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A Mobile-Integrated Deep Learning Framework for Early Detection of Maize Diseases

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Abstract: Maize is a cornerstone of food security and economic stability in Nigeria, yet its production is severely hampered by crop diseases that cause significant yield losses and threaten the livelihoods of millions of smallholder farmers. Despite advances in machine learning (ML) and deep learning (DL) for plant disease detection, existing solutions often lack generalizability, scalability, and accessibility for resource-limited settings. This research used a robust, predictive system that leverages convolutional neural networks, specifically ResNet50 and EfficientNet trained on diverse, annotated datasets of maize leaf images. By integrating computer vision, transfer learning, and user-centric mobile application design, the system aimed to provide real-time, accurate diagnosis and actionable recommendations for disease management. This study compared the performance of the ResNet50 and the EfficientNet. At the end of the research, ResNet50 achieved marginally higher accuracy than EfficientNet under the same experimental conditions, although the performance difference is small and not statistically tested. The ResNet50 model was thereafter deployed into a scalable mobile application tool that can empower farmers and extension workers with early disease detection capabilities, potentially reducing crop losses, improving productivity, and enhancing food security across sub-Saharan Africa.

Index Terms: Maize Disease Detection, ResNet50, EfficientNet, AI deployment.

1. Introduction

Maize (Zea mays L.) stands as one of Africa's most important cereal crops, both nutritionally and economically. In Nigeria, maize is a cornerstone of food and feed systems, forming a dietary staple for millions and a primary input for livestock production. The sector's scale is enormous as Nigeria was projected to produce 12 million metric tons from 5.8 million hectares in 2024/2025, securing its position as the continent's second-largest maize producer [1]. Yet despite this prominence, maize production in Nigeria is plagued by chronic challenges: national average yields remain below 2 tonnes per hectare, starkly beneath global benchmarks, while annual production deficits approach 4 million metric tons [2].

A major contributor to these low yields and persistent deficits is the incidence and spread of devastating maize diseases. Pathologies such as Maize Streak Virus, Gray Leaf Spot (*Cercospora zeae-maydis*), and Northern Leaf Blight

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(*Exserohilum turcicum*) routinely cause yield losses ranging from 15% up to total crop failure, particularly in the absence of resistant cultivars and timely disease management [3,4]. Beyond direct yield reductions, these diseases also diminish grain quality, contribute to mycotoxin contamination, and increase both input costs and demand for skilled labour [5,6,7].

Currently, disease diagnosis and management remain largely reactive and suboptimal. Most smallholder farmers, who make up the bulk of Nigeria's maize growers, lack reliable access to agricultural extension services, laboratory diagnostics, or scientific tools for accurate disease identification and early intervention [8,9,10]. This diagnostic gap prolongs response times and exacerbates economic losses.

Addressing this challenge calls for a robust, proactive, and accessible system that harnesses modern technology to improve maize health surveillance. Recent advances in remote sensing, mobile computing, and especially machine learning (ML) provide unprecedented opportunities to develop data-driven solutions for crop disease detection [4]. By integrating field-level data, smartphone-enabled imaging, and deep learning algorithms, researchers and practitioners can now strive toward predictive disease monitoring systems that support early intervention and smart management choices. Such innovations hold transformative potential for boosting yields, safeguarding food security, and has the potential to support improved decision-making.

Machine learning (ML) which is a subset of artificial intelligence (AI) is at the forefront of these developments. ML empowers computers to learn complex patterns directly from large datasets, enhancing prediction and detection capabilities across a wide range of fields, from autonomous vehicles to language processing and healthcare diagnostics [11, 12]. In agriculture, and particularly plant disease identification, ML (and its subfield, deep learning) has demonstrated the potential to rival or even surpass traditional expert-driven approaches by leveraging rapid computational advances and the proliferation of accessible data sources.

It is within this context that this research proposes a mobile-integrated deep learning framework for the early detection of maize diseases in Nigeria. By aligning novel machine and deep learning techniques with real-world agronomic needs, this work aims to bridge the critical gap in timely, accurate maize disease diagnostics, contributing directly to regional food security and resilience. The main contributions of this study are:

(i) Development of a mobile-integrated maize disease detection pipeline that bridges MATLAB-based model training with real-time TensorFlow Lite deployment for on-device inference in low-resource environments.
(ii) Construction and harmonization of a multi-source maize leaf image dataset collected from PlantVillage, FUTA WASCAL, and IITA, with explicit normalization of acquisition conditions.
(iii) A comparative evaluation of ResNet50 and EfficientNet under identical preprocessing, training, and deployment constraints, highlighting performance–efficiency trade-offs rather than raw accuracy alone.
(iv) Practical deployment insights for agricultural decision support systems targeting smallholder farmers in sub-Saharan Africa.

