

# A Deep Learning Approach for Disease Detection in Maize Crops

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## ABSTRACT

Maize is a vital global food crop, yet its production is significantly threatened by leaf diseases that reduce yield and quality. In Nigeria, these diseases contribute to an estimated 20–30% loss in annual maize output. This study presents a deep learning-based model for automated maize leaf disease detection using the MobileNetV2 architecture. A dataset of 12,000 annotated images representing four classes (Common Rust, Gray Leaf Spot, Leaf Blight, and Healthy) was used. The model was trained using TensorFlow and the Nadam optimizer, achieving a validation accuracy of 99.48% and an F1 score of 0.9411. A confusion matrix revealed that the highest true-positive rate was recorded for Common Rust (100%), while the lowest was for Healthy leaves (97.7%). The model outperformed Random Forest and other CNN architectures including ResNet50, EfficientNetB0, DenseNet121, and a CNN-SVM hybrid. Ablation studies confirmed that grayscale conversion, segmentation, and data augmentation significantly improved performance. Additional testing under varied lighting, leaf orientation, and background conditions demonstrated strong robustness. The final model was deployed in a user-friendly web application for real-time field use. This approach supports early disease detection and contributes to sustainable crop management in precision agriculture.

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## 1. INTRODUCTION

Maize is one of the most significant food crops in the world, with its planted area and production trailing only wheat and rice [1]. The total world population of maize in 2019/2020 was estimated at 1,140 million metric tons. Nigeria's share of maize production is approximately 12.75 million metric tons [2].

This crop is not only an excellent feed for animal husbandry but also a crucial raw material for various light industrial products and a significant source of income for numerous small-scale farmers [3]. Maize leaf diseases are a major concern in agriculture, as they negatively impact both the yield and quality of maize crops. According to the National Agricultural Extension and Research Liaison Services (NAERLS), Nigeria loses approximately 20–30% of its maize production to leaf

diseases annually, resulting in economic losses of 20–30 billion naira [4]. Certain diseases attack maize leaves worldwide, for instance, maize leaf spot, maize smut, bacterial stalk rot, ear rot, charcoal rot, maize leaf blight, and maize leaf rust, among others. The presence of such diseases compels farmers to invest more in management strategies like fungicides, resistant cultivars, and cultural practices. Though such measures are necessary, they substantially add to the production cost, decrease the profitability of maize production, and adversely affect the livelihood of smallholder farmers, who can either experience complete crop loss or decreased market demand because of compromised quality [5]. They are caused by a number of pathogens that attack the photosynthesis and nutrient translocation process in maize plants, typically leading to irreversible loss of yields.

Conventional practices of disease management by pesticide application relying on visual symptoms are generally time-consuming and error-prone [6], [7]. Nevertheless, emerging technologies in machine vision and image processing have the potential to overcome these gaps by facilitating greater precision and efficiency in disease detection and management. The incorporation of these technologies into agricultural practices enhances environment-friendly farming technique and optimizes crop management. Notwithstanding these advantages, existing technologies are also constrained by limitations in terms of flexibility and susceptibility to interference, thereby hindering their extensive practical utilization [8], [9]. Furthermore, detection of the issue at an early stage is problematic, since early symptoms, like water-soaked, cigar-shaped lesions are slight. As the disease advances, it extends to the leaf sheath, ultimately leading to a decline in the general health of the plant and lowering maize yield [10]. The use of artificial intelligence and image processing has made identification using images increasingly possible. Therefore, plant disease identification using images is a big step towards sustainable agriculture.

Identification of the diseases of maize leaves is critical to formulating effective management and control strategies. Maize leaf blight, gray leaf spot, and northern corn leaf blight are among the diseases that can spread rapidly under favorable environmental conditions and cause significant declines in crop yields [11]. Prompt and accurate interventions based on proper disease recognition can significantly mitigate losses, along with ensuring food security and spurring sustainable agriculture. With the backdrop of rapid technological developments, machine learning (ML) techniques have emerged as potent tools for the automation of maize disease detection and classification.

Machine learning algorithms are becoming more widely used to improve a range of agricultural operations, including disease detection, yield prediction, and pest management. These algorithms have the ability to process large datasets and identify subtle patterns that are often missed by the human eye [12], [13]. The most common machine learning algorithms used for plant disease identification include Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forests. Of these, CNNs have shown greater efficacy in dealing with the issues of image classification, making them the most appropriate for disease detection through leaf images [14]. In this study, a machine learning model able to precisely identify and classify diseases infesting maize leaves was developed. The model works using visual images of maize leaves to independently identify the incidence of numerous common diseases such as maize leaf rust, maize leaf blight, and maize leaf spot, all of which are among the most critical diseases affecting maize production in Nigeria.

