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Deploying mobilenet for efficient and real-time identification of castor leaf diseases using smartphone applications

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Abstract
The increasing need for sustainable agriculture has necessitated the development of automated systems for plant disease detection. This study presents a robust deep learning approach to classify Castor (*Ricinus communis*) leaf diseases using high-resolution images. A dataset comprising 930 images, representing six categories (Healthy, Seedling Blight, Leaf Blight, Rust, Brown Leaf Spot, and Bacterial Leaf Spot), was collected across diverse environmental conditions in Nigeria using a Google Pixel 6 Pro smartphone. Data preprocessing techniques, including resizing, normalization, and augmentation, were applied to enhance model generalization. A MobileNet architecture, fine-tuned with pre-trained ImageNet weights, was utilized due to its computational efficiency and suitability for mobile deployment. The model achieved an exceptional overall accuracy of 96.6%, with precision, recall, and F1 scores exceeding 86.7% across all disease categories. Minor misclassifications occurred between visually similar diseases, such as Rust and Bacterial Leaf Spot. The trained model was optimized using TensorFlow Lite and integrated into a Flutter-based mobile application, enabling real-time disease detection on smartphones. The app processes leaf images locally, ensuring privacy, and provides actionable recommendations to aid timely interventions. The system's high accuracy and mobile compatibility demonstrate its potential for large-scale adoption, empowering farmers with an accessible and efficient tool for Castor crop disease management. This research highlights the efficacy of lightweight deep learning models and mobile technology in advancing precision agriculture, particularly in resource-limited settings.

Keywords: Sustainable agriculture, castor leaf disease detection, mobilenet architecture, data augmentation, transfer learning

Introduction
Agriculture remains a pillar of world food safety and economic prosperity, particularly in developing countries such as Nigeria, where it employs roughly half of the population who work and contributes significantly to the country's GDP [6] a valuable crop, is critical to this sector. Castor, which is native to Ethiopia, grows best in well-drained, damp soils like the banks of rivers, paths, and farm land edges. While commonly naturalised in tropical and subtropical climates, particularly the southwest region of the United States, it is grown worldwide for its seeds, which yield castor oil, a significant industrial resource. However, the presence of ricin in all sections of the castor plant makes them very hazardous [14].
Diseases, such as microbial and bacterial infections, have a significant impact on the health of castor plants, reducing the production rate and economic value. These problems highlight the necessity of quick diagnosis and appropriate management measures in castor farming to ensure maximum productivity [7, 21]. The swift and legitimate identification of plant diseases is crucial for reducing crop losses and increasing agricultural productivity. Current developments in algorithms for image processing and machine learning have drastically improved the detection of illnesses by allowing for prompt and precise identification, which supports successful management options. By averting vast crop damage, these technologies contribute significantly to decreasing economic losses and guaranteeing food security.
Investigations have pointed out the successful use of deep learning algorithms in accurately diagnosing plant diseases [5], as well as the vital role of agriculture with precision in boosting sustainability via improved image sensors [18]. Furthermore, the incorporation of techniques for processing digital images has expanded opportunities for quantifying and categorising diseases that affect plants [2], highlighting the growing role of technology in tackling agricultural difficulties.
The combined use of powerful deep learning models and mobile technologies has received a lot of interest in recent years. Smartphone-based solutions are becoming increasingly prevalent simply because of their easy availability and convenience. Researchers have shown that similar procedures are beneficial in a variety of crops. A 2023 experiment described a smartphone application that used deep learning models to detect and diagnose diseases in maize crops, demonstrating the practical utility of this sort of technology in agro contexts [11]. In a comparable vein a study published in 2022 developed a smartphone-based solution that used machine learning techniques to diagnose plant illnesses and make meaningful treatment recommendations, highlighting the value of mobile platforms for vegetative management of health [3]. A 2022 thorough review also highlighted developments regarding based on imagery crop diagnosis by employing machine learning methods, emphasising the application of machine intelligence within contemporary agriculture and how it can be integrated into readily available systems such as smart phones for productive management of diseases [26]. The results presented support the rising use of mobile-based approaches for bettering sustainable agricultural practices and production. Despite the global importance of castor plants, few research have focused on disease detection. The current investigation attempts to fill that gap by proposing a reliable, feasible and adaptable methodology for identifying castor leaf diseases.

