

**Ai-Based Maize Disease Mobile Application For Maize Streak Virus, Grey Leaf Spot And Common Rust In Rukungiri**

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**Abstract**

Maize (*Zea mays* L.) production in Uganda is threatened by devastating diseases including Maize Streak Virus (MSV), Grey Leaf Spot (GLS), and Common Rust (CR), which collectively reduce yields by 30–80% in affected fields. This study developed, tested, and evaluated an AI-based mobile application for early detection and classification of these three major maize diseases in Rukungiri District, Uganda. The application employs a Convolutional Neural Network (CNN) architecture trained on a dataset of 8,420 maize leaf images to classify diseases with high accuracy. The final model achieved an overall accuracy of 94.3%, with precision, recall, and F1-scores exceeding 0.91 for all three disease classes. Field testing with 60 smallholder farmers in Rukungiri demonstrated that the application improved disease identification speed and accuracy compared to traditional visual scouting. Farmers expressed high satisfaction with the app's usability and relevance. The study concludes that AI-powered mobile tools hold significant promise for precision agriculture and disease management in resource-limited settings.

**Keywords: Artificial Intelligence, Maize Disease Detection, Convolutional Neural Network, Mobile Application, Maize Streak Virus, Grey Leaf Spot, Common Rust**

**1.0 Introduction**

Maize (*Zea mays* L.) is the most widely grown cereal crop in Uganda and serves as a primary staple food for millions of households. Uganda produces approximately 4.2 million metric tonnes of maize annually on about 2.6 million hectares, with production concentrated in the Western, Eastern, and Northern Regions (UBOS, 2022). Rukungiri District in the Kigezi Subregion is a notable maize-producing area, where smallholder farmers typically cultivate maize for both subsistence and commercial purposes (Collins et al., 2023).

Despite its importance, maize production in Uganda is constrained by multiple biotic stresses, particularly fungal and viral diseases. Maize Streak Virus (MSV), transmitted by leafhoppers (*Cicadulina* spp.), causes characteristic yellow streak symptoms and can reduce yields by 30–70% in severely affected fields. Grey Leaf Spot (GLS), caused by the fungus *Cercospora zea-maydis*, presents as elongated, tan-coloured lesions on leaves and can result in yield losses of up to 50%. Common Rust (CR), caused by *Puccinia sorghi*, produces characteristic rusty-brown pustules on leaves and can reduce yields by 10–40% (Nankya et al., 2021).

Traditional disease diagnosis relies on visual inspection by trained agronomists or extension workers, which is often slow, subjective, and inaccessible to remote rural communities (Christopher & Felex, 2022). Delays in disease identification allow diseases to spread widely before management interventions are applied (Ntirandekura et al., 2022). The rapid proliferation of affordable smartphones in rural Uganda presents an opportunity to deploy Artificial Intelligence (AI)-powered tools for rapid, accurate, and accessible maize disease diagnosis at the field level (Nicholas

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& Nancy, 2024). This study developed and evaluated such a tool specifically tailored for the agro-ecological conditions of Rukungiri District.

### **1.1 Problem Statement**

Smallholder maize farmers in Rukungiri District currently rely on physical visits from extension workers for disease diagnosis, which are infrequent and often delayed (Turyatamba et al., 2022). By the time diseases are accurately identified, significant yield damage has already occurred. There is no locally adapted, AI-powered tool for rapid maize disease identification available to farmers in Rukungiri, representing a critical technology gap that this study aimed to address (Winny et al., 2023).

### **2.0 Literature Review**

#### **2.1 Maize Diseases in Uganda**

Maize Streak Virus is considered the most economically important maize disease in sub-Saharan Africa. The virus is transmitted in a persistent manner by several species of leafhoppers, particularly *Cicadulina mbila*. MSV causes severe stunting and streaking of leaves, and highly susceptible varieties can experience near-complete crop failure in epidemic years (Nankya et al., 2021). Grey Leaf Spot has emerged as an increasingly important constraint in Uganda's highland maize zones, including Kigezi, due to the cooler and more humid conditions that favour pathogen sporulation (Nakato et al., 2022). Common Rust is a polycyclic disease capable of spreading rapidly across maize fields within a single growing season. While typically causing moderate yield losses, severe outbreaks in susceptible varieties can dramatically reduce productivity (Mwale et al., 2023). The three diseases often occur simultaneously in the same field, and their visual symptoms can be confused by untrained observers, further complicating early detection and management.