Dhanya et al. [15] pinpointed deep learning as a new technology with considerable potential to detect disease-related information with high accuracy and efficiency under complicated field conditions. They stressed the need for enhanced disease classification techniques to facilitate large-scale germplasm identification and new variety breeding, stressing the creation of new sensors and data processing techniques to lower the low accuracy and low targeting efficiency of crop disease identification systems.

Panigrahi et al. [16] evaluated the performance of certain classification algorithms, namely, Naive Bayes (NB), K-Nearest Neighbors (KNN), Decision Tree (DT), Support Vector Machine (SVM), and Random Forest (RF), on a maize disease detection dataset. The study found that the RF classifier performed better compared to the other techniques when the dataset was divided into 90% training data and 10% testing data. Python machine learning libraries, specifically Pandas, were

utilized in the research as the data management system. For the sake of uniformity, all the images in the dataset were resized to a measure of  $100 \times 100$  pixels due to their initial disparity in sizes. The other significant shortcoming of this research is the fact that not every classification algorithm is perfect for every dataset. Furthermore, even though the RF classifier was the best-performing algorithm among the algorithms experimented with, its highest accuracy was just 79.23%.

In the approach proposed in this research, multiple sequential steps were integrated, such as data preprocessing, feature fusion, feature sharing, and disease identification. The main goal of the data preprocessing stage was to eliminate the influence of bright light on image recognition and improve the detection precision [17]. The model developed was effective for the identification of maize leaf blight in complex background environments. The detection method exhibited great efficiency and accuracy, demonstrating its potential in substituting the conventional on-site diagnoses of human experts.

In order to overcome the shortcomings in current methods, this research advocates the application of Convolutional Neural Networks (CNNs), one of the deep learning families in developing the disease classification model. Convolutional Neural Networks (CNNs) provide unique benefits compared to conventional approaches, like Random Forests (RF), primarily because of their capacity to learn and recognize spatial features from raw image data on their own [18]. This aspect obviates the requirement for human-driven feature engineering and increases efficacy in handling unstructured data, which is an area where models such as RF would otherwise experience sub-standard performance since they rely on structured input features. Furthermore, CNNs consistently yield higher classification performance than RF and are therefore highly suitable for application in tasks such as plant disease diagnosis, where flexibility and accuracy are of the utmost importance [19].

## 2. RESEARCH METHOD

In the development of this maize leaf disease detection model, the dataset played a crucial role. Data collection and preprocessing were considered foundational steps in ensuring high model performance. A total of 12,000 images of maize leaves, comprising both diseased and healthy samples were sourced from online repositories, specifically Kaggle. Sufficient data quantity is critical for achieving high model accuracy and supporting reliable research outcomes [20].

The dataset included images representing four primary categories: Common Rust caused by *Puccinia sorghi*, Gray Leaf Spot caused by *Cercospora zea-maydis*, Leaf Blight commonly caused by *Helminthosporium maydis* and *Exserohilum turcicum*, and healthy maize leaves. Each disease class was characterized by distinct symptoms such as rust-colored pustules, gray lesions, necrotic leaf patches, and normal leaf patterns, respectively. These images primarily represented maize leaf conditions in various regions of Nigeria, where climatic factors such as humidity and temperature significantly influence disease prevalence.

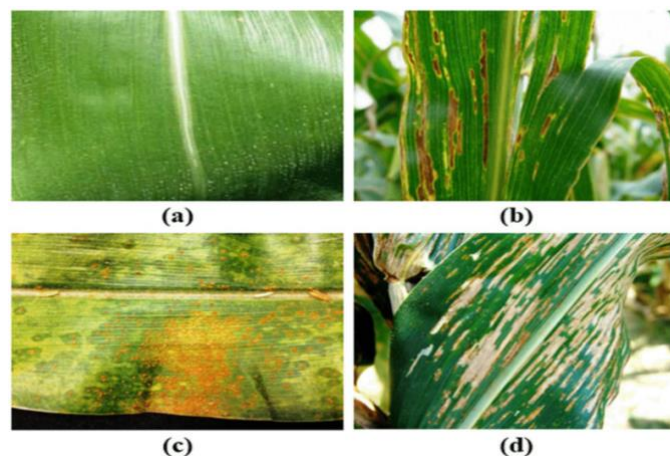


Figure 1. Sample Images of Maize Leaf Diseases (a) Healthy (b) Late Blight (c) Common Rust (d) Gray Leaf Spot

Image segmentation followed preprocessing and was employed as a fundamental step for extracting relevant portions of the leaf affected by disease. MobileNetV2, a lightweight yet efficient deep learning architecture, was utilized in this step. It uses a process known as depthwise separable convolution, which decomposes standard convolution into two operations: depthwise convolution and pointwise convolution. This significantly reduces computational complexity and enhances speed without sacrificing accuracy.