MobileNet, a light-weight convolutional neural network (CNN) architecture, is increasingly an increasingly popular option for applications in the real world, especially for environments with limited resources. MobileNet, which was developed to improve computational performance yet preserve exceptional precision, is suited for mobile devices and edge devices in agricultural applications [10]. By bringing together computing efficiency and accuracy, MobileNet supports real-time plant disease detection applications, solving critical difficulties in agricultural diagnoses [10]. These findings highlight MobileNet's ability to providing scalable and economically viable prevention and control solutions spanning a wide range of agricultural contexts.

Materials and Method

Dataset collection

The collection of images used for the current investigation includes photographs with high resolution of Castor (*Ricinus communis*) leaves in both healthy and sick states. A combined collection of 930 pictures were acquired from diverse regions in Abuja, Kaduna, Plateau, and Bauchi utilising the Google Pixel 6 Pro mobile equipped with a 50-megapixel lens. The photos were taken under a variety of environmental circumstances to ensure that the dataset is diverse and suitable for training a model that can generalise across varied environments. The set of data is classified in the following six groups: healthy, Seedling blight (*Phytophthora parasitica*), Leaf blight (*Alternaria ricini*), Rust (*Melampsora ricini*), Brown leaf spot (*Cercospora ricinella)*, Bacterial leaf spot (*Xanthomonas campestris pv Ricinicola*). The photographs were meticulously labelled in order to help with precise illness diagnosis [20]. The superior quality of the photographs, affords a thorough perspective of the plant's status, making it a great starting point for training deep neural network models for plant disease diagnosis. The dataset collection technique guarantees that the model will recognise illnesses in a variety of environmental circumstances in addition to capturing small changes in how the illness appears on castor leaves. This variation in image capturing is critical to improve the illness detection model's robustness and accuracy. Figure 1 depicts an overview of exemplary samples from the available data set.

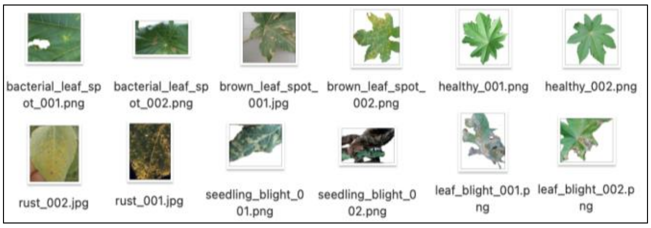

Fig 1: Dataset sample

Data preprocessing

Prior to introducing the photos into the model, processes for preprocessing were used to ensure coherence as well as enhance the model's capacity to generalise:

- **Image Resize:** Every photograph had their dimensions reduced to 224 pixels by 224 pixels in accordance with the input size criteria of MobileNet, an increasingly common lightweight framework for portable applications [10].
- **Data Augmentation**: To mitigate overfitting while boosting model resilience, methodologies for augmentation were implemented, particularly TensorFlow's ImageDataGenerator and Albumentations. we adopted horizontal flipping, rotation, scaling, and contrast modifications to deliberately boost the total amount of the training dataset [23].
- **Normalization**: Every values of pixels were normalised by dividing by 255 to range them between 0 and 1, which helps accelerate model convergence and minimises computing overhead [15].

1. MobileNet architecture

MobileNet is being utilised as an underlying architecture for illness detection because of its computational efficiency and compatibility with mobile and embedded devices. The MobileNet model employs depthwise separable convolutions, which substantially decrease the amount of parameters and computational cost when compared to traditional convolutions [10].