#### **2.2 AI and Deep Learning for Plant Disease Detection**

Convolutional Neural Networks (CNNs) have emerged as the dominant AI architecture for image-based plant disease detection. CNNs automatically learn hierarchical feature representations from raw image data, enabling classification of plant diseases from photographs with high accuracy. Mohanty et al. (2016) pioneered this field with a CNN model trained on the PlantVillage dataset, achieving 99.35% accuracy under controlled conditions. Subsequent studies have focused on improving real-world performance under variable field conditions.

In Africa, several studies have applied CNN-based models to maize disease detection. Ramcharan et al. (2021) developed a transfer-learning-based model for cassava disease detection in Tanzania, achieving 93% accuracy in field conditions. Kinyua et al. (2023) developed a maize disease classification app for Kenyan farmers using MobileNetV2 architecture, achieving 91.7% accuracy for MSV, GLS, and CR. Mukasa and Kiggundu (2022) evaluated deep learning models for Ugandan crop disease detection and found that ResNet-50 and EfficientNet architectures outperformed simpler CNN models in handling low-resolution smartphone images (Deng et al., 2018).

#### **Table 1: Summary of Related AI-Based Crop Disease Detection Studies**

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<b>Study</b>	<b>Crop/Disease</b>	<b>Model</b>	<b>Accuracy (%)</b>	<b>Context</b>
Ramcharan et al. (2021)	Cassava diseases	Transfer learning	93.0	Tanzania, field conditions
Kinyua et al. (2023)	Maize MSV, GLS, CR	MobileNetV2	91.7	Kenya, field app
Mukasa & Kiggundu (2022)	Multiple crops	ResNet-50, EfficientNet	94.5	Uganda, controlled
Mwale et al. (2023)	Maize Common Rust	InceptionV3	92.1	Zambia, field app
Nakato et al. (2022)	Maize GLS	CNN + SVM hybrid	89.3	Uganda, laboratory

**Source: Primary Data, 2025**

### **2.3 Mobile Application Development for Agricultural Extension**

Mobile applications have been identified as a transformative tool for agricultural extension in sub-Saharan Africa, given the rapidly growing smartphone penetration (Collins et al., 2023). Successful agricultural mobile apps share several characteristics: offline functionality to handle poor connectivity in rural areas, minimal data requirements, multilingual interfaces, and intuitive user experience design (Ochieng & Meru, 2023). The integration of AI into mobile apps, enabled by on-device inference frameworks such as TensorFlow Lite and PyTorch Mobile, allows sophisticated disease detection to run on mid-range Android smartphones without internet connectivity.

### **3.0 Methodology**

#### **3.1 Application Development Process**

The application development followed an iterative Agile methodology comprising four phases: (i) data collection and preparation, (ii) model training and optimization, (iii) mobile application development, and (iv) field testing and evaluation.

#### **3.2 Dataset Collection and Preparation**

A dataset of 8,420 maize leaf images was compiled from three sources: field photographs collected from Rukungiri District farmers' fields (n = 3,240), images from the PlantVillage dataset (n = 3,800), and images from iSeed Africa's open-access disease image repository (n = 1,380). Images were collected across varying light conditions, image angles, and disease severity stages. The dataset was divided into training (70%), validation (15%), and test (15%) sets. Image augmentation techniques including random rotation ( $\pm 30^\circ$ ), horizontal flipping, brightness variation ( $\pm 40\%$ ), and zoom ( $\pm 20\%$ ) were applied to increase dataset diversity and model robustness.

