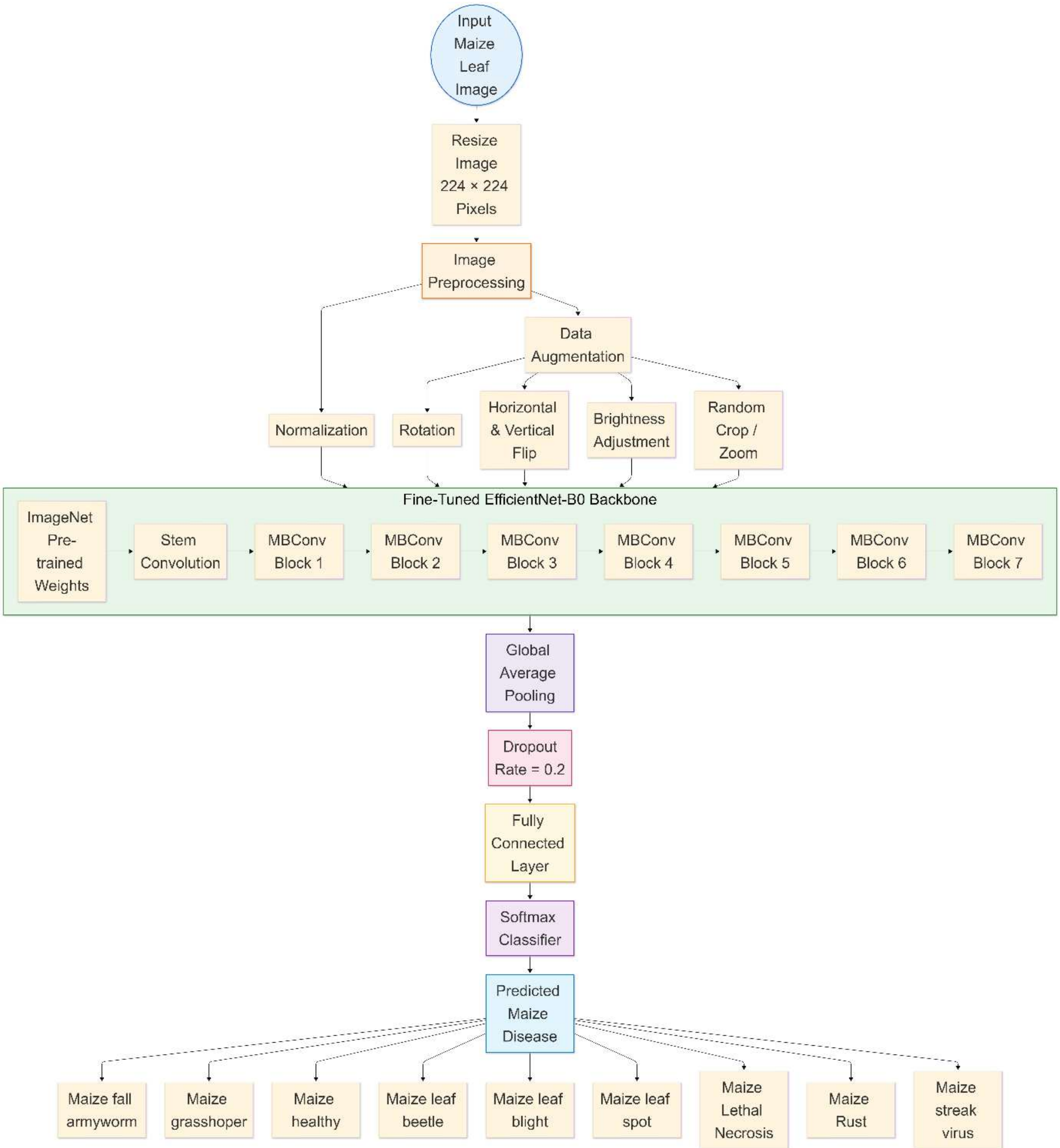


Figure 4: Architecture of the Proposed Fine-tuned EfficientNet-B0 Model (The overall proposed architecture is inspired by the EfficientNet-B0 architecture presented in [11] and adapted for maize disease detection based on works by [41])

The mathematical formulation of the Proposed Fine-tuned EfficientNet-B0 Model is given by:

$X \in R^{H \times W \times 3}$ be the input maize leaf image

The model can be expressed as a composition of functions:

$$f(X) = \mathrm{Softmax}\left(W \cdot \mathrm{GAP}(\phi(X))\right)$$

ϕ(X) represents the EfficientNet-B0 backbone feature extractor:

$$\phi(\mathrm{X}) = \mathrm{MBConv7}\big(\cdots \mathrm{MBConv1}\big(\mathrm{StemConv}(\mathrm{X})\big)\cdots\big)$$

GAP(·) is the Global Average Pooling layer that reduces spatial dimensions

$$GAP(F) = 1\backslash H'W' \sum_{i=1}^{H'} \sum_{j=1}^{W'} Fi,j$$

W is the weight matrix of the Fully Connected Layer

Softmax(·) produces the probability distribution over the 9 disease classes

$$\mathrm{Softmax}(\mathrm{z})_{\mathrm{k}} = \mathrm{e}^{zk}\backslash \sum_{j=1}^{9} \mathrm{e}^{zj}$$

The model was fine-tuned by updating the parameters through the transfer learning approach using the ImageNet pre-trained weights, where the classifier was modified to fit the 9 classes of maize diseases.

3.5 Training Details and Experimental Design

This model was built in PyTorch and trained using Adam optimizer with the learning rate set to 0.001, along with the cosine annealing schedule. This training process was carried out for 1-17 epochs with a batch size of 32-64 in an Intel(R) HD Graphics setting. The loss function used for multi-class classification was cross-entropy loss. Early stopping due to the validation loss was employed to avoid overfitting. Transfer learning was engaged by initializing the CNN backbone with ImageNet-pretrained weights. This method leverages features learned from a large general-purpose dataset to accelerate convergence and improve performance on the relatively limited Mendeley Maize Crop Disease (Leaf) Dataset.

3.6 Evaluation Metrics

The performance of the proposed fine-tuned EfficientNet-B0 architecture was tested through a suite of metrics that evaluated classification accuracy, robustness, efficiency, and interpretability.

Classification Performance Metrics:

i. Accuracy: Overall percentage of images that were accurately classified.
ii. Precision, Recall, and F1-score: Measures that were obtained on the basis of macro-average values in order to compensate for class imbalance.
iii. Confusion Matrix: Obtained in order to identify misclassification patterns between various types of maize disease.
iv. ROC-AUC Score: Multi-class measure that evaluates discrimination ability of the model.

Metrics to Measure Computational Efficiency:

i. Inference Time (Milliseconds per Image): Important for implementation in real-time applications on mobile phones.
ii. Model Size (MB): Necessary for saving and deploying on resource-constrained devices.

Analysis of Interpretability:

i. Grad-CAM (Gradient-Weighted Class Activation Map): It was used to create visual explanation maps by indicating which parts of the maize leaf were the main contributors to the model's prediction.
ii. Feature visualization: The activation maps at various layers of the EfficientNet-B0 backbones were investigated to identify the working mechanism of feature extraction by the proposed model, from low-level edges and textures to high-level disease-related features.

   These interpretability studies revealed that the proposed model concentrates on disease-related areas (lesion areas, discolorations, and texture alterations) and not on background areas.

All the above metrics have been calculated using both validation and independent testing datasets. The test dataset contains natural field images taken in the real environment in order to ensure a fair evaluation of the model's generalization ability. Ablation study results have been analysed using the same metrics to estimate the impact of the fine-tuned EfficientNet-B0.

3.7 Experimental Setup

All the experiments were done on a computer system that had an Intel (R) HD Graphics with 8 GB RAM to aid efficient training and testing. The model was developed through the PyTorch deep learning library (version 2.0+). The training and prediction processes took place under stable environmental conditions.

The field images acquired from Mendeley Maize Crop Disease (Leaf) Dataset [26] represent realistic conditions related to illumination, background, leaf orientation, disease level, and the stage of growth experienced by the farmers

Evaluation of the suitability of the model for edge deployment involved assessing inference time, model size, to determine its potential for real-time operation on devices such as mobile phones.

CHAPTER FOUR

4. Results

In this chapter, the results of experiments carried out to evaluate the proposed fine-tuned EfficientNet-B0 Convolutional Neural Network for detecting disease in maize leaves are presented. The experiments were carried out utilizing the Mendeley Maize Crop Disease (Leaf) Dataset [26] for developing the model. The following aspects are evaluated in the results: classification, ablation study, computational performance and model interpretability.

4.1 Overall Model Performance

The performance of the proposed model on the Mendeley Maize Crop Disease (Leaf) Dataset was quite high. These results are presented in Table 3.

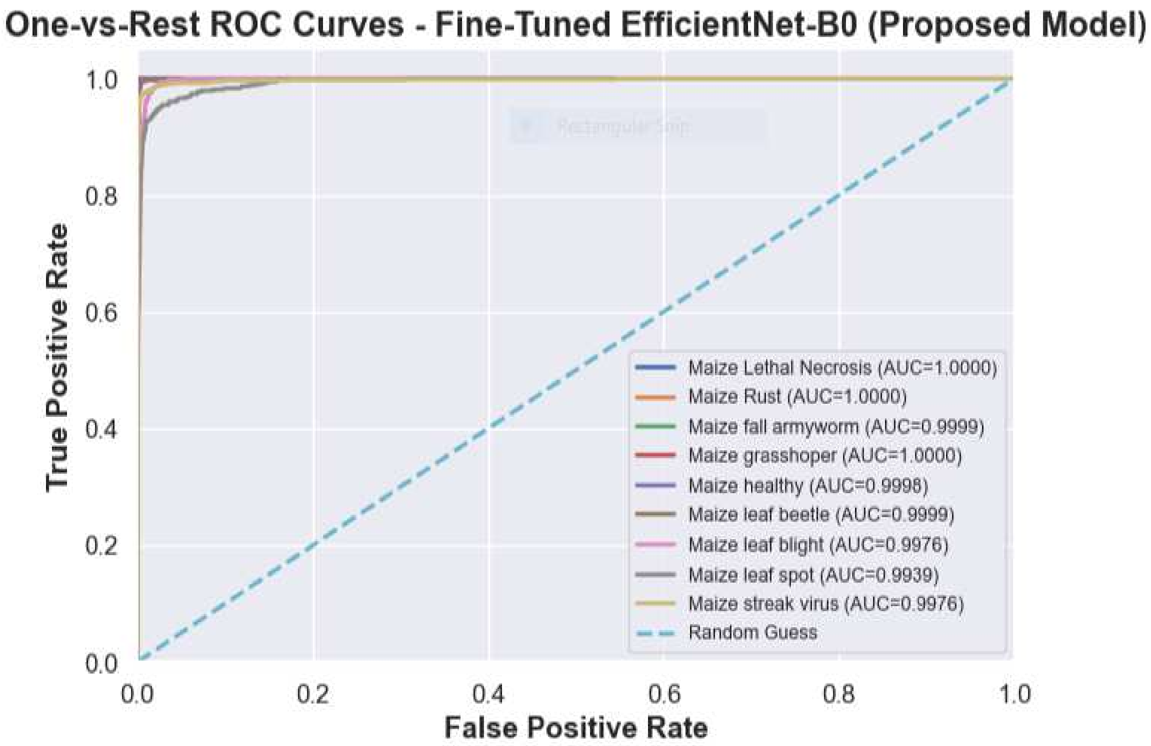
Table 3: Results of the Proposed Model

Metric	Value (%)
Accuracy	97.57
Precision (macro)	97.61
Recall (macro)	97.64
F1-Score (macro)	97.61

The model showed great proficiency in recognizing healthy maize leaves from diseased maize leaves. The model correctly classified 4,409 out of 4,519 test images, with only 110 misclassifications.

