Unveiling Agricultural Insights: Optimizing Transfer Learning Models with Grad-CAM to Improve Maize Disease Detection

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Abstract. Agriculture is the backbone of a country's economy and food production. Crop diseases cause economic instability and a decrease in agricultural production. Maize, one of the most cultivated crops in the world, is prone to various diseases that adversely affect its yield and quality. Most farmers face challenges in controlling and detecting these diseases. Thus, early detection of diseases is essential for farmers to avoid further losses. To overcome this challenge, this study focuses on deep learning techniques such as EfficientNetV2B2, ResNet50, InceptionV3, VGG16, and Xception for maize crop disease detection. It uses a maize crop image dataset from the Nelson Mandela African Institution of Science and Technology and the Tanzania Agricultural Research Institute. The dataset consists of 17,277 images divided into three classes, namely healthy, Maize Lethal Necrosis (MLN), and Maize Streak Virus (MSV). Although all the models achieved promising results, EfficientNetV2B2 showed the overall highest accuracy, reaching 92%. Finally, for transparent decision-making, Gradient Weighted Class Activation Mapping (Grad-CAM), an Explainable Artificial Intelligence (XAI) technique, was integrated with EfficientNetV2B2 to enhance model interpretation. The results of this research are poised to develop AI applications in agriculture, enabling timely and transparent diagnosis of maize diseases.

Keywords: maize diseases detection · transfer learning · Grad-CAM · XAI · EfficientNetV2B2 · ResNet50 · InceptionV3 · VGG16 · Xception.

1 Introduction

Agriculture plays a critical role in maintaining global food security and economic stability [10]. Among the staple crops, maize (Zea mays), commonly known as corn, have formed the backbone of human diets. Across Sub-Saharan Africa it is widely cultivated, particularly in Tanzania alone, maize cultivation spans over 5 million hectares, with an average annual consumption of 128 kg per person [11]. Beyond food, maize is crucial for livestock feed, biofuel, and biodegradable plastics [12].

Despite its importance, maize production faces various challenges, specially several diseases such as Northern Leaf Blight, Common Rust, Gray Leaf Spot, Maize Lethal Necrosis (MLN), and Maize Streak Virus (MSV). Among these, MLN and MSV are two devastating diseases that pose a significant threat to maize crops, particularly in Sub-Saharan Africa.

MLN, caused by maize chlorotic mottle virus (MCMV) and sugarcane mosaic virus (SCMV), causes yellowing, necrosis, stunting and plant death, resulting in significant yield losses. MSV, which is spread by leafhoppers, causes leaf drop and reduced grain quality. Outbreaks of MLN and MSV have been reported across Africa, including Kenya, Ethiopia, Nigeria, Tanzania, Uganda, and Rwanda. These diseases have severe socio-economic impacts, reducing crop yields, increasing prices, and threatening food security. Traditional assessment methods are slow and often inaccessible to smallholder farmers, emphasizing the need for more accurate and efficient methods.

Recent research has leveraged advancements in AI, particularly deep learning techniques using Convolutional Neural Networks (CNNs) [15], [16] and machine learning models, to classify maize diseases. Where CNN models have shown superior performance in disease diagnosis compared to traditional machine learning models. Despite progress, there remains a lack of reliable studies specifically addressing the diagnosis of MLN and MSV, which are critical for farmers and stakeholders. Furthermore, there is a noticeable gap in the application of XAI techniques in these studies. While XAI offers transparency and insights into the decision-making processes of diagnostic models, essential for building trust and understanding among farmers.

In this study, we utilize five CNN models including EfficientNetV2B2, ResNet50, InceptionV3, VGG16, and Xception due to their proven effectiveness. This study not only aims to diagnose maize image disease, but also incorporates XAI to enhance the reliability and usability of these diagnostic tools in practical agricultural applications. The results of this research helps to develop AI applications in agriculture, enabling timely and transparent diagnosis of maize diseases in Sub-Saharan Africa.

The main contribution 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.

2 Literature Review

Maize, or corn, is a versatile crop capable of thriving in various climates, and its leaf abnormalities can be effectively categorized and identified using deep learning and machine learning techniques. Paper [5] addresses the challenge of accurately detecting maize leaf diseases, specifically Northern Leaf Blight, Northern

Leaf Spot, and Gray Leaf Spot (GLS), under different environmental conditions. Utilizing the CD&S dataset of 1,597 images, the study introduces MaizeNet, a deep learning model that combines Faster-RCNN with ResNet-50 and spatial-channel attention mechanisms. Through extensive experimentation, MaizeNet achieves an impressive accuracy of 97.89%, significantly improving disease spot localization and detection accuracy even in cluttered backgrounds and varying lighting conditions.