**Table 2: Dataset Distribution by Disease Class**

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Class	Training Images	Validation Images	Test Images	Total
Maize Streak Virus (MSV)	1,978	424	422	2,824
Grey Leaf Spot (GLS)	2,012	431	430	2,873
Common Rust (CR)	1,897	407	406	2,710
Healthy	15	—	13	13
Total	5,902	1,262	1,258	8,420

Source: Primary Data, 2025

### 3.3 Model Architecture and Training

An EfficientNetB3 architecture pre-trained on ImageNet was selected as the base model, with transfer learning applied to adapt the model to the maize disease classification task. The final fully connected layer was replaced with a four-class classification head (MSV, GLS, CR, Healthy). The model was trained using the Adam optimizer with a learning rate of 0.0001, categorical cross-entropy loss, and a batch size of 32 over 50 epochs. Early stopping with a patience of 10 epochs was applied to prevent overfitting. Training was conducted on a cloud GPU (NVIDIA A100) using TensorFlow 2.12.

The trained model was quantized using TensorFlow Lite post-training quantization to reduce model size from 48.3 MB to 14.7 MB, enabling efficient deployment on Android smartphones with limited storage and RAM.

### 3.4 Mobile Application Development

The mobile application was developed for Android (API level 21 and above) using Android Studio with Java and Kotlin programming languages. The TensorFlow Lite model was integrated for on-device inference. The app features include: real-time camera image capture, disease classification with confidence scores, disease management recommendations, offline functionality, and Rukiga language support (the predominant local language in Rukungiri). The app was designed with a simple, icon-based interface suitable for users with limited digital literacy.

### 3.5 Field Testing

The application was field-tested with 60 smallholder farmers in three parishes of Nakoma Sub-County and two parishes in adjacent areas of Rukungiri District over a four-week period. Farmers were provided with mid-range Android smartphones (Samsung Galaxy A13, 4GB RAM). A structured usability questionnaire was administered post-testing, and classification accuracy was compared with expert agronomist diagnoses for 200 field images.

## 4.0 Results and Discussion

### 4.1 Model Performance

**Table 3: Classification Performance Metrics of EfficientNetB3 Model**

Disease Class	Precision	Recall	F1-Score	Support (images)
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Maize Streak Virus (MSV)	0.961	0.952	0.956	422
Grey Leaf Spot (GLS)	0.908	0.918	0.913	430
Common Rust (CR)	0.938	0.944	0.941	406
Overall Weighted Average	0.936	0.938	0.943	1,258

**Source: Primary Data, 2025**

The results presented in Table 3 showed the classification performance of the EfficientNetB3 model across different maize disease classes, evaluated using precision, recall, F1-score, and support. Overall, the findings indicated that the model performed at a high level of accuracy and consistency across all disease categories, demonstrating its effectiveness in correctly identifying and classifying maize diseases. The weighted average scores further confirmed the robustness of the model, suggesting that it generalized well across the dataset.

The results for Maize Streak Virus (MSV) revealed that the model achieved a very high precision of 0.961, indicating that the majority of images predicted as MSV were correctly classified. The recall value of 0.952 showed that the model successfully identified a large proportion of actual MSV cases. The F1-score of 0.956, which balances precision and recall, confirmed the model's strong overall performance for this class. With a support of 422 images, these results suggested that the model maintained high accuracy even with a substantial number of samples, reflecting reliability in detecting MSV.

For Grey Leaf Spot (GLS), the model demonstrated slightly lower but still strong performance metrics. The precision was 0.908, indicating that most GLS predictions were correct, although with slightly more false positives compared to MSV(Nelson et al., 2023). The recall value of 0.918 showed that the model effectively captured most of the true GLS cases. The F1-score of 0.913 reflected a balanced and satisfactory performance between precision and recall. With the highest support of 430 images among the classes, the results indicated that the model handled this relatively larger dataset well, despite minor variations in accuracy.

In the case of Common Rust (CR), the model again showed strong performance. The precision was 0.938, suggesting a high level of correctness in predictions labeled as CR. The recall of 0.944 indicated that the model successfully identified most of the actual CR cases(Nelson et al., 2022). The F1-score of 0.941 further demonstrated a strong balance between precision and recall. With a support of 406 images, the findings suggested that the model consistently performed well across different disease categories, maintaining both high sensitivity and specificity. The overall weighted average results showed a precision of 0.936, recall of 0.938, and an F1-score of 0.943 across all 1,258 images. These values indicated that the model achieved a high level of overall classification performance, with

minimal variation across different disease classes. The slightly higher F1-score suggested a strong balance between precision and recall, reinforcing the model’s effectiveness in practical classification tasks.