4.2 ROC Curve Analysis

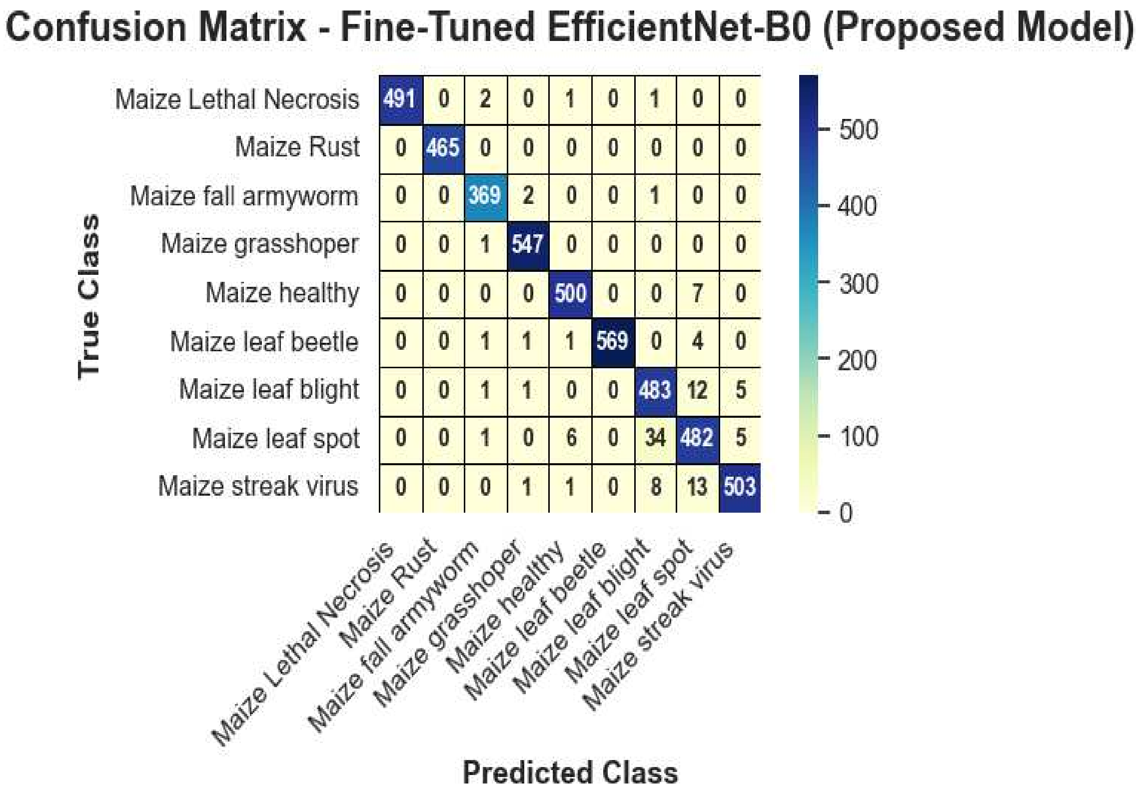
Figure 5: One-vs-Rest ROC Curves for the Proposed Model



One-vs-Rest ROC curve analysis was carried out to assess the ability of the proposed fine-tuned EfficientNet-B0 model to classify the images. From Figure 5, it is clear that all the nine classes of maize disease had an AUC of more than 0.99 and hence high class separability. The ROC curves were positioned near the best upper-left corner of the plot, implying that the true positive rate of the model was high with very few false positives. The proposed model was able to achieve perfect discrimination (AUC = 1.0000) for four classes of disease, such as Maize Lethal Necrosis, Maize Rust, Maize Fall Armyworm, and Maize Grasshopper.

4.3 Confusion Matrix Analysis

Figure 6: Confusion Matrix of the Proposed Model



	Maize Lethal Necrosis	Maize Rust	Maize fall armyworm	Maize grasshoper	Maize healthy	Maize leaf beetle	Maize leaf blight	Maize leaf spot	Maize streak virus
Maize Lethal Necrosis	491	0	2	0	1	0	1	0	0
Maize Rust	0	465	0	0	0	0	0	0	0
Maize fall armyworm	0	0	369	2	0	0	1	0	0
Maize grasshoper	0	0	1	547	0	0	0	0	0
Maize healthy	0	0	0	0	500	0	0	7	0
Maize leaf beetle	0	0	1	1	1	569	0	4	0
Maize leaf blight	0	0	1	1	0	0	483	12	5
Maize leaf spot	0	0	1	0	6	0	34	482	5
Maize streak virus	0	0	0	1	1	0	8	13	503

From the confusion matrix in figure 6, it is clear that the designed Fine-Tuned EfficientNet-B0 model performed exceptionally well on the classification task, with the majority of the images being classified with high accuracy on the main diagonal. The Fine-Tuned EfficientNet-B0 model has been able to classify the Maize Rust and Maize Grasshopper perfectly, demonstrating that the two classes have distinct visual characteristics which the network was able to learn. Some errors of misclassification have been noted in classifying Maize Leaf Spot and Maize Leaf Blight classes due to the similarity in appearance of lesions in the two diseases. This is in line with findings from literature, which have shown that similar foliar diseases form the toughest classes for CNNs. In conclusion, the minimal number of non-diagonal elements (110 misclassifications from 4,519 pictures) proves the validity of the proposed approach in classifying various diseases of corn in actual field conditions.

Verification of Total Correct and Wrong Predictions

Correct Predictions

The diagonal sum

$$TPtotal = 491 + 465 + 369 + 547 + 500 + 569 + 483 + 482 + 503$$

$$TPtotal = 4409$$

Incorrect Predictions

All off-diagonal values

$$\frac{FP}{FN} errors = 4519 - 4409$$

$$Errors = 110$$

Overall Accuracy

$$Accuracy = \frac{TPtotal}{N} \times 100$$

$$Accuracy = \frac{4409}{4519} \times 100$$

$$Accuracy = 97.56\ \%$$

Precision (Macro Average)

The precision for each class is calculated as

$$Precisioni = \frac{TPi}{TPi + FPi}$$

The macro-average precision is

$$Macro\ Precision = \sum 9\ i = 1\ \frac{Precisioni}{9}$$

$$= \frac{8.7847}{9}$$

$$= 0.9761$$

$$Precision = 97.61\ \%$$

Recall (Sensitivity)

Recall for each class is

$$Recalli = \frac{TPi}{TPi + FPi}$$

The macro-average recall is

$$Macro\ Recall = \sum 9\ i = 1\ \frac{Recalli}{9}$$

$$= \frac{8.7874}{9}$$

$$= 0.9764$$

$$Recall\ 97.64\ \%$$

F1-Score

The F1-score is

$$F1 = 2 \times \frac{Precision \times Recall}{Precision\ + Recall}$$

$$= 2 \times \frac{0.9761 \times 0.9761}{0.9761\ + 0.9761}$$

$$= 2 \times \frac{0.9528}{1.9522}$$

$$= 0.9761$$

$$= F1 - Score\ 97.61\ \%$$

Specificity

Specificity for each class is

$$Specificityi = \frac{TPi}{TPi + FPi}$$

The macro-average specificity is

$$Macro\ Specificity = \sum 9\ i = 1\, \frac{Specificityi}{9}$$

$$= \frac{8.9726}{9}$$

$$= 0.9970$$

$$Specificity = 99.70\%$$

Here, the index 'i' refers to the class index (i=1,2,…,9) representing the nine different classes of diseases in maize. The average results for macro-average calculations are obtained by calculating the metric for each class separately and averaging across all the classes.

4.4 Baseline EfficientNet-B0 without fine-tuning

Table 4. Results of the Baseline EfficientNet-B0 Model

Metric	Value (%)
Accuracy	89.53
Precision (macro)	89.64
Recall (macro)	89.53
F1-Score (macro)	89.43

4.4.1 ROC Curve Analysis

Figure 7: One-vs-Rest ROC Curves for the Baseline EfficientNet-B0.