The study [3] presents a mobile system for detecting and classifying maize leaf diseases to combat significant agricultural losses in Punjab, Pakistan. Using a dataset of over 2,000 images across various growth stages and weather conditions, researchers implemented deep learning models, from YOLOv3-tiny to YOLOv8n, with YOLOv8n proving most effective, achieving high precision and a detection speed of 69.76 FPS. This research underscores deep learning's potential for real-time agricultural disease management. Similarly, another study [9] focused on improving corn leaf disease identification using Support Vector Machine (SVM) and Convolutional Neural Networks (CNNs) like AlexNet and ResNet50. With over 3,000 preprocessed corn leaf images from Embu County, Kenya, CNN models, particularly AlexNet, outperformed SVM classifiers, achieving accuracy rates of 98.3% and 96.6%, respectively, highlighting deep learning's role in enhancing crop protection and supporting sustainable agricultural practices.

The paper [7] addresses low agricultural productivity caused by plant diseases, particularly in maize, emphasizing the need for early disease detection to minimize farmer losses. Utilizing supervised machine learning models like Naive Bayes, K-Nearest Neighbor, Support Vector Machine, Decision Tree, and Random Forest, the study analyzes high-resolution maize leaf images and achieves a maximum accuracy of 79.23% with the Random Forest classifier using a dataset of 3,823 images. Similarly, [8] focuses on grapes and tomatoes, employing the VGG16 model for disease detection and classification, utilizing data augmentation, hyperparameter tuning, and model optimization to attain accuracy rates of 98.40% for grapes and 95.71% for tomatoes. Both studies underscore the significance of early disease detection and showcase how machine learning and deep learning techniques can enhance agricultural practices and food production.

One study [6] achieved 98.6% accuracy in classifying corn diseases and healthy plants using deep transfer learning with CNNs on a dataset of 3,852 images. Another paper [4] proposed a method for detecting maize foliar disease in complex environments with an LS-RCNN and CENet cascade network, which demonstrated higher F1-scores and faster training through a two-stage transfer learning strategy. Both studies highlight the potential of deep learning to enhance agricultural practices by enabling accurate disease identification and efficient crop management.

Another study [1] introduced LeafDoc-Net, a lightweight transfer-learning model for accurately identifying leaf diseases across various plant species, even with limited image data. This model combines DenseNet121 and MobileNetV2, incorporating enhancements like global average pooling and batch normalization. Evaluated on cassava and wheat leaf disease datasets, LeafDoc-Net outperformed existing models in most performance metrics, with room for future improvements. Similarly, paper [2] presented MFaster R-CNN, tailored for detecting corn leaf diseases using a dataset of 697 images captured in diverse weather conditions. By enhancing the Faster R-CNN framework with batch normalization and a mixed cost function, MFaster R-CNN showed superior performance, demonstrating its practical potential for agricultural disease control.

In summary, most research in this field focuses on classification and detection, particularly corn leaf diseases. However, certain diseases, like MLN, remain underexplored. While some studies have addressed different crop diseases, there has been limited work on maize leaf disease detection using deep learning, as depicted in table 1. The need for explainable AI in this area is crucial. To keep pace with technological advancements, creating a detection tool for farmers, especially in Tanzania, is essential to combat these diseases.

Table 1. Comparison of Different Papers With Our Paper

Paper	Maize Disease Analysis	MLN	MSV	Dataset Used	ML & DL	XAI
[1]	-	-	-	-	≡	≡
[9]	≡	≡	≡	=	≡	-
[8]	-	-	-	≡	≡	-
[2]	≡	-	-	-	≡	-
[6], [4]	≡	-	-	=	≡	-
[5], [3], [7]	≡	-	-	=	≡	-
Our Paper	≡	≡	≡	≡	≡	≡

≡ *Covered* = *Partially Covered* - *Not Covered*
Dataset image used <1000: -; Dataset image used 1000 to 5000: =;
Dataset image used >5000: ≡

3 Methodology

The methodology utilized in this study, as shown in figure 1 below, involves collecting and preparing images of healthy and diseased samples, focusing on MLN and MSV. We carefully select, resize, and normalize the data to create a robust dataset. Clear labeling of disease stages ensures that the dataset accurately reflects real-world conditions.