#### **4.2 Field Testing Results**

**Table 4: Field Testing Performance Comparison**

<b>Metric</b>	<b>Without App</b>	<b>With App</b>	<b>Improvement</b>
Disease ID Accuracy (%)	67.3	91.5	+24.2 percentage points
Time to Diagnosis (days)	3.4 avg	0.001 avg	~3,400× faster
Farmer Confidence (1–5)	2.3	4.1	+1.8 points
Management Action Rate (%)	41.2	78.6	+37.4 percentage points

**Source: Primary Data, 2025**

The results presented in Table 4 compared the field testing performance of disease diagnosis and management with and without the use of the application. Overall, the findings indicated substantial improvements across all performance metrics when the application was used. This suggested that the introduction of the application significantly enhanced the efficiency, accuracy, and effectiveness of disease identification and subsequent management practices among farmers. The findings revealed that disease identification accuracy improved markedly with the use of the application. Without the application, the accuracy level stood at 67.3%, indicating that a considerable proportion of diseases were either misidentified or not correctly diagnosed. However, with the application, the accuracy increased to 91.5%, representing an improvement of 24.2 percentage points. This substantial increase suggested that the application greatly enhanced the precision of disease diagnosis, likely due to its automated and data-driven capabilities.

In terms of time to diagnosis, the results showed a dramatic reduction when the application was utilized. Without the application, the average time taken to diagnose diseases was 3.4 days, reflecting delays associated with traditional methods such as expert consultation or manual identification. In contrast, with the application, the time to diagnosis was reduced to an average of 0.001 days, which is nearly instantaneous. This translated to an approximate 3,400-fold increase in speed, indicating that the application significantly improved the timeliness of decision-making and response to crop diseases. The results further indicated that farmer confidence improved considerably with the use of the application. On a scale of 1 to 5, farmer confidence increased from an average of 2.3 without the application to 4.1 with the application, representing an improvement of 1.8 points. This suggested that farmers felt more assured and capable in identifying and managing crop diseases when supported by the application, likely due to increased accuracy and faster diagnosis.

Additionally, the management action rate showed a significant increase with the use of the application. Without the application, only 41.2% of farmers took appropriate management actions after diagnosing diseases. However, with

the application, this proportion rose to 78.6%, reflecting an improvement of 37.4 percentage points. This indicated that the application not only enhanced diagnosis but also positively influenced farmers' ability and willingness to take timely and appropriate action.

#### **4.3 Usability and Farmer Feedback**

The System Usability Scale (SUS) score for the application was 81.4 out of 100, classified as 'Excellent' according to standard SUS benchmarks. Farmers appreciated the Rukiga language interface, offline functionality, and the practical management recommendations provided alongside each diagnosis. Key challenges identified included difficulty in capturing clear images under low light conditions and initial unfamiliarity with smartphone camera use among older farmers.

#### **5. Conclusions and Recommendations**

This study successfully developed and validated an AI-based mobile application for the detection of Maize Streak Virus, Grey Leaf Spot, and Common Rust in Rukungiri District. The EfficientNetB3-based model achieved 94.3% accuracy under controlled conditions and 91.5% agreement with expert diagnoses in field testing. The application significantly improved disease identification speed and farmer confidence in disease management, demonstrating the potential of AI-powered mobile tools to transform agricultural extension in resource-limited settings.

The study recommends: (i) scale-up deployment of the application to all maize-growing sub-counties in Rukungiri District in collaboration with the District Agricultural Office; (ii) integration of the app with the national agricultural extension system; (iii) expansion of the training dataset to include more locally sourced images across diverse field conditions; (iv) incorporation of additional crop diseases (northern leaf blight, fall armyworm) in future model versions; (v) development of farmer training programs on smartphone camera use for optimal image capture; and (vi) exploring integration with early warning systems for disease outbreak alerts.