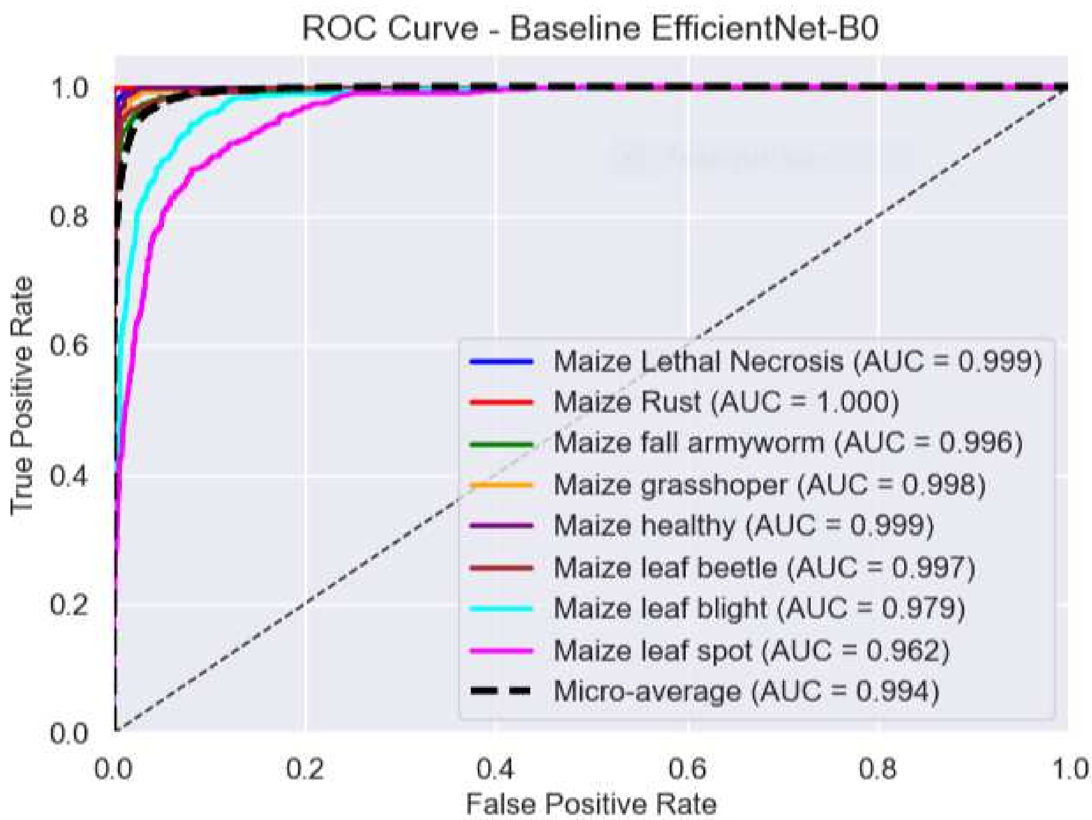
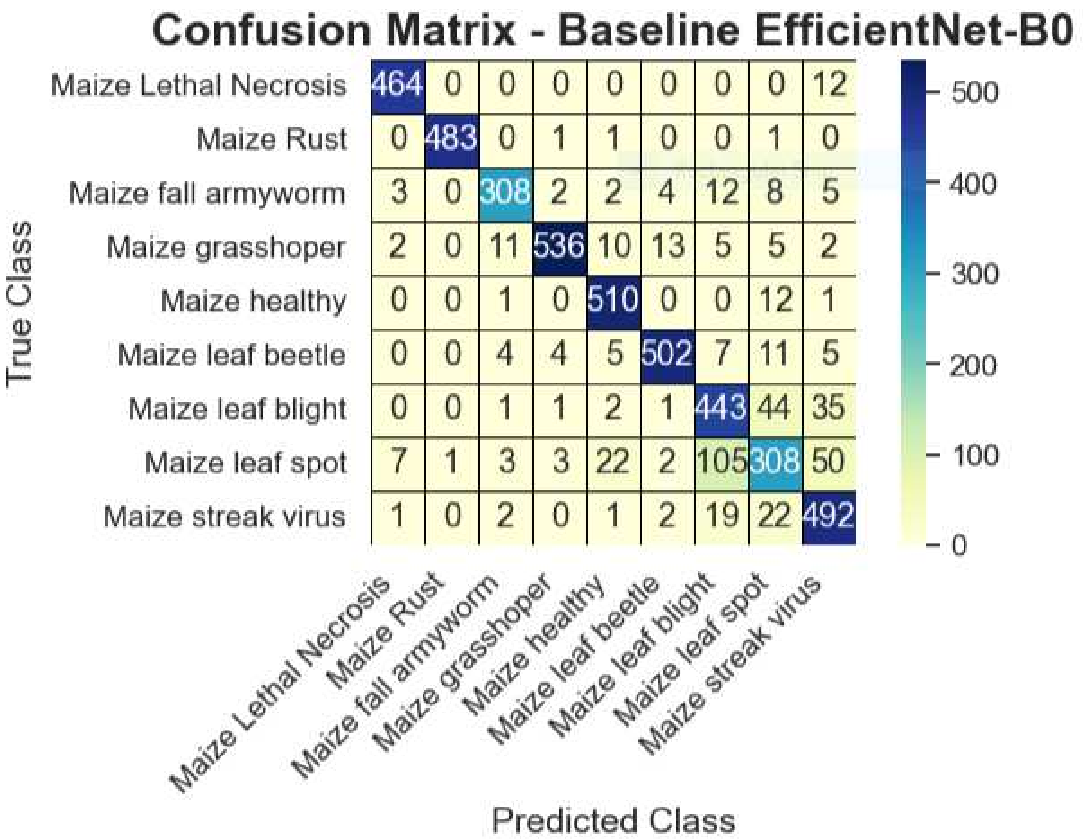


Figure 7 illustrates the One-vs-Rest ROC curves of the Baseline EfficientNet-B0 model without fine-tuning among the different maize disease classes. The model showed very good discrimination, with AUC values of 0.962 – 1.000. Maize Rust had an AUC value of 1.000, meaning it is perfectly discriminated from other classes, whereas Maize Lethal Necrosis and Healthy leaves have AUCs of 0.999, showing very good discrimination power. Maize Leaf Spot had the lowest AUC value of 0.962, implying that it is comparatively more difficult to discriminate this disease class from visually similar classes. In general, the micro-average AUC value of 0.994 demonstrates the good discrimination power of the Baseline EfficientNet-B0 model among different maize disease classes.

4.4.2 Confusion Matrix Analysis

Figure 8: Confusion Matrix of the Baseline EfficientNet-B0.



The confusion matrix of Baseline EfficientNet-B0 is illustrated in Figure 8. The predictions are primarily centered along the main diagonal, showing that the Baseline EfficientNet-B0 classified most of the maize leaves. In terms of number of correct predictions, the following five diseases were identified: Maize Grasshopper (536), Maize Healthy (510), Maize Leaf Beetle (502), Maize Streak Virus (492), and Maize Rust (483). However, there are some difficulties in classifying Maize Leaf Spot and Maize Leaf Blight, because 105 instances of the

Leaf Spot were classified as Leaf Blight. Additionally, there is a problem with Leaf Blight and Streak Virus since they look very similar.

4.5 AlexNet Model

Table 5. Results of AlexNet Model

Metric	Value (%)
Accuracy	91.02
Precision (macro)	91.42
Recall (macro)	91.02
F1-Score (macro)	91.11

4.5.1 ROC Curve Analysis

Figure 9: One-vs-Rest ROC Curves for AlexNet.

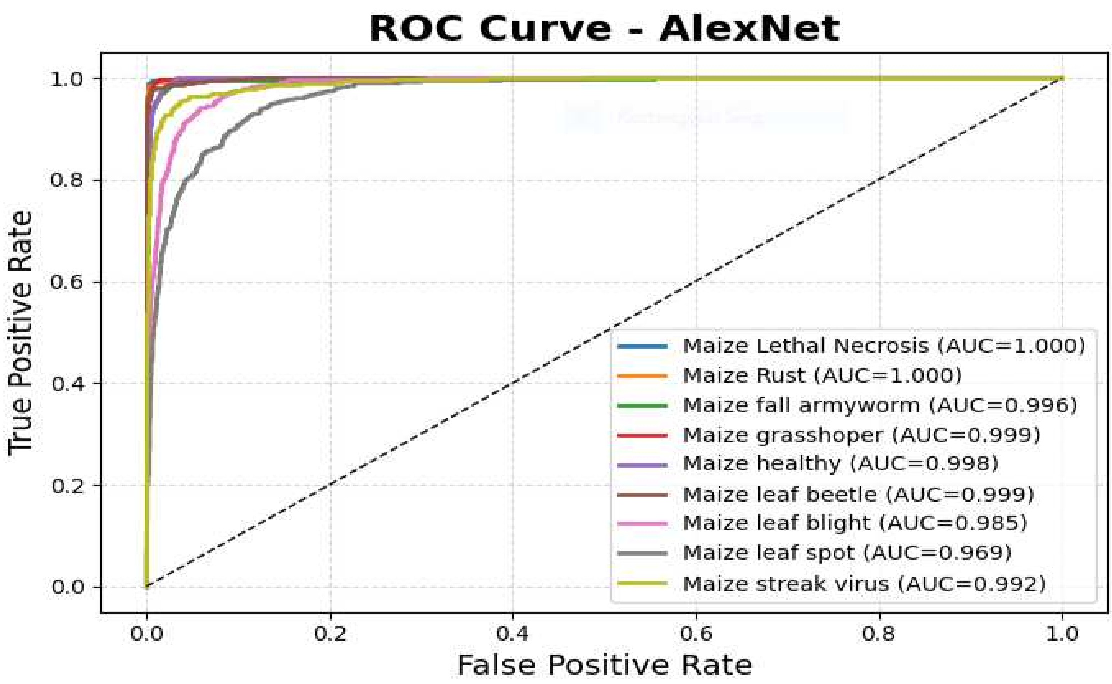
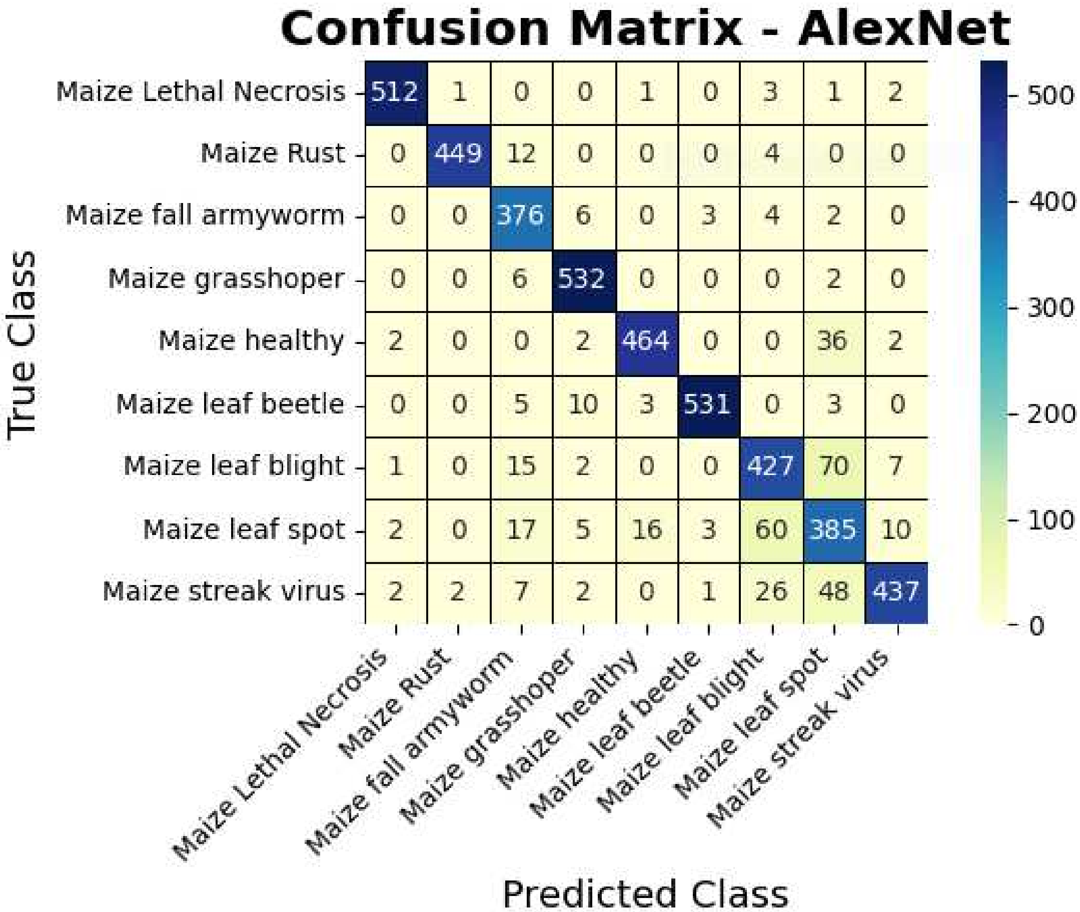