3.1 Dataset

During the data acquisition phase, maize leaf images were collected using AdSurv's mobile application on Samsung phones. Data collection occurred over six months, from February to July 2021, by a team from the Nelson Mandela African Institution of Science and Technology and the Tanzania Agricultural Research Institute. This dataset was gathered to support plant disease diagnosis for farmers.

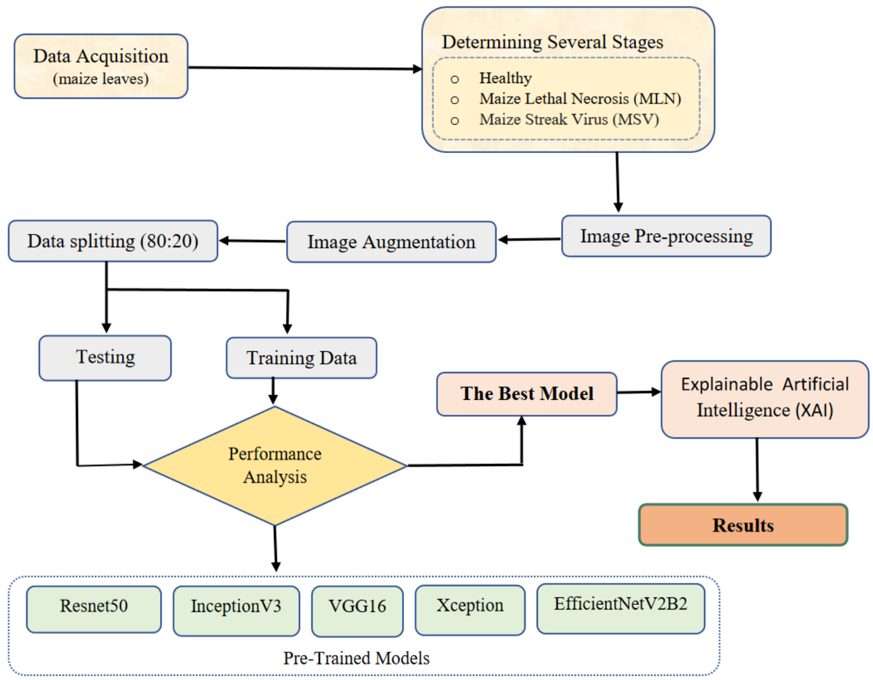

Fig. 1. Workflow of the proposed methodology for maize disease diagnosis.

In total, 17,277 labeled images were collected: Healthy – 5,542, MLN – 5,068, and MSV – 6,667. Additionally, the team recorded crop status, variety, age, and geographic location at both district and sub-county levels, making the dataset well-suited for learning experiments.

3.2 Data Preprocessing

The original data set was subjected to quite extensive pre-processing to improve its quality and applicability. Firstly, the raw images that had been made through the use of AdSurv were 'cleaned' of similar ones, meaning that images were purged to keep the dataset's integrity intact. Furthermore, the images were tagged according to their class, that is to say, whether they were healthy, exposed to Lethal Necrosis, or affected by the Streak Virus to help with the proper classification and annotation, required for the computer vision tasks translated to later stages. Finally, the images were renamed to facilitate data management.

3.3 Transfer Learning Models

Transfer learning helps pre-trained models learn new tasks using existing knowledge, especially with limited data. It's widely used in computer vision tasks like diagnosis and prediction, popularized by AlexNet's success in the ImageNet competition. Pre-trained features like edge and pattern detection are fine-tuned to improve performance. Unlike multitask learning, which learns tasks simultaneously, transfer learning progressively transfers knowledge, making it ideal for scenarios requiring gradual training and flexibility.

ResNet50 To enhance deep network training, residual learning with skip connections effectively addresses the vanishing gradient problem. A transfer learning model based on ResNet50, a 50-layer deep convolutional network developed by Microsoft Research in 2015, was utilized. Its architecture includes convolutional layers for feature extraction, identification blocks, convolutional blocks for feature modification, and fully connected layers for classification. Trained on the large-scale ImageNet dataset, ResNet50 achieved a top-5 error rate of 6.71%, comparable to human performance. Its high accuracy, fast convergence, and efficient training make it a preferred model for applications like medical image analysis, object detection, and facial recognition.