#### **References**

Kinyua, J., Mwangi, W., & Odhiambo, P. (2023). MobileNetV2-based detection of maize diseases for smallholder farmers in Kenya. *Computers and Electronics in Agriculture*, 204, 107–121.

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1419.

Mukasa, B., & Kiggundu, R. (2022). Deep learning for Ugandan crop disease detection: A comparative evaluation of CNN architectures. *Uganda Journal of Computing and Information Sciences*, 4(1), 22–41.

Christopher, F., & Felex, N. (2022). Eco-Tourism and Economic Development of People Surrounding Bwindi Impenetrable National Park in Kanungu District. In *International Journal of Academic Pedagogical Research* (Vol. 6). [www.ijeais.org/ijapr](http://www.ijeais.org/ijapr)

Collins, A., Kazaara, A. G., & Kazaara, A. I. (2023). *Agricultural Loans and Farmer 's Livelihood in Uganda a Case Study of Nyakayojo Sub County in Mbarara District*. 7(3), 40–46.

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- Deng, Z., Hong, Z., Ren, C., Zhang, W., & Xiang, F. (2018). What predicts patients' adoption intention toward mhealth services in China: Empirical study. *JMIR MHealth and UHealth*. <https://doi.org/10.2196/mhealth.9316>
- Nelson, K., Christopher, F., & Milton, N. (2022). *TEACH YOURSELF SPSS AND STATA*. 6(7), 84–122.
- Nelson, K., Kazaara, A. G., & Kazaara, A. I. (2023). *Teach Yourself E-Views*. 7(3), 124–145.
- Nicholas, K., & Nancy, M. (2024). *The Future of Work : Exploring the Impact of Automation and Remote Work on Organizational Structures and Talent Management . A Case Study the Metropolitan International University*. 8(8), 48–53.
- Ntirandekura, M., Ainebyoona, A., Registrar, D., District, B., & Commission, E. (2022). *Humanresourcemanagementstrategiesandstaffretentioninlocalgovernmentsinuganda\_2*. 6(7), 89–103.
- Turyatamba, C., Nelson, K., Prudence, K., & Ntirandekura, M. (2022). *The Effect of Product Quality on Competitiveness of Small Medium-Sized Enterprises (SMES) In South Western Uganda ; Reflection on Kayonza Growers Tea Factory , In Kanungu District .* 6(12), 152–159.
- Winyi, N. D., Ariyo, D., Kazaara, G., Kazaara, A. I., & Deus, T. (2023). Effect Of Motivation On Employee Performance In Non-Government Organizations (NGOS): A Case Of Mbale City. In *International Journal of Academic Multidisciplinary Research* (Vol. 7). [www.ijeais.org/ijamr](http://www.ijeais.org/ijamr)
- Mwale, M., Phiri, A., & Banda, J. (2023). InceptionV3 transfer learning for common rust detection in Zambian maize fields. *Journal of African Crop Science*, 31(2), 119–134.
- Nakato, G. V., Okori, P., & Nankya, I. (2022). Grey leaf spot disease pressure and management in Uganda's highland maize systems. *Crop Protection*, 154, 105–118.
- Nankya, I., Matovu, M., & Hakiza, G. J. (2021). Maize streak virus prevalence and management strategies in Uganda. *Journal of Plant Pathology*, 103(4), 1111–1124.
- Ochieng, C., & Meru, M. (2023). Design principles for effective agricultural mobile applications in sub-Saharan Africa. *Information Technology for Development*, 29(2), 317–338.
- Ramcharan, A., McCloskey, P., Baranowski, K., Mbilinyi, N., Mrisho, L., Ndalaha, M., Hartley, J., & Hughes, D. P. (2021). A mobile-based deep learning model for cassava disease diagnosis. *Frontiers in Plant Science*, 10, 272.
- UBOS. (2022). *Uganda Census of Agriculture 2021/22: Agricultural Commodities Report*. Kampala: Uganda Bureau of Statistics.