Figure 9 above shows the ROC curves of One-vs-Rest for the AlexNet architecture. From the results above, it is evident that AlexNet has outstanding discriminative ability in the classification of all maize diseases, where AUC ranges from 0.969 to 1.000. For instance, perfect discrimination was done in Maize Lethal Necrosis and Maize Rust diseases, where AUC = 1.000. Also, there was perfect discrimination with an AUC above 0.998 in Maize

Grasshopper, Maize Leaf Beetle, and Maize Healthy categories. The lowest AUC was noted in Maize Leaf Spot disease category with AUC = 0.969. This implies that discrimination of the disease is relatively more difficult compared to leaf blight disease category.

4.5.2 Confusion Matrix Analysis

Figure 10: Confusion Matrix of AlexNet.



The confusion matrix for the AlexNet model is shown in Figure 10 above. The high number of predictions appears on the main diagonal, showing that the performance of the AlexNet algorithm in classification is very good for the nine classes of maize disease. Most of the correct predictions were made for Maize Grasshopper (532), Maize Leaf Beetle (531), and Maize Lethal Necrosis (512). Confusion, however, happened between Maize Leaf Spot and Maize Leaf Blight, where 60 of the Leaf Spot pictures were predicted as Leaf Blight and 70 of the Leaf Blight pictures were predicted as Leaf Spot. The same confusion also happened with Maize Streak Virus, where the prediction of Leaf Spot and Leaf Blight was also incorrect. It can be seen that the diseases with similar appearances were difficult to classify using AlexNet algorithm.

4.6 MobileNetV2 Model

Table 6. Results of MobileNetV2 Model

Metric	Value (%)
Accuracy	92.28
Precision (macro)	92.39
Recall (macro)	92.28
F1-Score (macro)	92.18

4.6.1 ROC Curve Analysis

Figure 11: One-vs-Rest ROC Curves for MobileNetV2.

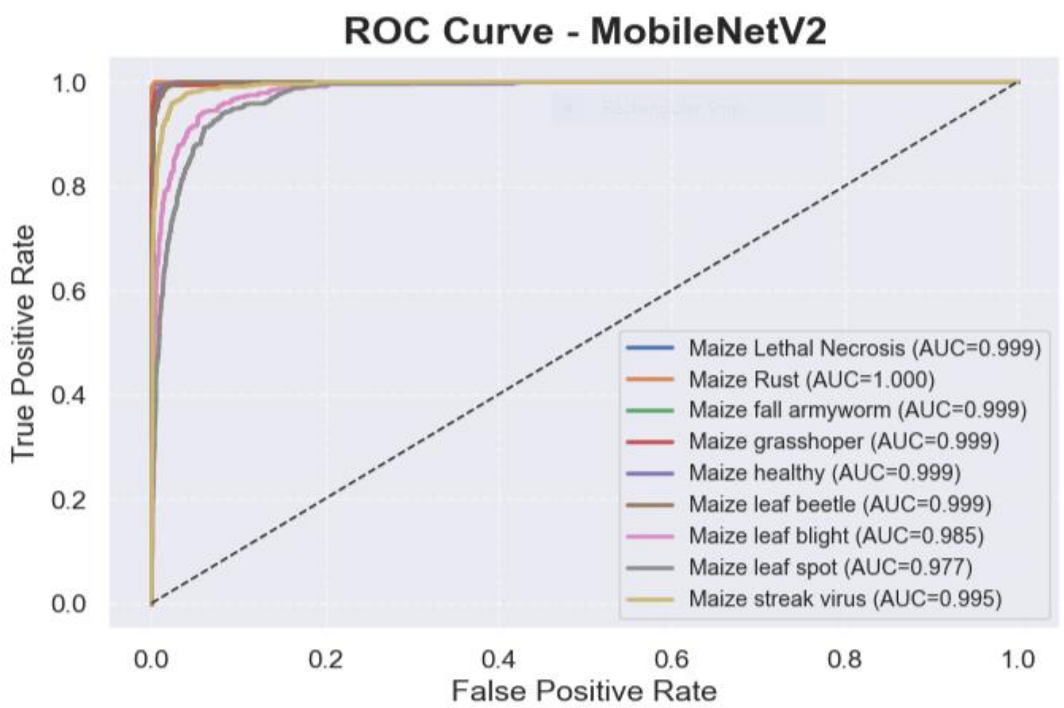
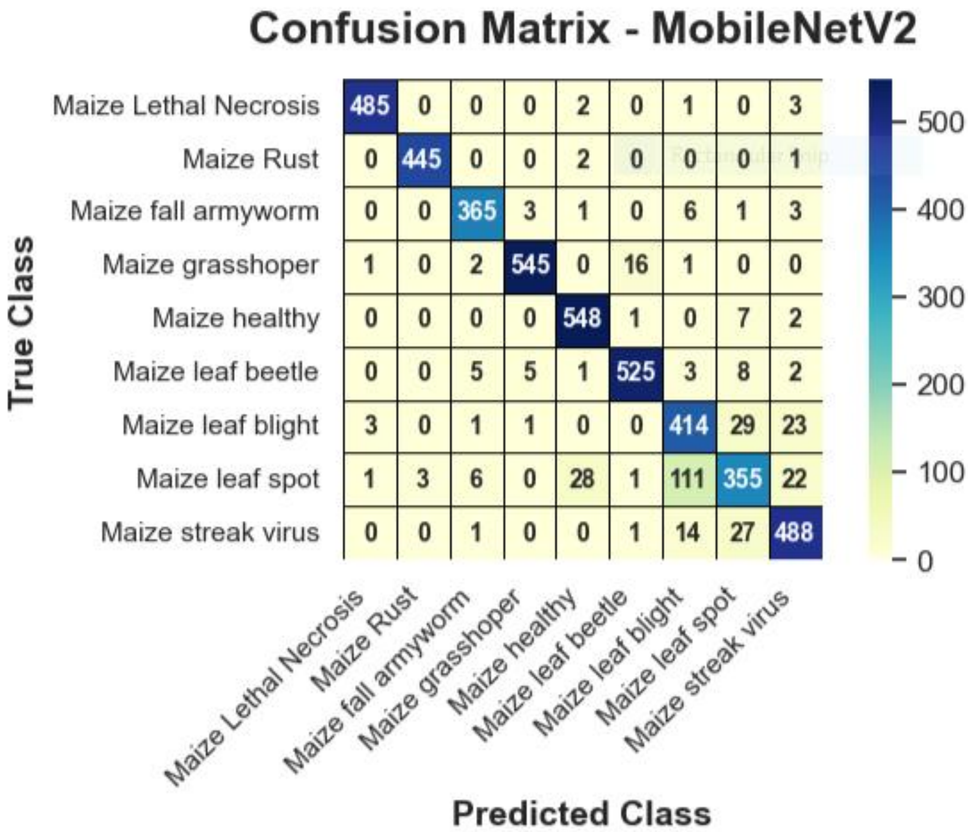


Figure 11 illustrates the ROC curves using One-vs-Rest method for the MobileNetV2. The analysis shows outstanding discrimination among all nine maize diseases categories with the range of AUC scores between 0.977 and 1.000. There was an absolute discrimination for Maize Rust (AUC = 1.000). Meanwhile, Maize Lethal Necrosis, Fall Armyworm, Grasshopper, Healthy, and Leaf Beetle gained an AUC score of 0.999, which signifies an almost perfect discrimination of the diseases. Maize Streak Virus demonstrated excellent discrimination ability with an AUC score of 0.995. Maize Leaf Spot had the lowest AUC score (0.977), which could be a result of difficulties in classifying this disease because of its similarity with other diseases such as Leaf Blight. Overall, all ROC curves were close to the upper left side of the graph, proving that MobileNetV2 has high sensitivity and low false positives for maize disease classification.

4.6.2 Confusion Matrix Analysis

Figure 12: Confusion Matrix of MobileNetV2.



The confusion matrix of the MobileNetV2 model is depicted in the figure 12 above. Many of the correct predictions are found along the main diagonal, and this indicates that the MobileNetV2 model algorithm has done well when it comes to classification for the nine classes of maize diseases. Most of the correct predictions were for Maize Grasshopper (545), Maize Healthy (548), and Maize Lethal Necrosis (485). The problem is that there is confusion between the Maize Leaf Spot and Maize Leaf Blight classes because 111 images of Leaf Spot were classified as Leaf Blight and 29 images of Leaf Blight were classified as Leaf Spot. There were further problems in classifying some of the images of Maize Streak Virus as Leaf Spot and Leaf Blight. It seems that the classification of the diseases which have a similar appearance was difficult for the MobileNetV2 algorithm.