2. Literature Review

The last few years have witnessed significant advancements in the application of machine learning (ML) and deep learning (DL) to plant disease prediction and precision agriculture. As research has shifted from traditional manual methods to sophisticated automated systems, several trends and persistent gaps have emerged.

Ullah et al., [13] presented the use of a CNN model for automatically detecting and classifying maize leaf diseases, focusing on preprocessing techniques like noise reduction and color space conversion (RGB to HSI) to enhance image quality. By training the CNN on a dataset of 4000 images and splitting the data for training (75%) and testing (25%), the model achieved an impressive accuracy of 96.53%. They highlighted how CNN excels in classifying diseases such as northern leaf blight and Gray leaf spot and demonstrates its clear advantage over traditional models like KNN and Ensemble learning, which achieved much lower accuracies. However, its limitation is that the study primarily focused on a pre-existing dataset rather than real-world conditions, making its results more applicable to controlled environments rather than field use.

Ashwini et al., [14] emphasized the application of CNN for corn disease detection in real-world agricultural environments, focusing on how early detection can enhance crop yield and reduce economic losses for farmers. The methodology involved capturing maize leaf images from the field, processing them using CNN for feature extraction, and classifying diseases like rust and blight. Although specific accuracy rates are not provided, the study highlighted CNN's superior performance over traditional machine learning models in handling complex backgrounds and images taken under varied lighting conditions. The study's strength lies in its real-world applicability, showing how CNN can be used by farmers in practical scenarios, but it does not offer detailed performance metrics, making it harder to quantitatively assess the model's success

Recent studies have leveraged a broad spectrum of ML and DL models for disease detection and crop management. Deep learning, particularly convolutional neural networks (CNNs), has become the dominant approach for identifying plant diseases from leaf images. These models have achieved high accuracy across several crops and disease types, with transfer learning and optimized architectures further boosting performance [15, 16, 17]. Also, there is a growing trend

toward integrating ML models with IoT devices and smartphones, making real-time disease detection more accessible to farmers even in remote areas [16]

Studies have explored ensemble techniques such as Random Forest, Voting Regressor, Stacking Regressor and hybrid approaches that combine image features with environmental data to improve robustness and prediction accuracy [18,19]. Machine learning-driven decision support systems now offer actionable recommendations for disease management, irrigation, and fertilizer application, enhancing operational efficiency and sustainability [18,20].

Despite these advances, several critical gaps persist in literature and practice. Most models are trained on curated datasets collected under controlled conditions, which may not reflect the variability of real-world environments. This limits model generalizability across regions, crop varieties, and disease manifestations [17, 21]. While some studies incorporate weather and soil data, the integration of comprehensive environmental variables remains limited. Models often underperform when deployed in new agro-ecological zones due to insufficient adaptation to local conditions [18, 19]. High-performing DL models require substantial computational resources and large labeled datasets, posing challenges for smallholder farmers and regions with limited digital infrastructure. Efforts to develop lightweight, explainable AI models suitable for mobile and edge computing are ongoing but not yet widespread [21, 16].

Many current systems focus on single diseases, whereas practical applications demand models capable of simultaneous multi-disease detection and classification [21, 17]. While standalone disease detection tools are advancing, their seamless integration into broader farm management platforms encompassing yield prediction, resource optimization, and economic analysis is still emerging [19, 20].

The field is increasingly moving toward holistic, data-driven agriculture, where machine learning and deep learning models not only detect diseases but also support broader crop management decisions. However, realizing the full potential of these technologies requires annotated datasets that span diverse crops, disease conditions, and real-world acquisition environments. Furthermore, there is a growing need for adaptive models capable of learning from limited local data and transferring knowledge across contexts to enhance robustness and scalability. In this regard, this study emphasizes a mobile-based, user-centric design tailored to the constraints of smallholder farmers, prioritizing simplicity, interpretability, and accessibility. Considerations related to data privacy, ownership, and potential labour implications are also acknowledged.

Despite the high accuracies reported in existing studies, most rely on controlled datasets, lack deployment validation, and rarely address real-world constraints such as device limitations and intermittent connectivity. This study addresses these gaps by emphasizing deployability and cross-source dataset harmonization rather than algorithmic novelty.

3. Research Methodology

3.1. Research design

The process of detecting maize leaf diseases forms the foundation of the design model in this study. This is accomplished through the application of a Convolutional Neural Network (CNN) model, which processes and classifies images of maize leaves into disease categories. The systematic research methodology adopted to achieve this goal is shown in Fig. 1.