The model was initialised with pre-trained ImageNet weights to take advantage of transfer learning and avoid training from scratch on the short dataset. This allowed the machine to learn key features from the general ImageNet dataset before fine-tuning the algorithm to detect Castor leaf illnesses specifically.

2. Model Architecture Design

The model was developed through the addition of customised layers to the MobileNet:

- **Global Average Pooling**: MobileNet's output was routed through a GlobalAveragePooling2D layer that decreased dimensionality and retrieve important components of the image [16].
- **Fully Connected Layers**: To mitigate overfitting, a dense layer containing 1024 units and activation of ReLU was implemented, followed by a 0.5-rate dropout layer [25]. The final layer is a classifier using softmax, with six parameters matching to the six illness groupings, this is utilised for multiclass classification.
- **Freeze Pre-trained Layers**: Each of the layers of the MobileNet base model were halted to prevent their weights from updating throughout training, making sure just those custom layers were trained on the Castor leaf dataset.

3. Model training

Training went on using the aforementioned parameters:

- **Learning Rate**: An Adam optimiser having a learning rate of 1e-4 was utilised, which is typically recognised as efficient in training deep neural network models [12].
- **Loss Function**: The loss function was categorical cross-entropy, which is appropriate for multi-class classification problems [8].
- **Batch Size**: The model underwent training with a batch size of 32, which balanced memory utilisaton and convergence speed.
- **Epochs**: The model was trained for 20 epochs, with early stopping used in order to prevent overfitting and preserve computation time.
- **Validation and Testing**: The dataset was divided into 80% training and 20% testing, to ensure an unbiased assessment of the model's generalisation.

4. Mobile application integration

Once trained, the model was transformed to TensorFlow Lite for convenient mobile implementation. The model that had been trained was integrated into a mobile application built with Flutter, which is a cross-platform framework. Users can capture real-time photographs of Castor leaves with their smartphones and then get fast illness diagnoses straight on their devices.

Performance evaluation

The model's performance was evaluated based on the following metrics:

- **Accuracy:** The percentage of correctly classified images.
- **Precision, Recall, and F1-Score:** These metrics were calculated for each disease category to assess the model's accuracy in terms of true positives, false positives, and false negatives [24].
- **Confusion Matrix:** Confusion matrix was employed to identify incorrect classifications as well as assess the model's resilience across disease categories

Tools and libraries

The following libraries and frameworks were used for model implementation, training, and mobile app development:

1. **TensorFlow (v2.x):** Used for deep learning model construction, training, and evaluation.
2. **Keras:** Used for model building and fine-tuning.
3. **Albumentations:** Used for data augmentation during training, enhancing the generalization ability of the model.
4. **Flutter:** Used for developing the application for mobile devices. Flutter features a fluid, interactive user experience and easy integration with the deep neural networks model for real-time diagnosis of diseases.
5. **Dart:** The programming language used with Flutter to develop the mobile application.
6. **TPU v2-8 (Google Colab):** Employed for faster deep learning model training, which provides much quicker computing and reduces entire duration of training for huge models and datasets.

Interpretation of results

Model training and performance analysis

Our MobileNet-based deep learning approach was highly efficient and robust in distinguishing Castor leaf conditions. Training accuracy grew steadily across twenty epochs, reaching an impressive 99.83%, with validation accuracy soared at 97.50% at the eighteenth epoch and 96.25% at the end of Twenty epochs, as shown in figure 2. Both of the metrics improved significantly in the first five epochs, indicating that the pre-trained MobileNet layers adapted quickly to the new dataset. As shown in figure 3, the consistent decrease in both training and validation loss, most notably from 1.5871 to 0.0143 (training loss) and 1.3969 to 0.1639 (validation loss), demonstrates that the model has robust convergence. The insertion of dropout layers (with a 0.5 dropout rate) effectively mitigated overfitting, which is demonstrated by the parallel trends in training and validation accuracy curves. Using transfer learning with frozen base layers enabled the model to capitalise on pre-trained weights, resulting in more rapid convergence and outstanding performance with a small dataset.