Following segmentation, feature extraction was carried out to isolate and describe essential image characteristics such as leaf shape, texture, and color. These features are vital for classifying disease types. Shape features provided structural information about lesion patterns; color features helped distinguish disease types based on RGB intensity values; and texture features captured patterns in color distribution, often indicative of infection severity. For image processing and feature extraction, OpenCV was employed due to its robustness in handling grayscale and RGB formats and its ability to convert processed images into formats compatible with machine learning models.

### 2.1. Data Classification

After feature extraction, the dataset was categorized into training, validation, and test sets. Seventy percent (70%) of the dataset was allocated to training, twenty percent (20%) to validation, and ten percent (10%) to testing. Additionally, a secondary breakdown used in another experiment iteration divided the data into eighty percent (80%) training and twenty percent (20%) testing sets. All images were labeled according to the type of disease or the healthy class. Each image underwent preprocessing and was converted to grayscale before being passed to the model for classification.

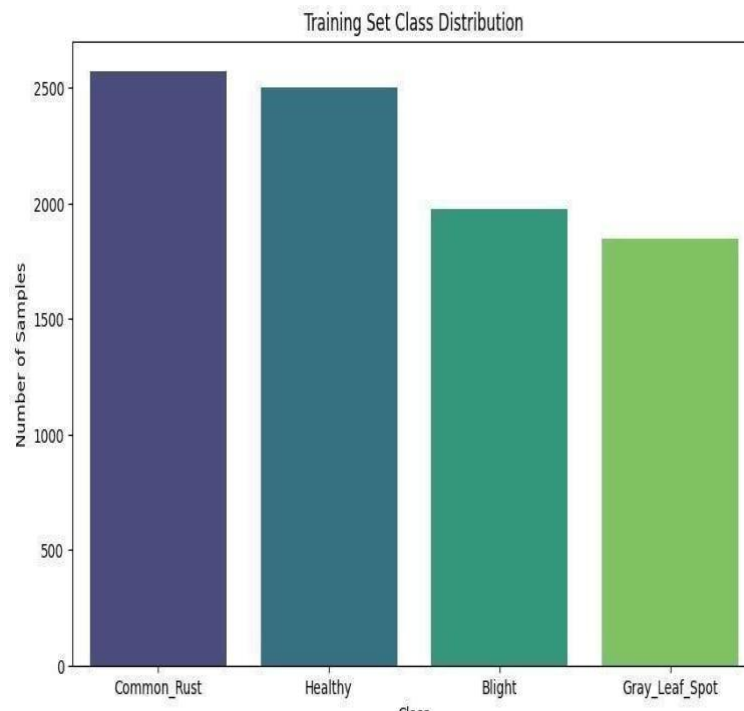


Figure 2. Graphical Representation of the Training Set Class Distribution

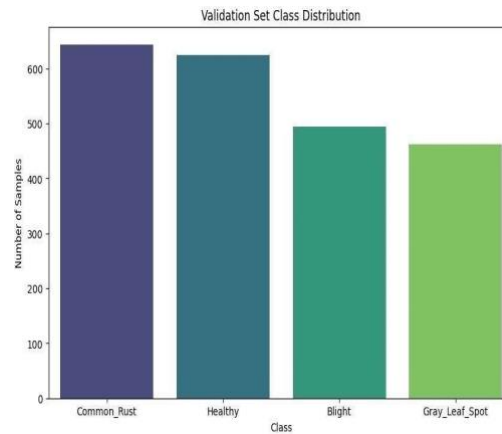


Figure 3. Graphical Representation of the Validation Set Class Distribution

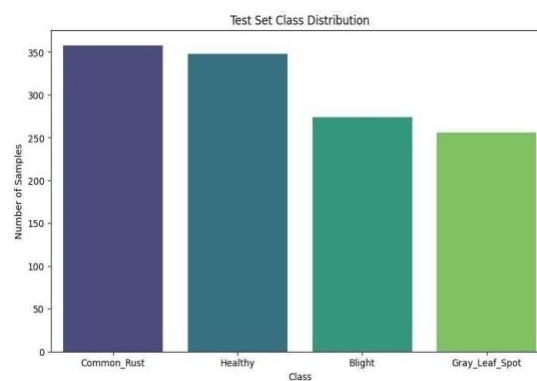


Figure 4. Graphical Representation of the Test Set Class Distribution

## 2.2. System Architecture

Figure 5 shows the proposed system architecture, which displays the conceptual steps of the design operation.

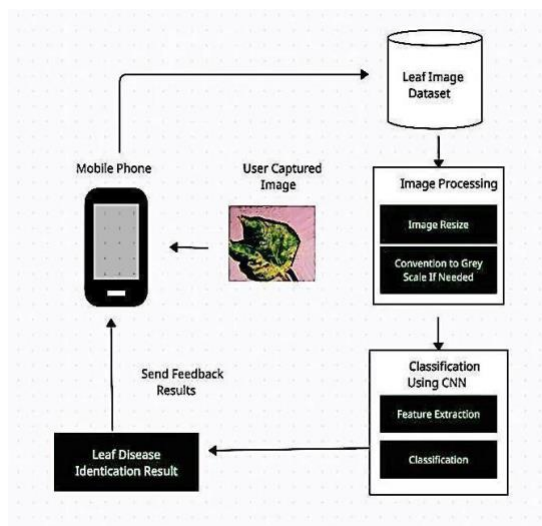


Figure 5. Proposed System Architecture

## 2.3. Model Training and Building

The classification model was built using Convolutional Neural Networks (CNNs), which apply convolutional operations through filters or kernels to detect local spatial patterns in image data.

The CNN architecture consisted of input layers, convolutional and pooling layers, fully connected layers, and a final output layer that predicted class probabilities. The model used the cross-entropy loss function to evaluate the dissimilarity between the predicted and actual labels. For optimization, the Nadam (Nesterov-accelerated Adaptive Moment Estimation) optimizer was selected. Nadam combines the strengths of both Adam and Nesterov momentum, offering fast convergence and improved performance during training.