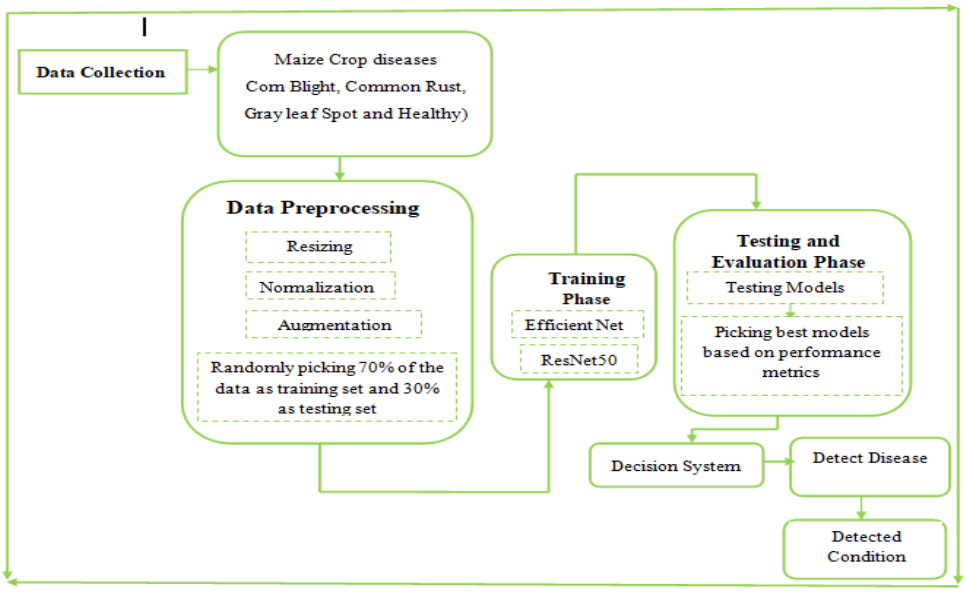


Fig. 1. System Architecture

3.2. Data Collection and Preprocessing

The dataset used in this study consisted of 4,000 annotated images of maize leaves affected by various conditions, including Maize Streak Virus, Gray Leaf Spot, Common Rust, and Northern Leaf Blight. The data were sourced from diverse agro-ecological zones through datasets curated by PlantVillage, FUTA WASCAL, and the International Institute of Tropical Agriculture (IITA). Specifically, 1,270 images were obtained from PlantVillage, 1,560 from FUTA WASCAL, and 1,170 from IITA.

To mitigate variations arising from differences in acquisition devices, lighting conditions, and background complexity across sources, all images were resized to a uniform resolution, colour-normalized, and subjected to identical augmentation pipelines. Histogram-based normalization and colour-space standardization were applied uniformly to ensure cross-source consistency. All datasets used are publicly available or institutionally authorized for academic research, and their usage complies with respective licensing and data-sharing policies.

The images were categorized into four classes: healthy, Gray Leaf Spot, Northern Leaf Blight, and Common Rust. Prior to model training, preprocessing techniques including noise reduction, image sharpening, and RGB-to-HSI colour space conversion were applied to enhance image quality. The RGB-to-HSI transformation was adopted based on prior studies indicating improved separation of chromatic features in plant disease imagery [13]. Although no ablation study was conducted, this preprocessing choice was empirically observed to stabilize model training. Data augmentation techniques such as horizontal flipping, rotation, and colour shifts were further applied to improve generalization and reduce overfitting.

3.3. Model Development

The architecture of the CNN model used in this study includes a series of convolutional layers that extract features from the pre-processed images. This was followed by pooling layers to down-sample the image data, reducing its dimensions while retaining critical features. Rectified Linear Unit (ReLU) activation functions were applied to introduce non-linearity, and fully connected layers were added at the end to classify the images based on the extracted features. Two convolutional neural network architectures were utilized which are ResNet50 and EfficientNet. ResNet50 which is known for its residual learning framework, enables training of deep models without gradient degradation, while EfficientNet employs compound scaling to optimize depth, width, and resolution simultaneously, achieving better performance with fewer parameters. Both models were trained and fine-tuned using transfer learning on the maize disease dataset, leveraging pretrained weights from ImageNet for faster convergence and improved accuracy.

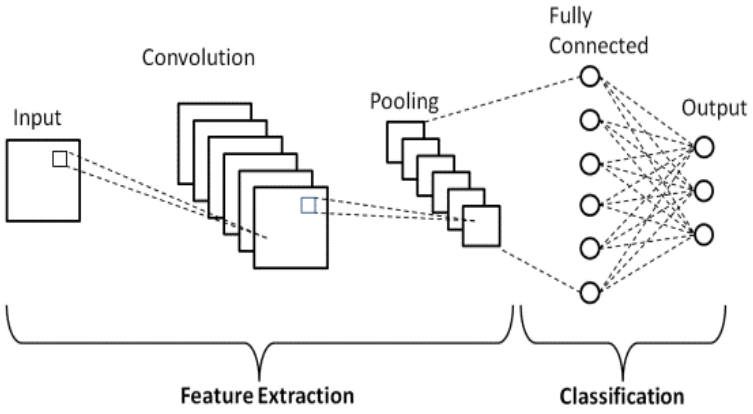


Fig. 2. CNN model Architecture.