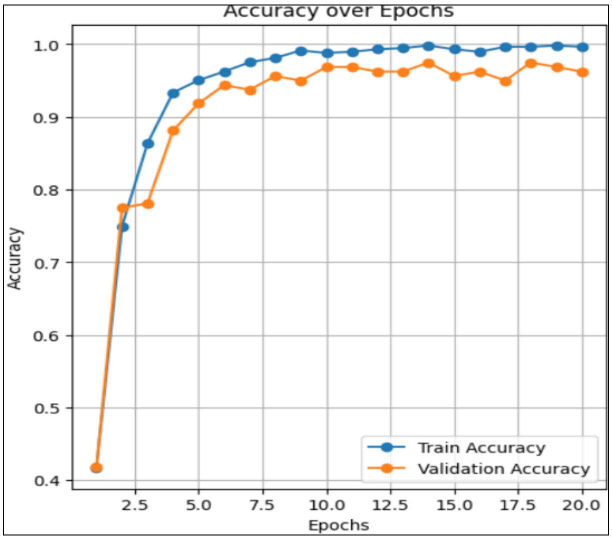

Fig 2: Training and Validation accuracy chart

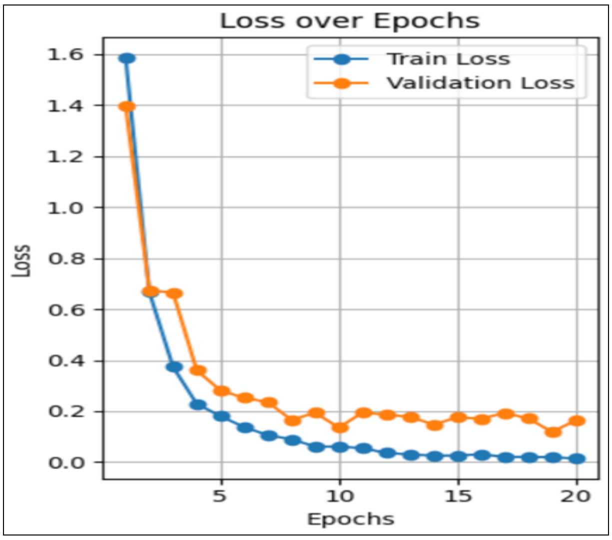

Fig 3: Training and Validation loss chart

Visualizations and trends

Charts of training and validation accuracy indicate convergence by epoch 14, implying that early stopping could minimise training time. The validation loss curve supports this, as further gains were negligible. Such evaluations emphasise the usefulness of training setups, including the Adam optimiser and the chosen learning rate.

Testing performance metrics

We used a comprehensive set of metrics to assess the effectiveness of our deep learning model in identifying different kinds of castor leaf diseases, comprising accuracy, precision, recall (sensitivity), and the F1 Score. These measurements offer a comprehensive picture of the model's prediction capabilities. Below, we detail the findings achieved by evaluating the model employing a six-class classification task on 186 photos.

a. Confusion matrix analysis

Figure 4 demonstrates the distribution of correctly and incorrectly categorised samples across six classes: *bacterial leaf spot, brown leaf spot, healthy, leaf blight, seedling* *blight*, and *rust*. The diagonal segments of the matrix reflect correctly identified occurrences (True Positives), whereas off-diagonal elements relate to misclassifications. The model had good precision and recall values across all classes, with slight misclassifications occurring mostly between visually comparable illnesses like rust and bacterial leaf spot. This demonstrates the model's robust capacity to recognise modest differences in illness patterns while preserving balanced performance across all classes.