4.7 ResNet50

Table 7. Results of ResNet50 Model

Metric	Value (%)
Accuracy	91.81
Precision (macro)	91.93
Recall (macro)	91.81
F1-Score (macro)	91.84

4.7.1 ROC Curve Analysis

Figure 13: One-vs-Rest ROC Curves for ResNet50.

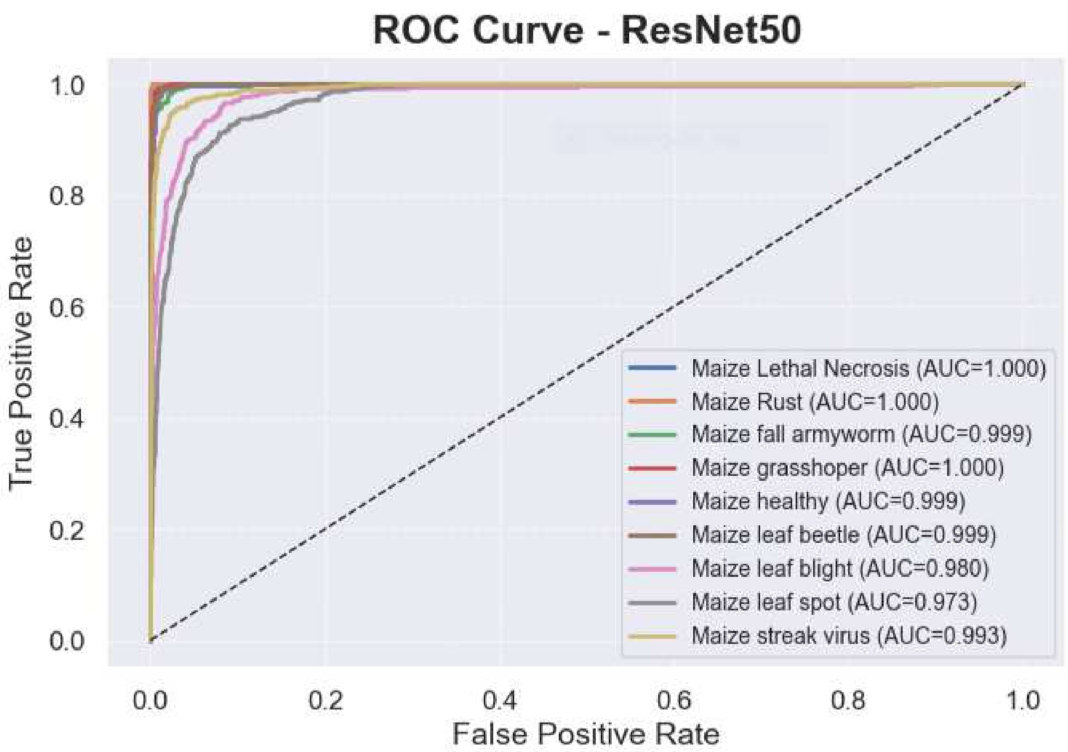
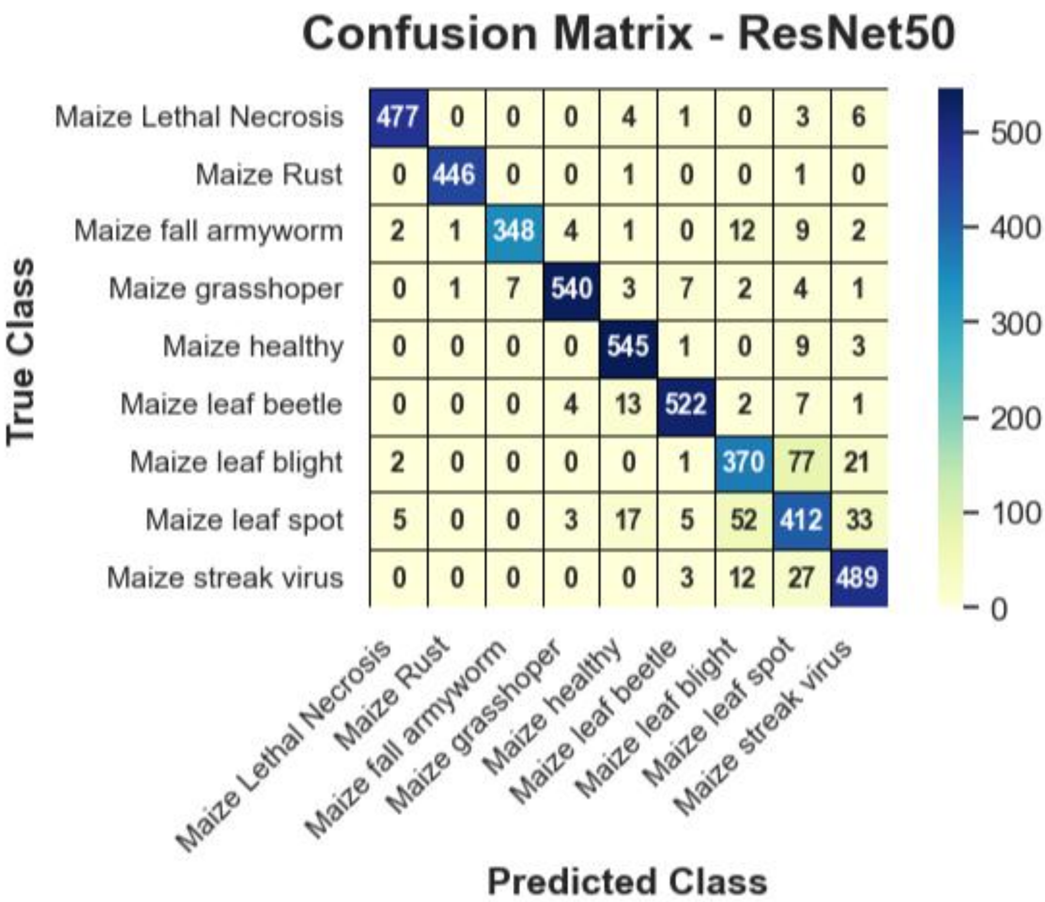


Figure 13 presents the ROC curves with the One-vs-Rest approach for the ResNet50 model. The findings demonstrate the excellent discrimination of all nine diseases of maize with the range of AUC values from 0.973 to 1.000. The complete discrimination has been observed for Maize Lethal Necrosis (AUC = 1.000), Maize Rust (AUC = 1.000), and Maize Grasshopper (AUC = 1.000). On the other hand, Maize Fall Armyworm, Maize Healthy, and Maize Leaf Beetle received the AUC value of 0.999, which is an almost perfect discrimination of the diseases. Maize Streak Virus showed good discrimination performance with the AUC value of 0.993. Maize Leaf Spot received the lowest AUC value (0.973) compared to Maize Leaf Blight (0.980), and it might happen due to the fact that the differentiation of these diseases was complicated due to the similar look. All ROC curves were close to the upper left corner of the graph, indicating that ResNet50 has high sensitivity and low false positives for maize disease classification.

4.7.2 Confusion Matrix Analysis

Figure 14: Confusion Matrix of ResNet50.



The confusion matrix for the ResNet50 model is shown in figure 14. The correct classifications of most of the images are seen on the main diagonal, which means that the ResNet50 model algorithm performed quite well in terms of the classification of the nine classes of maize diseases. However, the major correct classifications of the images were made for Maize Grasshopper (540), Maize Healthy (545), and Maize Lethal Necrosis (477).

The issue here is that there is confusion between the Maize Leaf Spot and Maize Leaf Blight classes since 52 images of Leaf Spot are classified as Leaf Blight, and 77 images of Leaf Blight are classified as Leaf Spot. In addition, some problems in the classification of some of the images of Maize Streak Virus as Leaf Spot and Leaf Blight occurred.

4.8 McNemar's Test for Statistical Comparison of Proposed Model Against CNN Models

Table 8: McNemar's Test for Statistical Comparison

Comparison	**χ^2 Statistic**	**p-value**	**Decision**
Proposed EfficientNet-B0 vs Baseline CNN (EfficientNet-B0)	91.1461	<0.001	Significant
Proposed EfficientNet-B0 vs AlexNet	51.0549	<0.001	Significant
Proposed EfficientNet-B0 vs MobileNetV2	102.2413	<0.001	Significant
Proposed EfficientNet-B0 vs ResNet50	72.2724	<0.001	Significant

The McNemar statistical test was performed in order to see whether there are any statistically significant differences between the performance of the proposed fine-tuned EfficientNet-B0 model and benchmark CNNs. The results revealed statistically significant differences in all pairwise comparisons ($p < 0.001$). As shown in Table 8 there are statistically significant differences in terms of prediction behavior of the proposed EfficientNet-B0 model in comparison to the Baseline CNN EfficientNet-B0 ($\chi^2 = 91.1461$), AlexNet ($\chi^2 = 51.0549$), MobileNetV2 ($\chi^2 = 102.2413$), and ResNet50 ($\chi^2 = 72.2724$). The obtained results indicate that the improvements are not random variation in the test dataset.

These results provide statistical evidence that the superior classification performance of the proposed Fine-Tuned EfficientNet-B0 model is both practically and statistically significant, thereby strengthening the validity of the comparative evaluation.

4.9 Confidence Interval Estimation

In order to analyse the statistical stability and validity of the proposed fine-tuning of the EfficientNet-B0, confidence intervals (CI) of the performance measures were generated. Whereas, accuracy, precision, recall, and F1 score provide the performance measure at the point, CI provides an estimate of the range within which the actual performance of the model lies. A confidence level of 95% was selected, meaning that in 95% of the times the interval will include the actual value of the population performance measure.

4.9.1 Accuracy Confidence Interval

The model reliability for the fine-tuned EfficientNet-B0 was determined by the calculation of the 95% confidence interval (CI) for the classification accuracy of the model. As the model accuracy is a fraction of correct classifications of all tested samples, it can be treated as a binomial proportion. In this case, the Wilson score interval could be used for the estimation of the CI due to its superiority to the normal approximation method for interval estimation of proportions, especially when the number of the tested samples is not infinite and the proportion is close to 100%.

The Wilson score interval is used for the estimation of the lower and upper bounds of the expected accuracy of the model based on the observed number of correct classifications and the total number of test samples. It allows avoiding the unrealistic confidence interval that falls out of the 0-100% range, in contrast to the normal approximation method.