InceptionV3 InceptionV3 is a CNN architecture developed by Google researchers in 2015, building on the earlier Inception V1 and V2 models. It is designed to be computationally efficient while delivering high performance in image classification tasks. The architecture uses a combination of convolutional, pooling, and inception modules to extract features from images. Inception modules allow the network to capture features at different scales by performing multiple convolutional operations simultaneously. InceptionV3 has demonstrated top-tier performance in various computer vision tasks, including object detection, image classification, and visual question answering. It achieved a 21.2% top-1 error rate and a 5.6% top-5 error rate in the 2012 ImageNet Large Scale Visual Recognition Challenge.

VGG16 VGG-16, introduced by K. Simonyan and A. Zisserman from Oxford in 2014, has become a cornerstone in computer vision. This 16-layer model, which placed second in the ILSVRC 2014 classification challenge, features convolutional layers with 3x3 filters, max-pooling, and fully connected layers. It achieved an impressive 92.7% top-5 accuracy on the ImageNet dataset, containing over 14 million images across 1,000 classes. VGG-16 improves on earlier models by using multiple 3x3 filters instead of larger kernels, enabling deeper networks. Its design uses 224x224 RGB input, consistent ReLU activation, and omits Local Response Normalization (LRN) to reduce computational cost. VGG-16 remains effective for large-scale image recognition when trained on NVIDIA Titan Black GPUs.

EfficientNetV2B2 EfficientNetV2, developed by Mingxing Tan and Quoc V. Le, is a highly efficient convolutional neural network that offers faster training speeds and better parameter efficiency than earlier models. Created through neural architecture search and scaling, it optimizes both model size and training speed, incorporating innovations like Fused-MBConv. EfficientNetV2 is up to

6.8 times smaller and significantly faster than other models. Additionally, its design supports progressive learning by increasing regularization alongside image size, ensuring accuracy while preventing overfitting. It outperforms most Vision Transformers (ViT) by 2% in accuracy and trains 5x-11x faster on the same computing resources.

Xception The Xception model, introduced by François Chollet in 2017, uses depth-wise separable convolutions to reduce parameters and computational costs while maintaining high performance. Xception's architecture includes entry and exit flows with ResNet-inspired skip connections and global depth-wise separable convolutions for capturing global context. Data augmentation and batch normalization further enhance training efficiency. In our study, Xception achieved 89% accuracy, 86% F1-score, and 86% recall in maize disease classification using an 80:20 training-to-test split with 10 epochs. Thus, Xception proves to be a highly efficient and robust model for various computer vision tasks.

3.4 Proposed Model

To classify maize diseases, we tested several CNNs known for their image recognition capabilities, as shown in the figure 2. EfficientNetV2B2 emerged as the most accurate model. It processes input images through convolutional layers, learning key features related to disease detection, such as textures, shapes, and color patterns. Pooling layers reduce dimensionality, focusing on essential elements. The extracted features are then fed into fully connected layers to classify the disease. EfficientNetV2B2's balance of size and performance makes it well-suited for handling maize disease images effectively.

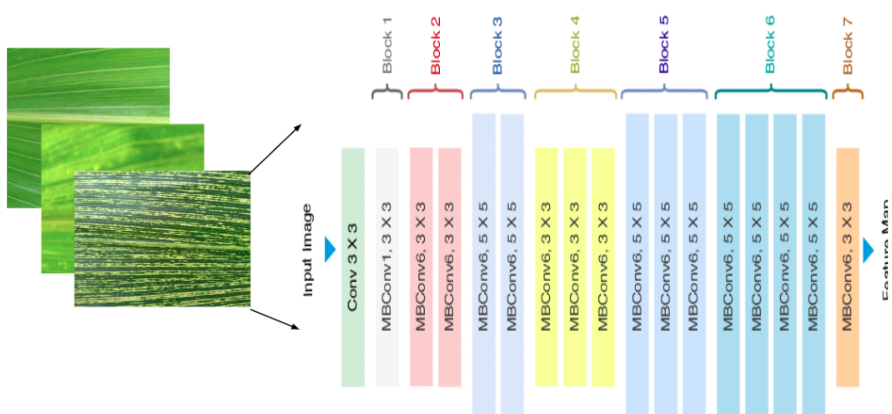

Fig. 2. The proposed model architecture.