3.4. Data Splitting

The dataset was divided into training and testing subsets, with 75% allocated for training and 25% for testing. To reduce the risk of overfitting and enhance internal robustness, k-fold cross-validation was applied during model development. Model training was conducted in a MATLAB environment using relevant computer vision libraries. Optimization techniques such as backpropagation, learning rate scheduling, and early stopping were employed, with the Adam optimizer and categorical cross-entropy loss function used for parameter updates.

Model performance was evaluated on the held-out test set using multiple metrics, including accuracy, precision, recall, F1-score, and specificity. Although cross-validation was applied within the dataset, all samples originated from the same aggregated data sources. External cross-location validation was not performed and is therefore identified as an important direction for future work.

3.5. Disease Detection

Once the models had been trained, they were used to classify maize leaf images into one of the four categories: healthy, Gray leaf spot, northern leaf blight, and common rust. The classification process was based on the features extracted from the images during the convolutional and pooling stages. The results were evaluated using a confusion matrix and performance metrics such as accuracy, precision, recall, and F1-score.

3.6. Training Configurations

Training was conducted using the Adam optimizer with an initial learning rate of 0.0001, batch size of 32, and 20 epochs. Early stopping was applied based on validation loss. Experiments were conducted using MATLAB's default random seed for reproducibility.

3.7. Model Deployment

Trained models were exported from MATLAB and converted to TensorFlow-compatible formats before being optimized and quantized using TensorFlow Lite. Post-conversion validation was conducted to ensure prediction consistency between the training and deployment environments.

The final model was encapsulated within a lightweight mobile application accessible to farmers and agricultural extension officers. Users can upload maize leaf images directly from their devices and receive near real-time diagnostic feedback. Based on predicted disease severity, the system provides tailored recommendations to support timely intervention. TensorFlow Lite enables efficient on-device inference, ensuring responsiveness under low-connectivity conditions. The application was developed using Flutter for cross-platform compatibility and integrated with a Python-based backend via Firebase APIs to support seamless user interaction. The architecture of the mobile application is shown in Fig. 3.

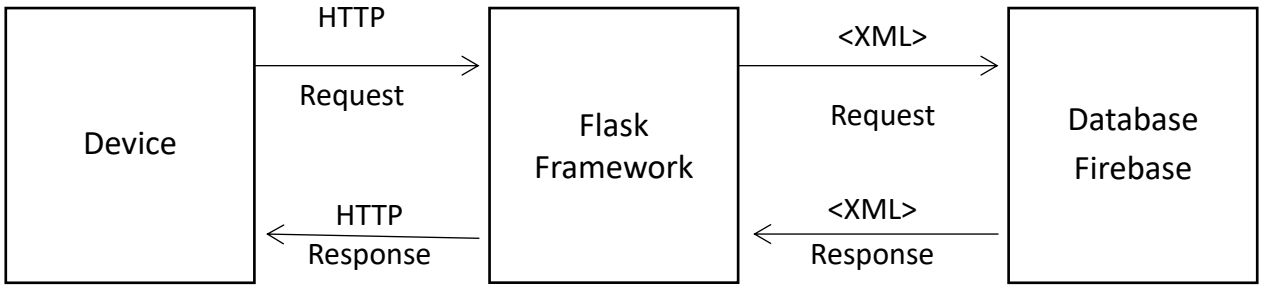


Fig. 3. Architecture of the mobile application

4. Results

To predict and classify maize leaf diseases, we utilized a dataset comprising 4000 maize leaf images, categorized into four distinct groups: healthy, Gray leaf spot, northern leaf blight, and common rust. Preprocessing techniques, including noise reduction and RGB to HSI color space conversion, were employed to enhance the images. This transformation limits the number of hues, making it easier to identify critical features within the dataset.

The models used to train the dataset used are ResNet50 and EfficientNet which are architectures of deep learning neural networks. These architectures consist of multiple layers designed for image classification tasks, including convolutional layers for feature extraction, pooling layers for down-sampling and fully connected layers for final classification. Neural Networks have been widely recognized for their ability to automatically extract and learn critical image features without manual intervention.

The dataset was divided into training and testing sets, with 75% allocated for training and 25% for testing. The models were trained in a MATLAB environment, utilizing built-in functions from computer vision libraries. The training process involved optimization techniques such as back propagation, early stopping, and learning rate adjustments to improve model performance. The training performance of the ResNet50 and EfficientNet models are shown in fig. 4 and 5.