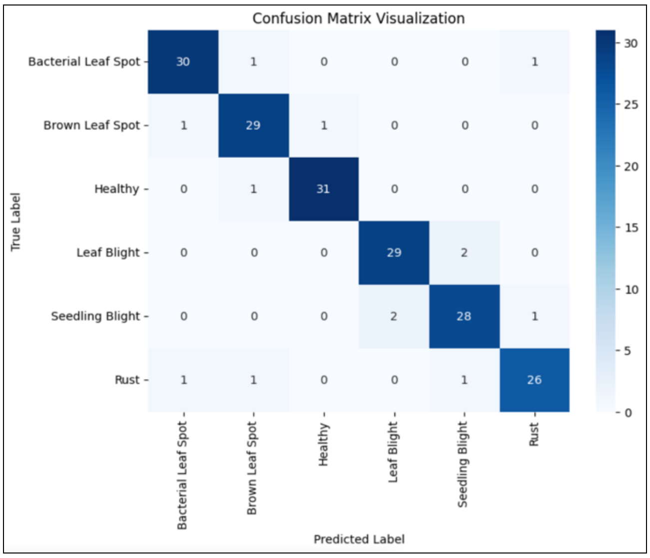

Fig 4: Confusion matrix

b. Overall accuracy

The overall Accuracy of the model was computed as:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

From the confusion matrix, we obtained:

- **Total True Positives (TP):** 173
- **Total False Positives (FP):** 15
- **Total False Negatives (FN):** 11
- **Total True Negatives (TN):** 557

The Overall Accuracy of the model was calculated to be:

$$\text{Accuracy} = \frac{730}{756} = 0.96560 \approx 0.966\ (96.6\%)$$

This result highlights the model's exceptional overall performance, in successfully classifying the majority of the test samples.

c. Class-wise precision, recall, and F1 Score

To provide a more granular evaluation, we analyzed the Precision, Recall, and F1 Score for each individual class.

- **Precision** measures the ratio of correctly predicted positive observations to the total predicted positive observations:

$$\text{Precision} = \frac{TP}{\text{TP+FP}} \quad (2)$$

- **Recall (Sensitivity)** indicates the ability of the model to correctly identify positive samples:

$$\text{Recall} = \frac{TP}{\text{FN + TP}} \quad (3)$$

- **F1 Score** is the harmonic mean of Precision and Recall, providing a balanced measure of the two:

$$\text{F1 Score} = 2 \cdot \frac{Precision\ .\ Recall}{Precision + Recall} \quad (4)$$

Table 1: Showing class – wise Precision, Recall and F1 Score

Class	Precision	Recall	F1 Score
Bacterial Leaf Spot	0.882	0.938	0.909
Brown Leaf Spot	0.935	0.935	0.935
Healthy	1.000	0.969	0.984
Leaf Blight	0.906	0.935	0.920
Seedling Blight	0.933	0.933	0.933
Rust	0.867	0.929	0.897

Precision scores ranged from 86.7% to 100%, while Recall values varied from 92.9% to 96.9%. The F1 Scores are consistently high across all classes, confirming the model's robustness and dependability in distinguishing between healthy and diseased leaves. The Healthy class received a flawless Precision score of 1.000, suggesting that all predictions in this class were correct, with no false positives. The Recall score of 0.969 indicates that the model correctly identified almost every one of healthy samplesRegarding diseases groups which include Brown Leaf Spot and Leaf Blight, both recall and precision scores topped 90%, demonstrating the capacity of the model to distinguish between these diseases. Rust and Bacterial Leaf Spot had significantly lower Precision ratings (0.867 and 0.882, respectively), indicating considerable confusion between visually similar classifications. Despite this, recall levels remain high, indicating that the model prioritises sensitivity over false positives for these classes.

Mobile app integration

The model that was developed got optimised for mobile deployment by transforming it to TensorFlow Lite format, which drastically reduced its size and processing requirements. Being able to integrate into a smartphone application allows users to upload leaf photographs straight from the application's camera interface. The model processes the image locally, which protects privacy and reduces reliance on internet connectivity. The app's UI displays real-time predictions that categorise the leaf into one of six predetermined classes (e.g., healthy or ill) and make actionable suggestions.