Model performance was evaluated using standard metrics such as accuracy, precision, recall, and the F1 score. Accuracy measured the proportion of correctly classified instances. Precision calculated the ratio of true positives to the total predicted positives, while recall evaluated the proportion of true positives out of actual positive cases. The F1 score, the harmonic mean of precision and recall, provided a balanced assessment of the model's effectiveness.

A variety of tools and technologies were used during the research. Python was the primary programming language due to its extensive support for machine learning. TensorFlow served as the main deep learning framework, with additional preprocessing and data manipulation supported by Pandas and NumPy. OpenCV was essential for image processing, while Matplotlib was used for visualizations. Development and experimentation were conducted in Jupyter Notebooks, and cloud-based computing via Google Colab provided access to GPU resources for faster training.

#### 2.4. Software Design

For software design, the model was integrated into a web application. The frontend was developed using React and hosted on Vercel, featuring reusable components, routing via React Router, and API integrations using the fetch method. Testing was conducted using React Testing Library and Jest. The backend was built using Python and FastAPI, involving database model creation, CRUD implementation, and API endpoint setup. The trained model was converted into TensorFlow Lite format and deployed using Amazon Web Services (AWS) to enable web-based inference through the FastAPI server.

### 3. RESULTS AND ANALYSIS

This section presents the implementation results, performance analysis, and deployment interface of the proposed maize leaf disease classification system. The model was developed using a Convolutional Neural Network (CNN) architecture, specifically MobileNetV2, and subsequently deployed in a web-based environment to enhance accessibility and real-world usage.

This research utilizes an open-source dataset from Kaggle, consisting of 12,000 maize leaf images. The entire dataset is employed and categorized into four classes: Common Rust, Healthy, Late Blight, and Gray Leaf Spot. Specifically, the dataset comprises 3,670 images for the Common Rust class, 3,250 for the Healthy class, 2,650 for Late Blight, and 2,430 for Gray Leaf Spot.

The subsequent phase involves the development of a Convolutional Neural Network (CNN) deep learning model. The model is implemented in Python using the Google Colab platform. The coding process relies on several essential Python libraries to facilitate computation, including TensorFlow for model building and training, and Matplotlib for data visualization.