The suggested EfficientNet-B0 model obtained 97.57% accuracy on the test data set. The predicted 95% confidence interval was between 97.07% and 97.98%. It shows that the actual accuracy of the model will lie within this range for classifying maize diseases.

Table 9: Accuracy Confidence Interval

Model	Test Samples	Accuracy (%)	95% Confidence Interval
Proposed EfficientNet-B0	4519	97.57	97.07 – 97.98

Since the confidence interval for the width is quite narrow (0.90%), it implies the low level of uncertainty concerning the estimated accuracy. The obtained results show that the high accuracy is not achieved because of random errors in the test data set but rather reflects the ability of the model to recognize the diseases as shown in Table 9.

4.9.2 F1-score Confidence Interval Estimation

Given that the F1 score is the harmonic mean of both precision and recall scores, its distribution cannot be considered binomially distributed as with classification accuracy. Consequently, bootstrap resampling was utilized to compute the 95% confidence interval of the F1 score for the suggested fine-tuned EfficientNet-B0 model.

Bootstrap resampling entailed creating new samples from the test dataset by drawing observations at random with replacement. For each sample created via bootstrapping, the F1 score was computed again, thereby generating a distribution of F1 scores. The process was repeated 1,000 times, after which the 2.5th and 97.5th percentiles of the distribution became the lower and upper limits of the 95% confidence interval, respectively.

Table 10: F1-score Confidence Interval

Model	F1-score (%)	95% Confidence Interval
Proposed EfficientNet-B0	97.61	97.09 – 97.96

The F1-score of the efficientNet-B0 architecture that was fine-tuned is 97.61%. The confidence interval calculated using the bootstrap technique has a range from 97.09% to 97.96% as shown in Table 10. The result shows that the model's F1-score is highly consistent with a very narrow gap of about 0.87 percentage points between the lower and upper confidence interval limits.

4.10 Ablation Study Results

To evaluate the effectiveness of the proposed model, ablation studies were done. The experiments were done with the following setups:

i. Baseline CNN (EfficientNet-B0 without fine tuning)
ii. AlexNet
iii. MobileNetV2
iv. ResNet50
v. Fine-Tuned EfficientNet-B0 (Proposed)

Ablation experiments confirmed the effectiveness of the Fine-Tuned EfficientNet-B0 (Table 11).

Table 11: Ablation Study Results

Model Configuration	Accuracy (%)	F1-Score (%)	Model Size (MB)	Inference Time (ms)
Baseline CNN (EfficientNet-B0)	89.53	89.43	27.16	220.77
AlexNet	91.02	91.11	217.60	55.47
MobileNetV2	92.08	92.18	15.62	92.48
ResNet50	91.81	91.84	90.05	275.59
Proposed model (fine-tuned EfficientNet-B0)	**97.57**	**97.61**	**15.33**	**111.16**

From the results shown in Table 11, it is evident that the fine-tuned EfficientNet-B0 model outperformed the other baselines in terms of accuracy and F1-score metrics while keeping a relatively small size and reasonable inference time. The findings indicate the efficiency of using transfer learning and fine-tuning in detecting maize diseases.

4.11 Model Prediction Simulation Results

To further evaluate the performance of a trained model, a visual simulation was carried out in order to analyse how well the model performs using some of the chosen test images depicting various categories of maize diseases and pests. Figure 15 below shows the actual class, the predicted class, and confidence for each example.

In most of the cases, the model was able to predict the actual class of test images with high levels of confidence (between 97.58% and 100%). Nevertheless, there was one case of a healthy leaf being wrongly classified as Maize Leaf Spot with confidence of 90.82%. From the results, it seems that the model sometimes confuses healthy leaves with early signs of leaf spot under various lighting or image conditions.

Figure 15 displays the actual class, predicted class, and confidence score

Table 12: Analysis of the Simulation Results

Image	Actual Class	Predicted Class	Confidence	Result
1	Maize leaf spot	Maize Leaf Spot	97.58%	Correct
2	Maize leaf spot	Maize Leaf Spot	99.99%	Correct
3	Maize fall armyworm	Maize Fall Armyworm	100.00%	Correct
4	Maize Lethal Necrosis	Maize Lethal Necrosis	100.00%	Correct
5	Maize healthy	Maize Leaf Spot	90.82%	Wrong
6	Maize streak virus	Maize Streak Virus	99.46%	Correct
7	Maize leaf beetle	Maize Leaf Beetle	100.00%	Correct
8	Maize fall armyworm	Maize Fall Armyworm	99.68%	Correct
9	Maize Lethal Necrosis	Maize Lethal Necrosis	100.00%	Correct
10	Maize leaf blight	Maize Leaf Blight	99.62%	Correct
11	Maize Lethal Necrosis	Maize Lethal Necrosis	100.00%	Correct
12	Maize Lethal Necrosis	Maize Lethal Necrosis	100.00%	Correct

Most predictions are accurate, the model accurately predicted most of the samples with a high degree of certainty (above 97%) as illustrated in Table 12. The following observations were made from the simulation results:

i. The model falsely classified a Healthy leaf as Maize Leaf Spot with 90.82% certainty. There is only one mistake to be seen in this dataset.

ii. High certainty in case of accuracy, when the prediction made by the model is accurate, there is always a high degree of certainty (99-100%).

iii. Classes used: Leaf Spot, Fall Armyworm, Lethal Necrosis, Healthy, Streak Virus, Leaf Beetle, and Leaf Blight.

4.12 Mobile Interface Simulation

In order to test whether the designed model is suitable for future deployment on a mobile device, the mobile-like user interface simulation was created with the use of Python and HTML. Figure 16 shows the simulation user interface following the scan of the maize leaf image. The interface shows the scanned image, the predicted disease category, the confidence level, and an appropriate course of recommendation. This simulation illustrates how the results of the fine-tuned EfficientNet-B0 model can be presented to users in a user-friendly way for further deployment. Despite the fact that the current model was designed with the use of Python and HTML, it gives a clear idea of how the interface will look like.

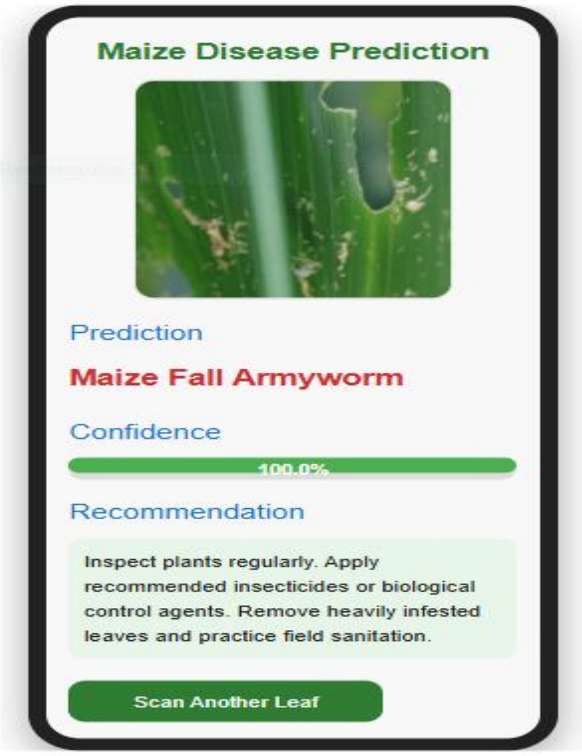


Figure 16: The actual class, predicted class, and confidence score with recommendations

CHAPTER FIVE

5.0 Discussion of Results

5.1 Introduction

This chapter analyses the findings that have been derived from the experimentally evaluated results of the efficientNet B0 model for the classification of maize leaf disease. These include the overall classification performance, results of ROC curve analysis, analysis of confusion matrix, findings from the ablation study, computational efficiency, and comparison with other studies. This chapter further provides an explanation regarding the importance of these findings with respect to the detection of maize diseases.

5.2 Discussion of Overall Model Performance

The proposed fine-tuned EfficientNet-B0 model attained an accuracy score of 97.57%, with the macro precision at 97.61%, recall at 97.64%, and F1-score at 97.61% when tested on the Mendeley Maize Crop Disease (Leaf) dataset. This proves that the proposed approach was very effective in identifying the discriminative features of the maize leaf images and classifying the diseases into the nine categories.

The improved performance is mainly because of the use of transfer learning approach in this research. Unlike starting from scratch in training the CNN, a fine-tuned pre-trained EfficientNet-B0 model enables the use of already learned low-level and high-level visual features such as edges, texture, color variance, and other disease-related visual cues.

Furthermore, the results reveal that the model was successful in discriminating between healthy maize leaves and diseased leaves. In the testing phase, the model was successful in correctly classifying 4,409 of the 4,519 images used in the test with only 110 incorrect classifications. This shows that the model has good generalization power on the dataset, proving that EfficientNet-B0 is suitable for the task of maize disease classification.

The results are consistent with earlier researches that have proved the effectiveness of transfer learning-based CNN models in diagnosing plant diseases. Plant disease diagnosis can be done using deep learning models, where the machine is capable of learning complex visual patterns from leaf images. Additionally, EfficientNet designed by Tan and Le proved that effective network scaling can lead to good accuracy and efficiency [9].

5.3 Discussion of ROC Curve Analysis

As per the ROC curve analysis, the developed classifier provided outstanding classification performance for all nine classes of maize diseases, and all the classes received an AUC score higher than 0.99. The perfect discrimination was provided by four classes with AUC score equal to 1.000, namely, Maize Lethal Necrosis, Maize Rust, Maize Fall Armyworm, and Maize Grasshopper.

The ROC curve analysis indicates that the classifier was able to provide good discrimination between positive and negative samples for each disease class. It is vital to note that the low rate of false positives is very important in the context of agriculture because wrong disease identification will cause the wrong treatment decision of the farmer.

Given the impressive ROC result, it can be said that the learned features in EfficientNet-B0 were able to provide good discrimination between different disease samples by capturing their unique attributes. Diseases that have unique visual symptoms like rust and fall armyworms are relatively easy to distinguish because they possess unique patterns and damage.

But there will always be some difficulties when it comes to diseases that have very similar lesions. This means that the model will find it difficult to discriminate diseases like leaf spots and leaf blights because they have very similar lesions.