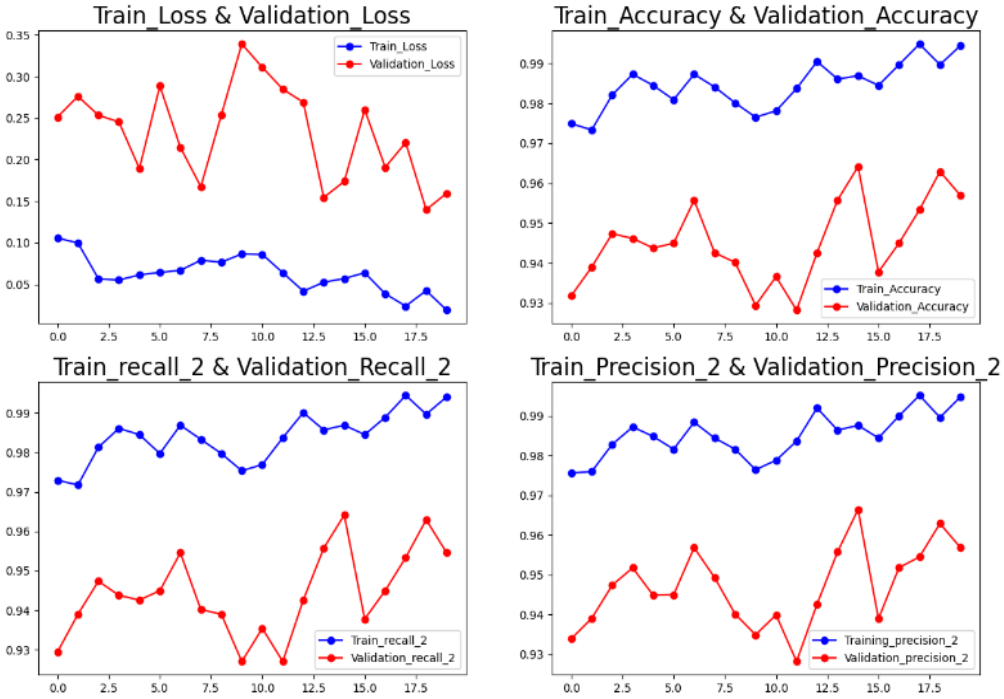


Fig. 4. Training and Validation Loss Graph of the ResNet50

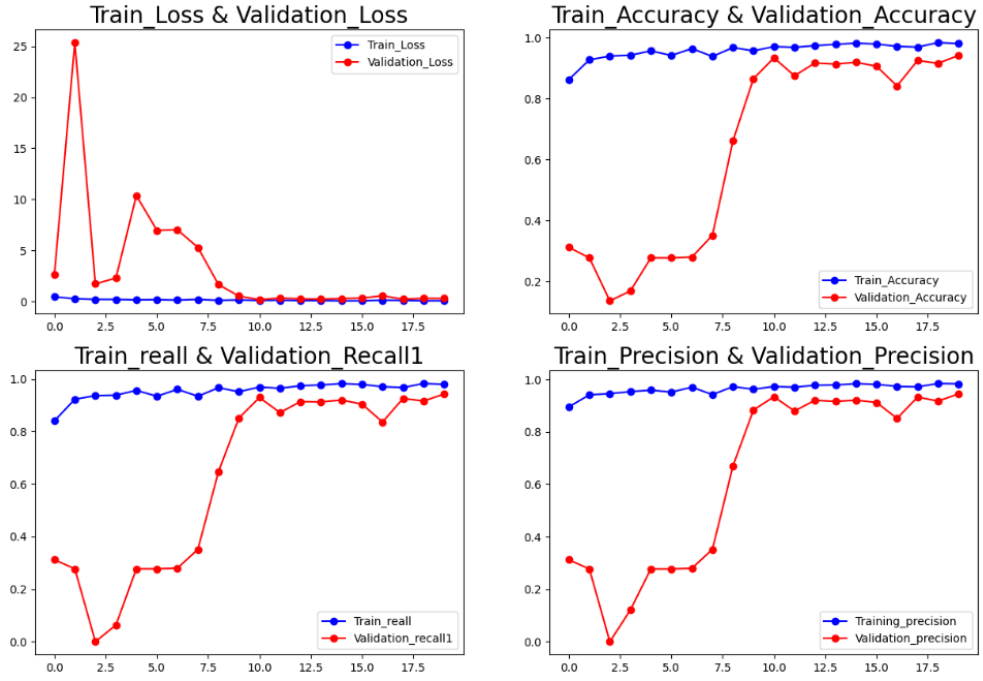


Fig. 5. Training and Validation Loss Graph of the EfficientNet

After training, classification performance was evaluated using confusion matrices and standard metrics including accuracy, precision, recall, and F1-score. The ResNet50 model achieved an accuracy of 96%, while EfficientNet achieved an accuracy of 95%, with both models successfully classifying maize leaf images into their respective categories. Training loss decreased steadily over 20 epochs, indicating strong convergence toward optimal solutions, as shown in Figs. 4 and 5. The confusion matrices presented in Figs. 6 and 7 illustrate true positive, true negative, false positive, and false negative classifications for both models.