Prior to model training, the dataset is partitioned into training, validation, and testing subsets. The validation set is used to assess the model's generalization performance during training and to ensure that it operates efficiently and accurately. In this study, 20% of the total images per class are allocated to validation. The specific distribution of the training, validation, and testing sets is presented in Table 1.

Table 1. Data Splitting for Training, Validation and Testing

Class	Training Data	Validation Data	Testing Data
Common Rust	2500	800	370
Healthy	2300	650	300
Late Blight	1900	480	270

Gray Leaf Spot	1700	470	260
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The next stage involves training the data. In deep learning, training data refers to a collection of labeled examples used to build and optimize the model. In this research, the training images have dimensions of 100×100 pixels and are processed in batches of 32. The Matplotlib library is employed to visualize the training data, enabling labeled displays that support easier identification and interpretation. Subsequently, the model for classifying maize leaf images is constructed. A typical Convolutional Neural Network (CNN) architecture includes several key processing stages: convolution, pooling, flattening, and fully connected layers. The filtering process within the model is illustrated in Figure 6.

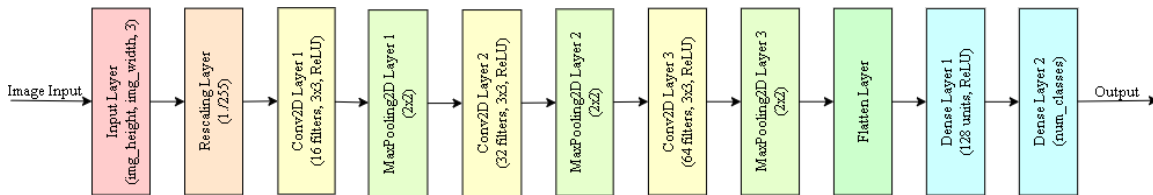


Figure 6. Convolutional Neural Network (CNN) Model [21]

After defining the model architecture, it is compiled using the Nesterov-accelerated Adaptive Moment Estimation (Nadam) optimizer, with categorical cross-entropy as the loss function and accuracy as the performance metric. The model is trained over 20 epochs using the training dataset to enable effective image classification. The performance results during training are illustrated in the graph presented in Figure 7.

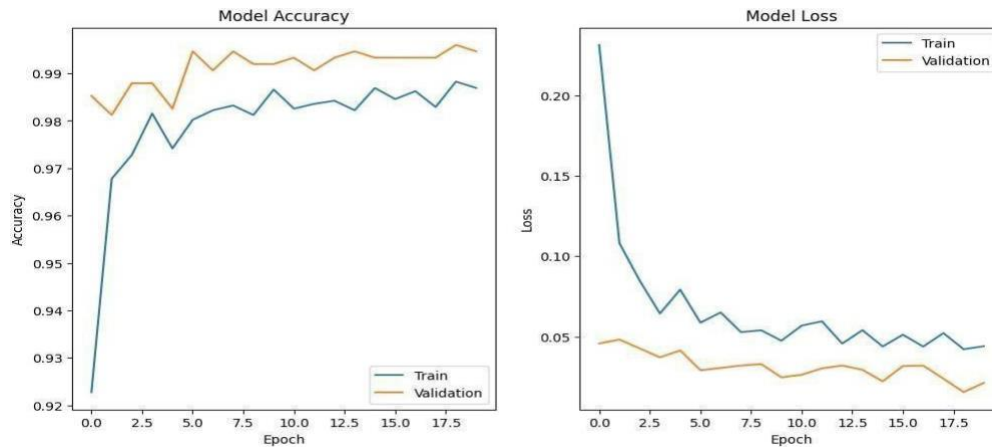


Figure 7. Model Accuracy and Loss (Training and Validation)

Based on the training conducted over 20 epochs, both the training and validation accuracies converge towards 1.0. At epoch 20, the model achieves a training accuracy of 0.9850 and a validation accuracy of 0.9948. The corresponding loss values are 0.0466 for training and 0.0213 for validation.