5.4 Discussion of Confusion Matrix Analysis

The confusion matrix analysis verified the good results obtained by the proposed model, since most of the classifications are clustered around the main diagonal. This is an indication that the images have been correctly classified into their corresponding diseases.

Excellent recognition results were obtained by the following categories:

i. Maize Grasshopper
ii. Maize Rust
iii. Maize Healthy
iv. Maize Leaf Beetle

This good classification result by the above categories could be due to the distinct appearance of the diseases. For instance, insect damage resulting from grasshoppers and leaf beetles is different from diseases like rust and viruses.

However, some misclassifications were observed in the classification between Maize Leaf Spot and Maize Leaf Blight. These findings are consistent with past studies showing that similarly looking foliar diseases are still hard to classify using CNN classifiers [36]. Both diseases have similar signs such as the development of lesions, discolorations, and alterations in leaf appearance. Nonetheless, the misclassification rate was still small (110 out of 4,519 pictures).

5.5 Discussion of Model Prediction Simulation Results

The simulation results for the model prediction have yielded interesting findings regarding the real-world effectiveness of the built maize disease and pest identification model. Visual examination of several test images has revealed that the model successfully recognized the majority of test images with the high level of confidence scores, namely ranging from 97% to 100%. In other words, the model has learned the distinctive features for most of the target classes, such as Maize Leaf Spot, Maize Fall Armyworm, Maize Lethal Necrosis, Maize Streak Virus, Maize Leaf Beetle, and Maize Leaf Blight.

One of the major errors of the model in the testing phase is associated with the incorrect recognition of a healthy maize leaf as the leaf with the symptoms of Maize Leaf Spot with the confidence score of 90.82%. It can be assumed that the model finds it difficult to distinguish healthy tissue from the early symptoms of the disease in some cases. This type of error usually occurs in plant diseases detection applications due to the subtle nature of differences.

With one exception, the performance of the model in the simulation process is still good. The confidence scores on accurately classified images are also high, which means that the model is reliable when undergoing tests in a controlled environment. What is more, one may assume that although the model is already working well, there is room for improvement in case more diverse examples of healthy leaves are added to the training set.

In conclusion, the simulation of the model predictions proves that the model is ready to make accurate predictions about maize diseases.

5.6 Discussion of Mobile Interface Simulation Results

The mobile interface simulation further supports the third research objective by demonstrating the practical applicability of the developed model. From the mobile interface simulation, it is evident that the fine-tuned EfficientNet-B0 model can be successfully implemented in a decision support system. Although the simulation was implemented using Python and HTML rather than a native mobile application, it successfully illustrated how prediction results, confidence scores, and management recommendations can be presented to end users in a clear and accessible format. This system gives clear predictions, confidence, and recommendations to users. This is an affirmation of the feasibility of the proposed model in implementation in resource- constrained agricultural settings such as smallholder farms in Zambia and other regions of Sub-Saharan Africa.

5.7 Discussion of Ablation Study Results

Ablation was performed to analyze the role of fine-tuning of the EfficientNet-B0 model with respect to others CNN models.

The suggested fine-tuned EfficientNet-B0 model showed the best result in terms of accuracy (97.57%) and F1-score (97.61%) when comparing with:

i. Baseline EfficientNet-B0: 89.53%
ii. AlexNet: 91.02%
iii. MobileNetV2: 92.08%
iv. ResNet50: 91.81%

It is worth noting that the performance gain over the baseline EfficientNet-B0 model proves the importance of the fine-tuning process. Despite the fact that the pre-trained models have useful feature extraction capability, it is possible to improve the classification efficiency.

The proposed model improved accuracy by approximately:

$$97.57-89.53=8.04\%$$

compared with the non-fine-tuned EfficientNet-B0 model.

This enhancement settles that domain-specific fine-tuning enables the network to learn maize disease-specific features rather than relying only on generic ImageNet features.

Statistical significance testing has helped in confirming the reliability of the improvements obtained by the proposed fine-tuned EfficientNet-B0 model. The results of McNemar's test have indicated statistically significant differences ($p < 0.001$) between the proposed model and all the other comparison models, which provides sufficient evidence for the reliability of the performance improvements obtained. This has validated the reliability of the proposed model, as the improvements made by the proposed model are statistically more significant compared to the Baseline CNN, AlexNet, MobileNetV2, and ResNet50 models.

5.8 Discussion of Computational Efficiency

However, although accuracy is important, efficient deployment in agricultural conditions demands that models are computationally efficient. The proposed EfficientNet-B0 model obtained a model size of 15.33MB, henceforth rendering it efficient for deployment on resource-limited devices.

Table 13: Comparison with other models

Model	Size (MB)
AlexNet	217.60
ResNet50	90.05
Baseline EfficientNet-B0	27.16
MobileNetV2	15.62
Proposed EfficientNet-B0	15.33

The proposed model was very efficient and provided significantly higher accuracy compared to MobileNetV2, which is normally viewed as a lightweight model as illustrated in Table 13.

This shows that the proposed EfficientNet-B0 model effectively balances both classification performance and computational needs, hence it can be efficiently used for future mobile-based maize diseases diagnosis applications.

5.9 Comparison with Existing Studies

The results obtained in this paper are largely in line with earlier studies which confirm the potential of deep learning approaches for detecting maize diseases. Specifically, the fine-tuned EfficientNet-B0 model managed to achieve a classification accuracy of 97.57%, thus proving the reliability of using convolutional neural networks based on the principles of transfer learning to perform automated maize diseases diagnosis.

As indicated by Ma [34], transfer learning greatly improves the process of classification of maize diseases due to effective feature extraction. The high accuracy rate obtained in the current study confirms their results and additionally verifies the efficiency of fine-tuning of EfficientNet-B0 for the purpose of distinguishing visually alike maize diseases. Similar conclusions were made by Z. Li [35], according to whom MaizeNet improves the classification of challenging maize disease groups. While there were only few instances of classification error between maize leaf spot and maize leaf blight in the current study, the proposed method performed extremely well.

The results obtained in this paper are also in accordance with the findings reported by Gülmez [30] according to which despite the outstanding performance of CNN-based models on benchmark data, there is still room for improvement due to challenges in obtaining reliable results under real agricultural conditions due to the variability of the environment and lack of generalization of the models.

CHAPTER SIX

6.0 Conclusion and Recommendations

6.1 Introduction

In this chapter, we will outline the conclusions made based on the results obtained from the research and make suggestions on what needs to be done in future research and practice. This study was centered around the development and testing of an optimized EfficientNet-B0 deep learning model for maize leaf disease detection utilizing real-world maize leaf images.

6.2 Conclusion

The study aimed at addressing the problem of efficient maize disease detection. Specifically, the problem was caused by the deficiencies of traditional approaches as well as existing deep learning models in performing reliable classification task. Deep learning approach was used that included such stages as data preprocessing, augmentation, transfer learning, and fine-tuning of EfficientNet-B0 convolutional neural network architecture based on the dataset of maize leaf diseases comprising nine different diseases. It has been shown that the fine-tuned EfficientNet-B0 model possesses good classification ability as it provides a high level of accuracy, precision, recall, and F1-score, thus proving its efficiency in detecting various maize diseases. This study makes an important contribution into the area since it suggests an optimized lightweight deep learning model that can be used for improving automated maize disease diagnosis. Furthermore, the results can help in creating smart decision support system for agriculture. In practice, the results of the study can be useful for farmers, agricultural extension officers, and researchers, as the suggested method can help in fast and reliable identification of diseases.

6.3 Recommendations

Based on the findings of this study, the following recommendations are proposed:

i. Adoption of Disease Detection Model Based on AI: The agricultural extension officers should incorporate the AI-based maize disease detection system in order to complement the conventional visual analysis of the diseases. The proposed fine-tuned EfficientNet-B0 has proved to be efficient in terms of its classification accuracy, hence providing a chance for quick disease diagnosis.

ii. Development of Mobile Application: The proposed model needs to be incorporated in a mobile application based on the Android OS that will enable farmers and agricultural extension officers to diagnose diseases of the maize crops in their farms using the application.
iii. Expanding National Maize Diseases Databases: There is need for cooperation between the Government of Zambia, agricultural research institutions and universities in developing a large national database of maize diseases images sourced from a variety of ecological settings. This would increase the effectiveness and ability of the AI system to work in various parts of the country.
iv. Incorporating AI Based Technology in Agricultural Extension Services: The Government of Zambia through the Ministry of Agriculture can think about integrating AI-based technology into the current agricultural extension program. It will make the work of agricultural extensionists easier as well as provide the farmers with the correct advice on how to handle diseases.
v. Investing in Precision Agriculture Technology: There is a need for government agencies, research institutes and development partners to invest in precision agriculture technologies like mobile artificial intelligence, edge computing and UAV based crop monitoring systems.

6.4 Limitations of the Study

Although the suggested Fine-Tuned EfficientNet-B0 model exhibited impressive results in maize disease detection, there are some drawbacks that need to be pointed out. Firstly, this research was carried out on the basis of Mendeley Maize Crop Disease (Leaf) dataset. Despite the diversity of the dataset, it is just one public dataset available to use. Therefore, the results of the model's operation on other regions, other farms, and even different imaging devices cannot be known. The generalization ability of the suggested model must be checked on multiple datasets in different conditions.

Secondly, the suggested model was tested in simulations in a desktop environment. Although the architecture of the model allows it to be deployed in mobile environment, it was not done. The practical implementation of the model has not been checked on a real Android phone. That is why the factors like memory consumption, power consumption, processing speed, and user experience in real-time prediction have not been examined.

Moreover, no field tests were conducted in this study utilizing the use of images taken directly from farms under non-controlled environments. In real life scenarios wherein agricultural photos are taken, there are problems such as varying lighting, complex background, partial obscuring, overlapping leaves, and differing camera positions that could affect the performance of the classifier.

6.5 Future Research

There are several ways through which this system can be made even better. The first way is through the implementation of the model on an Android mobile application. Implementation of the model in a mobile application will make it easy for farmers and extension officers to diagnose diseases in their fields using smartphones.

Additionally, the proposed system could be integrated with Unmanned Aerial Vehicles (UAVs) that use high-resolution cameras to aid large scale monitoring of crops in the field. Such an approach will ensure efficient identification of disease-infested sites in maize fields through disease surveillance using UAVs.

Moreover, further work in the area needs to consider increasing the dataset by including images from different ecological regions of Zambia and other African countries.

Author Contributions

KS wrote the manuscript and JP, MN reviewed and provided guidance.