Model Parameters An extensive analysis was conducted to optimize model performance, as detailed in table 2. Several CNN architectures were fine-tuned with distinct hyperparameters. For ResNet50, a batch size of 32, Adam optimizer (learning rate 0.001), and no dropout were used, as its residual connections reduce overfitting. InceptionV3 and VGG16 employed a batch size of 32, a 0.0001 learning rate, and a 0.5 dropout rate to mitigate overfitting in their deeper architectures. Xception followed with similar settings but leveraged depthwise separable convolutions. EfficientNetV2B2, with an initial learning rate of zero, relied on built-in regularization without dropout. All models standardized input size to 224x224x3 and used the Categorical Cross entropy loss function.

Table 2. Parameter Settings for Different Models

Parameter	ResNet50	InceptionV3	VGG16	Xception	EfficientNetV2B2
Batch Size	32	32	32	32	32
Optimizer	Adam	Adam	Adam	Adam	Adam
Learning Rate	0.001	0.0001	0.0001	0.001	0
Input Size	224×224×3	224×224×3	224×224×3	224×224×3	224×224×3
Dropout Rate	0	0.5	0.5	0.5	0
Loss Function	Categorical Crossentropy				

4 Results And Discussion

A concise overview of our findings from applying the different models to classify the dataset is presented in this section. Five models, VGG16, Inception, Xception, Rasnet50, and EfficientNetV2B2 were evaluated and their accuracy, recall, precision, and F1 score were compared.

A dataset split of 80/20 for training and validation respectively, together with 10 epochs and 383 batches, were used on all the models to train the datasets. The key performance metrics for all models are shown in table 3. The metrics provide insight into the model's ability to generalize, with attention to how they handle imbalanced classes.

Table 3. Comparison of Performance Metrics Across Various 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
EfficientNetV2B3	92	90	90	90

The various models for the classifications are analyzed. An accuracy of 87%, with F1 score of 77% suggests moderate performance by the VGG16. Inception had the lowest accuracy of 80%, with challenges in classifying smaller classes. Xception had 89% accuracy, but slightly overfitting. ResNet50 had 91% accuracy, excellent precision and recall, and minimal variance between training, validation, and test accuracies. EfficientNetV2B2 had the highest accuracy of 92%, with slightly overfitting issues but good recall and precision, especially for class distribution fluctuations.

Among all the models tested, EfficientNetV2B2 proved to be the most reliable model. It had a balanced performance with very high accuracy, precision, recall, and F1 scores. This model exhibits very minimal overfitting; it has consistently shown similar performances both in the training and test datasets, promising great potential when considering real-world applications. Moreover, the models VGG16 and Xception showed signs of overfitting, with large differences between the training accuracy and their test accuracy. ResNet50 and EfficientNetV2B2 had the best generalization, which is evident from their training accuracy being close to both validation and test accuracies. Inception, though consistent, gave the poorest overall performance and was hence not favorable for practical deployment. Indeed, considering the superior performance on a number of metrics, EfficientNetV2B2 models are reliable on datasets with fluctuating conditions, just like those in real-world environments.

5 Implementation of 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 [17]. For transparent decision-making, XAI techniques have been implemented. Grad-CAM and Integrated Gradient techniques were integrated with EfficientNetV2B2 to enhance model interpretation. In the below figures 3, 4, and 5 we can see the implementation of Grad-CAM XAI method with our high performing model, EfficientV2B2.

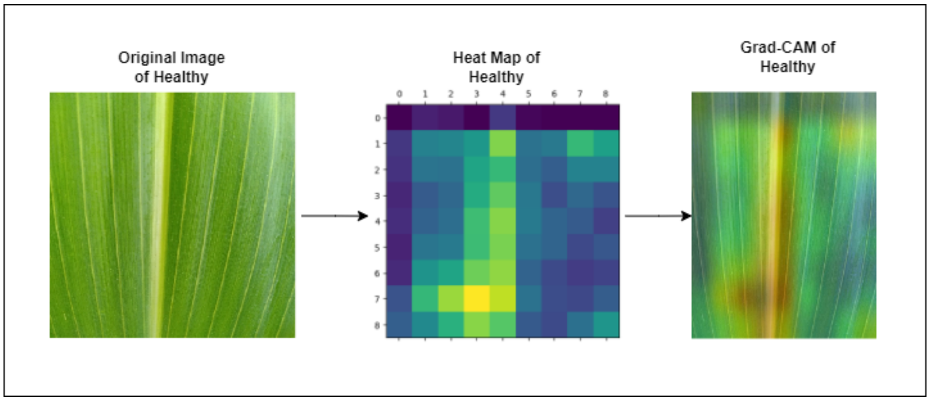

Fig. 3. Model Interpretability using Grad-CAM for Healthy.