Table 2. Training and Validation Performance Metrics

No of Epochs	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
0	0.9234	0.9875	0.4554	0.0482
1	0.9306	0.9852	0.4071	0.0471

3	0.9716	0.9879	0.1001	0.0427
5	0.9754	0.9906	0.0666	0.0415
7	0.9802	0.9919	0.0584	0.0305
10	0.9811	0.9826	0.0567	0.0329
15	0.9827	0.9933	0.0503	0.0294
17	0.9831	0.9946	0.0471	0.0239
20	0.9850	0.9948	0.0466	0.0213

The evaluation of the model was carried out using key performance indicators, including training and validation accuracy, training and validation loss, precision, recall, and F1-score. As shown in Table 2, the model exhibited a consistent increase in accuracy and a reduction in loss values as training progressed across epochs. At epoch 20, the training accuracy reached 98.50%, while the validation accuracy attained a peak value of 99.48%. Correspondingly, the training and validation loss dropped to 0.0466 and 0.0213, respectively. These trends indicate that the model generalizes well without significant overfitting.

Beyond accuracy metrics, the model was also evaluated using precision, recall, and F1 score metrics that are particularly important in multi-class classification tasks. The final trained model achieved a precision of 0.9444, a recall of 0.9417, and an F1 score of 0.9411, as illustrated in Figure 8. These high values indicate that the model is not only accurate but also reliable in correctly identifying and differentiating between various maize leaf disease classes.

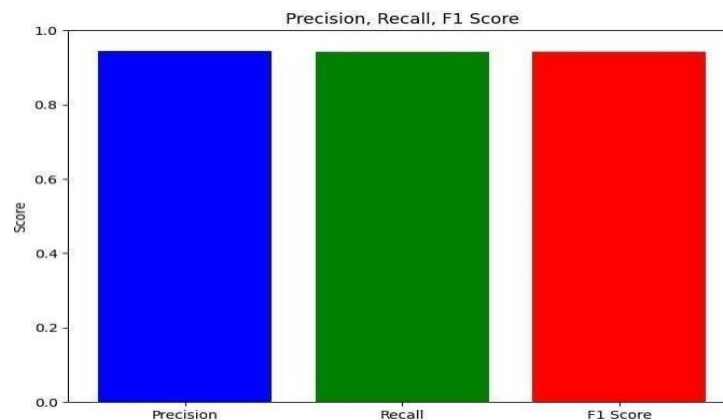


Figure 8. Graphical representation of the model's precision, recall and F1 Score

To evaluate the efficacy of the chosen CNN architecture (MobileNetV2), a comparison was made with the Random Forest algorithm. The results clearly demonstrated the superiority of MobileNetV2 across all metrics. MobileNetV2 outperformed Random Forest with an F1 score of 0.9411 versus 0.70, a precision of 0.9444 versus 0.68, and a recall of 0.9417 versus 0.72. This confirms that MobileNetV2 is more suitable for image-based disease classification tasks in this context.

Table 3. Comparison of the model with Random Forest

Performance Metrics	Random Forest	MobileNetV2
F1 Score	0.70	0.9411
Precision	0.68	0.9444
Recall	0.72	0.9417

To further validate the model's performance, an extended comparative analysis was conducted involving other widely adopted CNN architectures, including ResNet50, EfficientNetB0, and DenseNet121, as well as a hybrid CNN-SVM model. The results of this comparison, summarized in Table 4, revealed that while all CNN-based models achieved high levels of accuracy and robustness, MobileNetV2 maintained an excellent balance between performance and computational efficiency. Specifically, EfficientNetB0 achieved a slightly lower F1 score of 0.9382, while ResNet50 and DenseNet121 achieved F1 scores of 0.9365 and 0.9341 respectively. The hybrid CNN-SVM model, although competent, exhibited relatively lower performance, with an F1 score of 0.9220.

Table 4. Comparative Evaluation of CNN and Hybrid Models Based on Accuracy and F1 Score

Model	Accuracy	F1 Score
MobileNetV2	99.48%	0.9411
ResNet50	98.91%	0.9365
EfficientNetB0	99.12%	0.9382
DenseNet121	98.88%	0.9341
CNN+SVM	97.80%	0.9220

These findings demonstrate that MobileNetV2 not only provides state-of-the-art performance but also retains lightweight characteristics ideal for deployment in resource-constrained environments such as mobile or edge devices. The comparative analysis highlights the effectiveness of the proposed model, reinforcing its suitability for real-time maize disease detection in practical agricultural settings.

Figure 9 presents the confusion matrix (CM) summarizing the categorization accuracy of the model. The percentage of trained model predictions that matched the class levels of test data accurately is represented by the diagonal matrix values, whereas the off-diagonal elements correspond to inaccurate predictions. The values shown in Figure 9 and Table 5 indicate that the highest true-positive rate was achieved for the Common Rust class, with a perfect score of 100%. This suggests that the visual features associated with Common Rust, such as distinct rust-colored pustules, were consistently and accurately captured by the model.