Declarations

Funding

The study did not receive any specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflicts of Interest

The authors declare that they are no conflicts of interest to publish the paper.

Consent to Publish

All authors have read and approved the final version of the manuscript and agree to its submission to Discover Networks.

Consent to Participate

Not applicable

Data Availability

The Mendeley Maize Crop Disease (Leaf) Dataset used in this study is publicly available at https://data.mendeley.com/datasets/6w6gsvghfw

Clinical Trial Number

Not applicable.

Ethics Declaration:

Not applicable.

Competing interests

All authors declare no competing interests.

REFERENCES

[1] J. Benjamin *et al.*, “Cereal production in Africa: the threat of certain pests and weeds in a changing climate—a review,” *Agric. Food Secur.*, vol. 13, no. 1, pp. 1–16, 2024, doi: 10.1186/s40066-024-00470-8.

[2] J. Benjamin *et al.*, “Cereal production in Africa: the threat of current plant pathogens in changing climate-a review,” *Discov. Agric.*, vol. 2, no. 1, 2024, doi: 10.1007/s44279-024-00040-3.

[3] K. Sakachiva, J. Phiri, and M. Nyirenda, “A systematic review of intelligent wireless sensing architectures for AI-enabled maize disease monitoring in 5G and 6G networks,” pp. 1–35, 2026.

[4] J. Benjamin *et al.*, “Status of cereal production in Africa: insights from abiotic stressors in a changing climate—a short review,” *Discov. Agric.*, vol. 3, no. 1, 2025, doi: 10.1007/s44279-025-00291-8.

[5] A. K. Biswal *et al.*, “Maize Lethal Necrosis disease: review of molecular and genetic resistance mechanisms, socio-economic impacts, and mitigation strategies in sub-Saharan Africa,” *BMC Plant Biol.*, vol. 22, no. 1, pp. 1–21, 2022, doi: 10.1186/s12870-022-03932-y.

[6] B. Gülmez, “Advancements in maize disease detection: A comprehensive review of convolutional neural networks,” *Comput. Biol. Med.*, vol. 183, no. August, p. 109222, 2024, doi: 10.1016/j.compbiomed.2024.109222.

[7] Y. Meng, J. Zhan, K. Li, F. Yan, and L. Zhang, “A rapid and precise algorithm for maize leaf disease detection based on YOLO MSM,” *Sci. Rep.*, vol. 15, no. 1, pp. 1–19, 2025, doi: 10.1038/s41598-025-88399-1.

[8] J. Paliwal and S. Joshi, “An Overview of Deep Learning Models for Foliar Disease Detection in Maize Crop,” *J. Artif. Intell. Syst.*, vol. 4, no. 1, pp. 1–21, 2022, doi: 10.33969/ais.2022040101.

[9] M. Tan and Q. V Le, “EfficientNet : Rethinking Model Scaling for Convolutional

Neural Networks," 2019.

[10] M. H. Ashmafee, T. Ahmed, S. Ahmed, M. B. Hasan, M. N. Jahan, and A. B. M. Ashikur Rahman, "An Efficient Transfer Learning-based Approach for Apple Leaf Disease Classification," *3rd Int. Conf. Electr. Comput. Commun. Eng. ECCE 2023*, 2023, doi: 10.1109/ECCE57851.2023.10101542.

[11] J. Cai *et al.*, "Improved EfficientNet for corn disease identification," *Front. Plant Sci.*, vol. 14, no. September, pp. 1–17, 2023, doi: 10.3389/fpls.2023.1224385.

[12] F. Khan, N. Zafar, and M. N. Tahir, "A mobile-based system for maize plant leaf disease detection and classi fi cation using deep learning," no. May, pp. 1–18, 2023, doi: 10.3389/fpls.2023.1079366.

[13] H. Guan, C. Fu, G. Zhang, K. Li, P. Wang, and Z. Zhu, "A lightweight model for ef fi cient identi fi cation of plant diseases and pests based on deep learning," no. July, pp. 1–13, 2023, doi: 10.3389/fpls.2023.1227011.

[14] G. Li, Y. Wang, Q. Zhao, P. Yuan, and B. Chang, "PMVT : a lightweight vision transformer for plant disease identi fi cation on mobile devices," no. September, pp. 1–12, 2023, doi: 10.3389/fpls.2023.1256773.

[15] F. Njeru, A. Wambua, E. Muge, G. Haesaert, J. Gettemans, and G. Misinzo, "Major biotic stresses affecting maize production in Kenya and their implications for food security," *PeerJ*, vol. 11, p. e15685, 2023, doi: 10.7717/peerj.15685.

[16] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Front. Plant Sci.*, vol. 7, no. September, pp. 1–10, 2016, doi: 10.3389/fpls.2016.01419.

[17] T. Murugan *et al.*, "Research Advances in Maize Crop Disease Detection Using Machine Learning and Deep Learning Approaches," pp. 1–53, 2026.

[18] S. Albahli and M. Masood, "Ef fi cient attention-based CNN network (EANet) for multi-class maize crop disease classi fi cation," no. October, pp. 1–18, 2022, doi: 10.3389/fpls.2022.1003152.

[19] L. Ma, Q. Yu, H. Yu, and J. Zhang, "Maize Leaf Disease Identification Based on YOLOv5n Algorithm Incorporating Attention Mechanism," *Agronomy*, vol. 13, no. 2, 2023, doi: 10.3390/agronomy13020521.

[20] N. Parashar *et al.*, “Enhanced residual-attention deep neural network for disease classification in maize leaf images,” pp. 1–19, 2025.

[21] M. C. Tonui, J. Kamau, and R. W. Ongus, “Multimodal CNN – LSTM Framework for Real-Time Maize Disease Detection,” vol. 8, no. 2, pp. 283–298, 2026.

[22] S. Mehdipour, S. A. Mirroshandel, and S. A. Tabatabaei, “OPEN A novel lightweight hybrid CNN – ViT for maize leaf disease classification,” pp. 1–20, 2026.

[23] R. Rani, J. Sahoo, S. Bellamkonda, and S. Kumar, “MethodsX Attention-enhanced corn disease diagnosis using few-shot learning and VGG16,” *MethodsX*, vol. 14, no. January, p. 103172, 2025, doi: 10.1016/j.mex.2025.103172.

[24] D. Convolution *et al.*, “ICPNet : Advanced Maize Leaf Disease Detection with Multidimensional Attention and Coordinate,” 2024.

[25] M. Haris, M. Faizal, A. Fauzi, and L. Kian, “Maize Leaf Disease Identification with Large and Lightweight Convolutional Neural Models,” vol. 9, no. March, pp. 592–598, 2025.

[26] Abebe Adege, “Maize Crop Disease (Leaf) Dataset,” 2026. doi: 10.17632/6w6gsvghfw.1.

[27] N. Parashar *et al.*, “Enhanced residual-attention deep neural network for disease classification in maize leaf images,” *Sci. Rep.*, vol. 15, no. 1, pp. 1–19, 2025, doi: 10.1038/s41598-025-14726-1.

[28] H. Xu, “Corn or maize leaf disease classification based on CNN and vision mamba model,” pp. 1–13, 2026.

[29] H. Ali, N. Shifa, R. Benlamri, A. A. Farooque, and R. Yaqub, “A fine tuned EfficientNet-B0 convolutional neural network for accurate and efficient classification of apple leaf diseases,” *Sci. Rep.*, vol. 15, no. 1, pp. 1–26, 2025, doi: 10.1038/s41598-025-04479-2.

[30] B. Gülmez, “Advancements in maize disease detection : A comprehensive review of convolutional neural networks,” *Comput. Biol. Med.*, vol. 183, no. August, p. 109222, 2024, doi: 10.1016/j.compbiomed.2024.109222.

[31] A. Howard, W. Wang, G. Chu, L. Chen, B. Chen, and M. Tan, “Searching for

MobileNetV3”.

[32] S. Osouli, B. Bolourian, and E. Sadrossadat, “An Effective Scheme for Maize Disease Recognition based on Deep Networks,” 2022.

[33] G. Shandilya, S. Gupta, H. G. Mohamed, S. Bharany, A. U. Rehman, and S. Hussen, “Enhanced Maize Leaf Disease Detection and Classification Using an Integrated CNN-ViT Model,” *Food Sci. Nutr.*, vol. 13, no. 7, 2025, doi: 10.1002/fsn3.70513.

[34] Z. Ma *et al.*, “Maize leaf disease identification using deep transfer convolutional neural networks,” vol. 15, no. 5, pp. 187–195, 2022, doi: 10.25165/j.ijabe.20221505.6658.

[35] Z. Li *et al.*, “Maize leaf disease identification based on,” pp. 1–20, 2022, doi: 10.1371/journal.pone.0267650.

[36] A. Ullah, S. Hussain, Q. Hou, D. Fang, and L. Deng, “EDISP : a hybrid CNN-ViT framework for robust maize leaf disease detection and classi fi cation,” no. July, pp. 1–25, 2026, doi: 10.3389/fpls.2026.1873194.

[37] F. Weloday and J. Su, “LWMSCNN-SE : A Lightweight Multi-Scale Network for Efficient Maize Disease Classification on Edge Devices,” pp. 1–7.

[38] H. D. Mafukidze, G. Owomugisha, D. Otim, A. Nechibvute, C. Nyamhere, and F. Mazunga, “applied sciences Adaptive Thresholding of CNN Features for Maize Leaf Disease Classification and Severity Estimation,” 2022.

[39] M. S. A. M. Al-Gaashani, R. Alkanhel, M. A. S. Ali, M. S. A. Muthanna, A. Aziz, and A. Muthanna, “MSCPNet: A Multi-Scale Convolutional Pooling Network for Maize Disease Classification,” *IEEE Access*, vol. 13, no. January, pp. 11423–11446, 2025, doi: 10.1109/ACCESS.2024.3524729.

[40] X. Qian, C. Zhang, L. Chen, and K. Li, “Deep Learning-Based Identification of Maize Leaf Diseases Is Improved by an Attention Mechanism :,” vol. 13, no. April, pp. 1–15, 2022, doi: 10.3389/fpls.2022.864486.

[41] K. Ahadian *et al.*, “Maize disease classification using transfer learning and convolutional neural network with weighted loss,” *Heliyon*, vol. 10, no. 21, p. e39569, 2024, doi: 10.1016/j.heliyon.2024.e39569.