Although accuracy is reported for baseline comparison with prior studies, macro-averaged precision, recall, and F1-score were emphasized to account for potential class imbalance. The relatively balanced class distribution reduced severe bias; however, future evaluations will incorporate confidence intervals and statistical significance testing to further strengthen robustness claims.

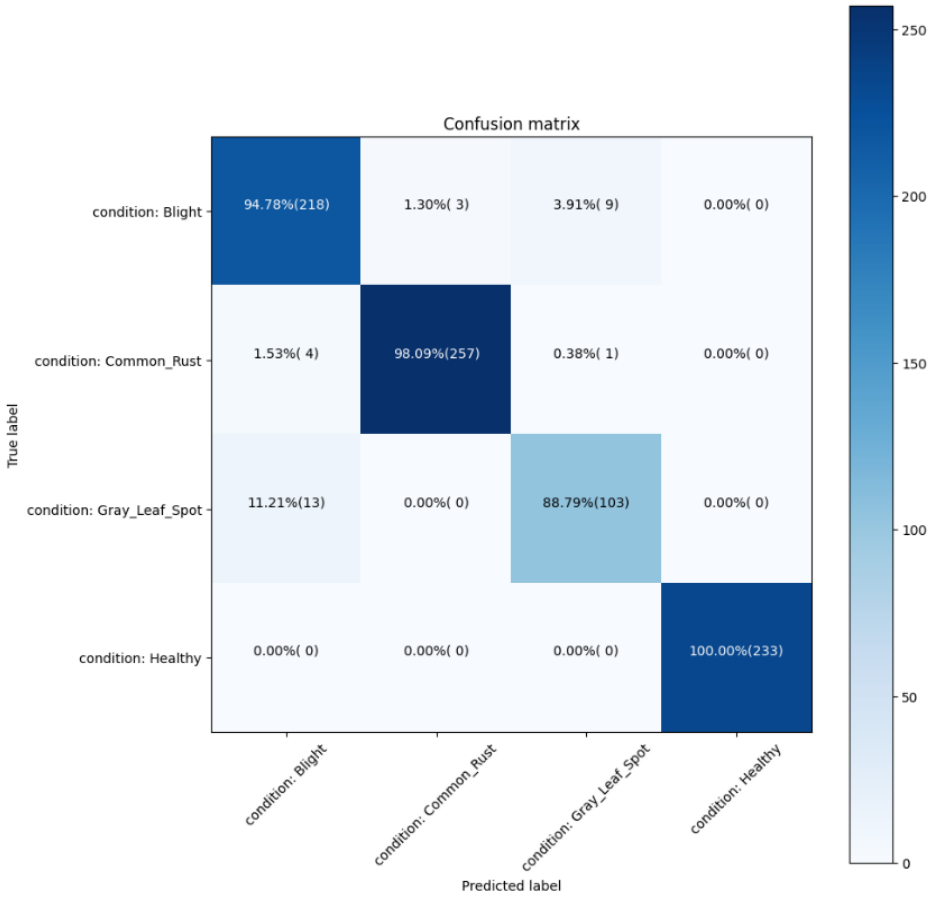


Fig. 6. Confusion Matrix of the ResNet50 model

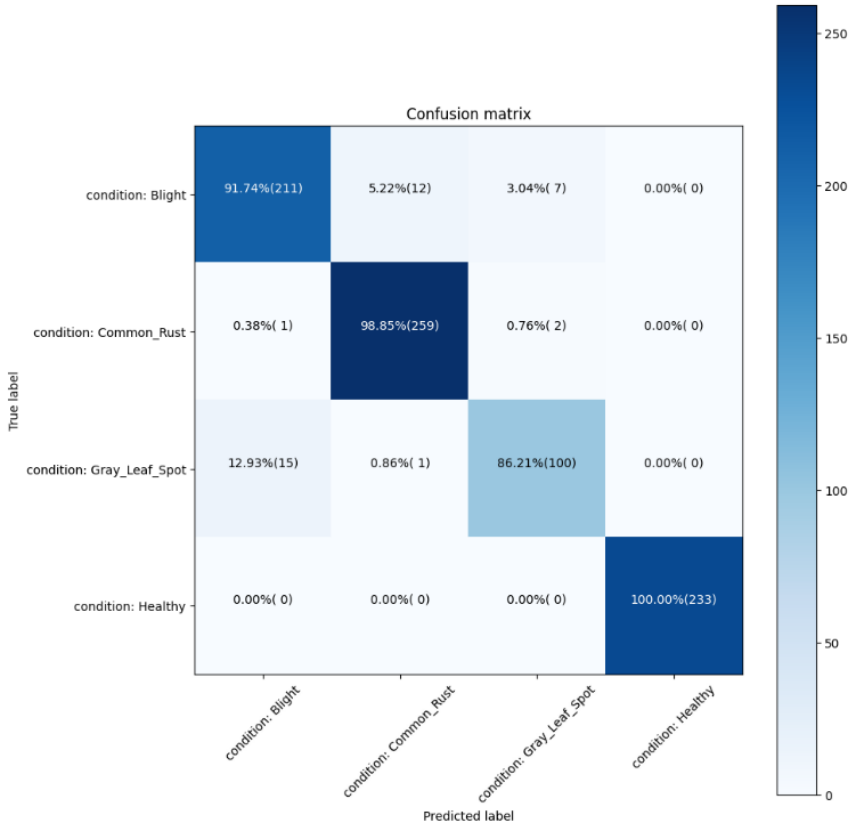


Fig. 7. Confusion Matrix of the EfficientNet Model

The performance of the ResNet50 model for maize crop disease prognosis and diagnosis is reflected in its overall metrics. The model achieved an accuracy of 96%, demonstrating its high reliability in distinguishing between different disease conditions. The precision values for each condition (Northern Leaf Blight, Common Rust, Gray Leaf Spot, and Healthy) are remarkable, with the highest precision of 100% for the Healthy condition, indicating that the model made no false positive predictions for healthy crops.

Northern Leaf Blight: The model achieved a precision of 93%, recall of 95%, and F1-score of 94%, which indicates strong performance in identifying Northern Leaf Blight disease.

Common Rust: Precision was measured at 99%, with a recall of 98% and an F1-score of 98%, showing the model's effectiveness in diagnosing Common Rust, although with slight room for improvement in recall.

Gray Leaf Spot: The model demonstrated a precision of 91%, recall of 89%, and an F1-score of 90%, reflecting its reasonable ability to detect this condition, though it is slightly less accurate compared to other conditions.

Healthy: The model performed perfectly, achieving precision, recall, and F1-score of 100%, ensuring no misclassification of healthy crops. The classification report of the ResNet50 model is shown in fig. 8.

	precision	recall	f1-score	support
condition: Blight	0.93	0.95	0.94	230
condition: Common_Rust	0.99	0.98	0.98	262
condition: Gray_Leaf_Spot	0.91	0.89	0.90	116
condition: Healthy	1.00	1.00	1.00	233
accuracy			0.96	841
macro avg	0.96	0.95	0.96	841