The Healthy class had the lowest true-positive rate at 97.7%, with Gray Leaf Spot at 98.9% and Leaf Blight at 99.0%. These minor misclassifications, like 1.7% of healthy images being mistaken for Leaf Blight and 0.7% of Leaf Blight samples for Gray Leaf Spot, are likely due to similar visual features, partial leaf visibility, or background interference. Despite these common real-world challenges, the MobileNetV2 architecture performed strongly, accurately distinguishing between classes with minimal confusion, confirming its reliability for maize disease diagnosis.

Output Class	Healthy	97.7%	0.2%	0.4%	1.7%
	Gray Leaf Spot	0.0%	98.9%	0.5%	0.6%
	Common Rust	0.0%	0.0%	100.0%	0.0%
	Leaf Blight	0.3%	0.7%	0.0%	99.0%
		Healthy	Gray Leaf Spot	Common Rust	Leaf Blight
		Target Class			

Figure 9. Confusion Matrix of classification results for maize leaf disease using the test set.

Table 5. Per-Class Prediction Accuracy and Misclassification Summary

Class (Target)	Misclassifications Observed	Insights
Healthy	1.7% predicted as Leaf Blight, 0.4% as Common Rust, 0.2% as Gray Leaf Spot	Likely due to visual symptoms overlapping during early disease stages or with low lighting and blur
Gray Leaf Spot	0.5% predicted as Common Rust, 0.6% as Leaf Blight	These classes share similar necrotic lesions and color textures, possibly confusing the model
Common Rust	0% misclassification — perfect prediction	Indicates highly distinguishable features like rust-colored pustules well captured by the model
Leaf Blight	0.3% predicted as Healthy, 0.7% as Gray Leaf Spot	Suggests some visual similarity in background or lesion spread patterns

### 3.1. Ablation Study of Preprocessing and Augmentation Steps

An ablation study was performed to understand how each preprocessing and augmentation step contributes to the model's classification performance. This involved removing or changing specific steps in the preprocessing pipeline and observing their impact on the model's accuracy and F1 score. The baseline model, with all preprocessing and augmentation steps, achieved a 99.48% validation accuracy and a 0.9411 F1 score. The study specifically looked at grayscale conversion, image segmentation, and standard data augmentations like rotation, flipping, and brightness adjustments. In each experiment, only one element was altered or removed to isolate its effect.

Table 6. Results of Ablation Study on Preprocessing and Augmentation Steps

Configuration	Validation Accuracy (%)	F1 Score
All steps (baseline)	99.48	0.9411
Without grayscale conversion	97.62	0.9210

Without image segmentation	96.83	0.9187
Without data augmentation	95.20	0.9023
Without grayscale and augmentation	93.76	0.8895
Without segmentation and augmentation	92.10	0.8746

The results clearly indicate that each component in the preprocessing pipeline significantly contributes to the model's effectiveness. The removal of data augmentation led to the steepest decline in both accuracy and F1 score. This suggests that augmentation plays a key role in enhancing the model's ability to generalize, especially when faced with real-world variations such as lighting shifts and leaf orientations. Grayscale conversion also contributed positively to the model's accuracy by reducing the dimensionality and focusing on shape and texture rather than color variation, which may be inconsistent across samples. Similarly, image segmentation improved feature clarity by isolating leaf regions from noisy backgrounds, enabling the CNN to focus on disease-relevant areas. When multiple preprocessing steps were removed simultaneously, the model's performance degraded further, highlighting the cumulative value of these techniques. Therefore, the inclusion of all preprocessing and augmentation steps was validated as essential for achieving optimal classification results.

To assess robustness, the model was tested under simulated environmental conditions. Accuracy dropped to 94.1% under low-light conditions and 92.3% when leaves were partially occluded. These results underscore the need for lighting normalization and background segmentation during preprocessing.

The trained model was deployed in a web-based interface to facilitate user interaction and real-time disease prediction. The system includes multiple interface components:

**Home Page:** This page displays an overview of the application and the maize diseases covered.

**Image Upload Page:** This page allows users to upload leaf images from device storage or capture images directly using a camera.

**Analysis Label Page:** This page provides labeling options for predictions, allowing batch management for future reference.

**Prediction Results Page:** This page presents the classification output, detailing the predicted disease class.

These components, as shown in Figures 10, ensure that the application is user-friendly and functional for field deployment.