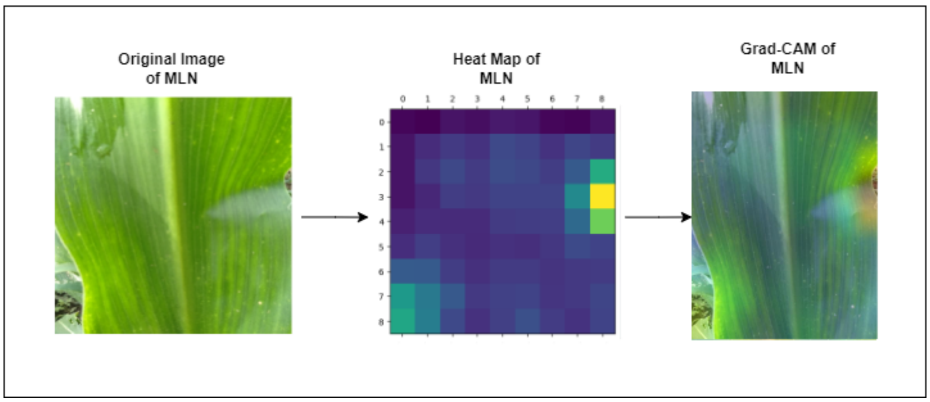

Fig. 4. Model Interpretability using Grad-CAM for MLN.

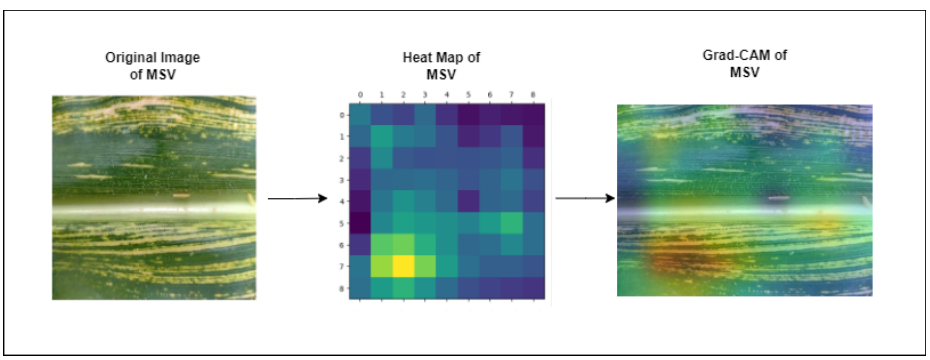

Fig. 5. Model Interpretability using Grad-CAM for MSV.

6 Conclusion

This study has successfully demonstrated the potential of deep learning techniques in detecting maize diseases, focusing on MLN and MSV. By employing transfer learning models, including EfficientNetV2B2, ResNet50, InceptionV3, VGG16, and Xception, we achieved a high accuracy rate, with EfficientNetV2B2 leading at 92%. The integration of XAI methods, such as Grad-CAM, significantly enhanced the transparency and interpretability of the model's decision-making process. This transparency is crucial in building trust among farmers and stakeholders, who rely on these tools for accurate disease diagnosis. Our findings highlight the transformative potential of AI in agriculture, particularly in Sub-Saharan Africa, where maize is a vital crop for food security and economic stability. By facilitating early disease detection and enabling timely intervention, our approach can significantly reduce crop losses, enhance yields, and contribute to the sustainability of maize farming practices. This study not only presents an effective framework for maize disease detection but also underscores the broader impact of integrating AI into agricultural practices to ensure food security.

7 Future Work

In the future, the large-scale deployment of our models will be a crucial area of focus, particularly in resource-constrained settings. Optimizing Deep Neural Networks (DNNs) and transformers for real-time use on mobile and edge devices will make advanced disease detection accessible to a broader range of farmers, enhancing the practicality of our approach. Expanding the dataset with images from diverse geographic regions and climatic conditions will further strengthen the robustness and generalizability of the models. Additionally, integrating these DNNs and transformers with IoT devices for continuous and automated crop monitoring will revolutionize early disease detection and management, as real-time data is essential for timely interventions. While our study has already used Grad-CAM for model interpretability, future work will involve implementing more advanced Explainable AI techniques to further enhance transparency and build trust.

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