weighted avg	0.96	0.96	0.96	841

Fig. 8. Classification Report of the ResNet50

The performance of the EfficientNet model for maize crop disease prognosis and diagnosis is reflected in its overall metrics. The model achieved an accuracy of 95%, demonstrating its high reliability in distinguishing between different disease conditions. The precision values for each condition (Northern Leaf Blight, Common Rust, Gray Leaf Spot, and Healthy) are remarkable, with the highest precision of 100% for the Healthy condition, indicating that the model made no false positive predictions for healthy crops.

Northern Leaf Blight: The model achieved a precision of 93%, recall of 92%, and F1-score of 92%, which indicates strong performance in identifying Northern Leaf Blight disease.

Common Rust: Precision was measured at 93%, with a recall of 89% and an F1-score of 91%, showing the model's effectiveness in diagnosing Common Rust, although with slight room for improvement in recall.

Gray Leaf Spot: The model demonstrated a precision of 86%, recall of 89%, and an F1-score of 87%, reflecting its reasonable ability to detect this condition, though it is slightly less accurate compared to other conditions.

Healthy: The model performed perfectly, achieving a precision, recall, and F1-score of 100%, ensuring no misclassification of healthy crops. The classification report of the EfficientNet model is shown in fig. 9.

	precision	recall	f1-score	support
condition: Blight	0.93	0.92	0.92	230
condition: Common_Rust	0.95	0.99	0.97	262
condition: Gray_Leaf_Spot	0.92	0.86	0.89	116
condition: Healthy	1.00	1.00	1.00	233
accuracy			0.95	841
macro avg	0.95	0.94	0.95	841
weighted avg	0.95	0.95	0.95	841

Fig. 9. Classification Report of the EfficientNet

Upon training and evaluating the models, the ResNet50 model proved to be the best of both architectures, and the model was deployed in a mobile application. The application is developed in such a way that the user uploads the image of a leaf and the application can tell what disease the plant is suffering from. The Homepage and Detection page of the application is shown in figures 10 and 11.