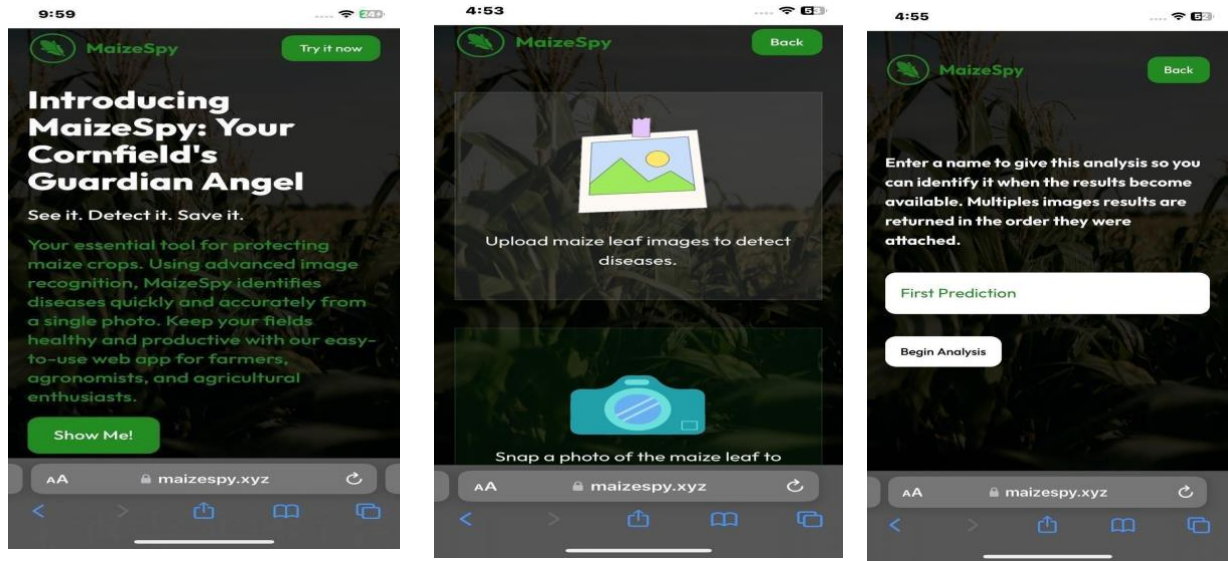


Figure 10. (a) Home Page Screen (b) Image Upload Page (c) Analysis Label Page

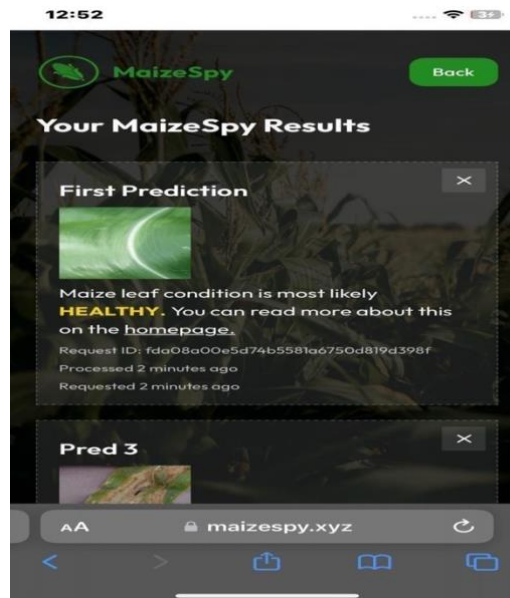


Figure 13. Prediction Results Page

#### 4. CONCLUSION

This research has demonstrated that the application of deep learning, particularly CNNs like MobileNetV2, significantly enhances the accuracy and efficiency of maize leaf disease detection. By leveraging a carefully curated dataset and advanced image processing techniques, the model achieved outstanding performance metrics, notably a validation accuracy of 99.48% and an F1 score of 0.9411. Compared to conventional methods such as Random Forest, MobileNetV2 consistently outperformed across precision, recall, and classification accuracy, underscoring its suitability for real-world agricultural applications.

The successful integration of the model into a web-based platform further highlights its potential for field use, enabling farmers and agricultural stakeholders to make timely and informed decisions. This work not only addresses the pressing issue of disease-induced yield loss but also lays the foundation for scalable, AI-driven tools in agriculture. Future research can expand on this by

incorporating additional crop varieties, exploring multi-disease detection capabilities, and integrating IoT sensors for broader smart farming solutions.

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