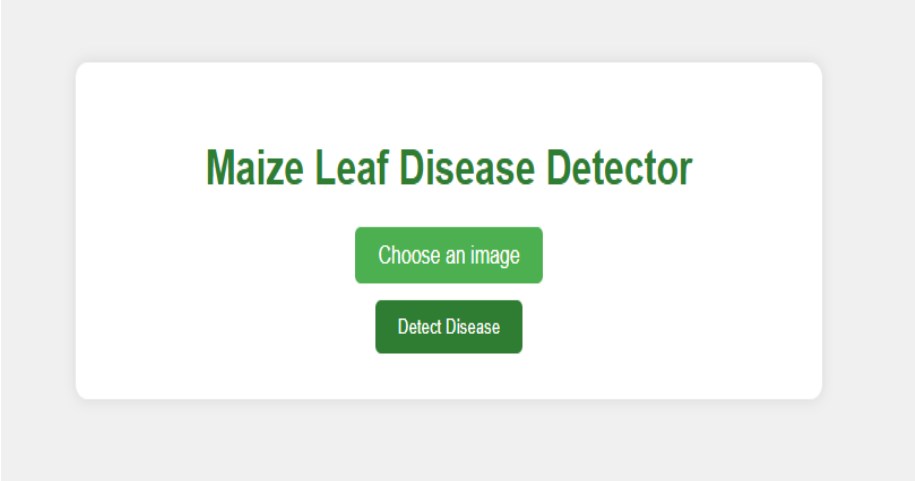


Fig. 10. Home page of the developed application

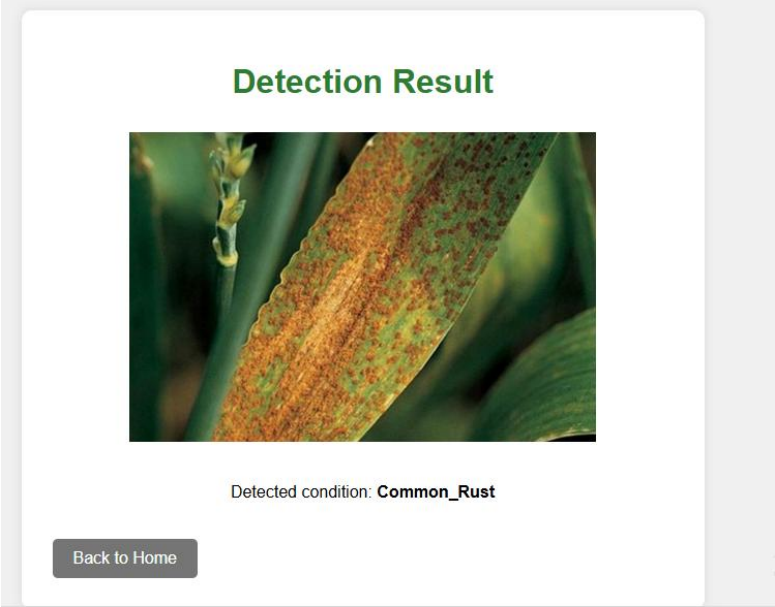


Fig. 11. The detection page where the result is shown

5. Conclusion

This research has successfully demonstrated the application of deep learning, particularly convolutional neural networks, in the detection of maize leaf diseases. Among the two models evaluated, ResNet50 had a comparable performance with the EfficientNet, achieving a classification accuracy of 96%. Its slightly better performance led to its integration into a user-friendly mobile application, offering a scalable solution for early disease diagnosis. This system has the potential to empower smallholder farmers and agricultural extension workers by enabling timely interventions, reducing crop losses, and improving maize productivity, thereby contributing to enhanced food security across sub-Saharan Africa. Future work can focus on expanding the model's generalizability through the inclusion of more diverse datasets spanning different agro-ecological zones, maize varieties, and environmental conditions. Additionally, future enhancements can explore the integration of real-time advisory systems, multilingual support, and offline functionality to increase usability in remote, resource-limited areas. Further research could also perform external cross-location validation and also explore the integration of other AI techniques, such as ensemble learning or multimodal data inputs (e.g., weather data, soil data), to improve predictive accuracy and practical decision support for farmers.

5.1. Recommendations

To build on the findings of this research, it is recommended that the maize disease detection system be tested extensively in real-world farming conditions to validate its robustness and usability outside of controlled environments. Efforts should be made to expand the training dataset by collecting more images from different regions and under varying field conditions to improve the model's adaptability and accuracy across broader contexts.

Moreover, the mobile application should be enhanced to support offline functionality, ensuring that farmers in remote areas without consistent internet access can still benefit from the diagnostic tool. There is also a need to link the app with localized agricultural extension services, so that disease diagnoses are accompanied by context-relevant treatment recommendations and best practices. Collaboration with government agencies, NGOs, and rural cooperatives will be essential to promote large-scale adoption, provide training, and integrate the technology into national agricultural support frameworks.

Finally, it is advisable to extend the system's capabilities to include other major crops affected by diseases in the region, thereby offering a more comprehensive plant health monitoring tool that can support a wider range of smallholder farming activities.

Acknowledgement

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Data Availability Statement

Some of the data that support the findings of this study are openly available in [22]

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