We used the smartphone application to perform a real-time test on a randomly picked sick leaf. The application produced an accurate diagnostic and then provided actionable advice customised to the detected ailment. This allows consumers to make more educated decisions about the care and management of their castor bean plants. Users have numerous alternatives from the same interface: they may retake the snapshot, upload a photograph from their smartphone's gallery, retain the outcomes of the diagnosis on their device, or instantly share them via platforms like as WhatsApp, email, or Bluetooth, as shown in Figure 5.

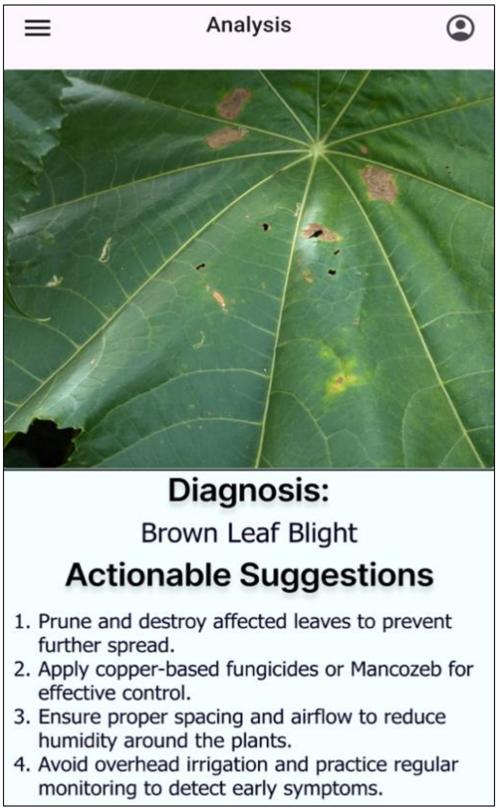

Fig 5: Mobile application analysis interface

Discussion of results

This research successfully created an effective deep learning model based on the MobileNet architecture for the categorisation of *Ricinus communis* (Castor) leaf conditions, with an overall accuracy of 96.6%. The results show the model's capacity to generalise across six different classes. *Healthy, Seedling Blight, Leaf Blight, Rust, Brown Leaf Spot,* and *Bacterial Leaf Spot* despite the underlying visual similarity between disease patterns.

Model performance analysis

The model's performance was thoroughly assessed using the Accuracy, Precision, Recall, and F1 Score criteria. According to the confusion matrix (Figure 4) and the class-wise evaluation (Table 1), the model had good precision (varying from 86.7% to 100%) and recall (92.9% to 96.9%), demonstrating its ability to properly categorise diseased and healthy leaves with low misclassifications.

- **Healthy Class:** The model achieved perfect precision of 100%, indicating that all predictions for this category were true positives. The recall score of 96.9% illustrates its dependability in detecting healthy leaves without missing important data.
- **Brown Leaf Spot and Leaf Blight**: The two categories attained balanced precision and recall scores of 90%, demonstrating the model's capacity to effectively identify between these conditions amid resemblance in their visual features.
- **Rust and Bacterial Leaf Spot**: Both of these categories have slightly lower precision (0.867 and 0.882, respectively), owing to misclassifications of superficially identical classes. However, their strong recall scores reflect the model's sensitivity in finding positive cases, even at the cost of occasional false positives.

The balanced F1 Scores across all classes, which range from 0.897 to 0.984, demonstrate the model's robustness and consistency. The use of methods for augmenting data such as flipping, rotation, scaling, and contrast adjustment considerably improved the model's generalisation ability. Furthermore, combining transfer learning techniques with pre-trained ImageNet weights enabled the model to achieve rapid convergence and good accuracy despite the small dataset size.

Convergence behavior

Training and validation accuracy trends (Figure 2) suggest swift convergence, with performance stabilising at epoch 14. The use of dropout layers (at a rate of 0.5) significantly reduced overfitting, as indicated by the parallel patterns in training and validation loss (Figure 3). The significant decrease in both training loss (from 1.5871 to 0.0143) and validation loss (from 1.3969 to 0.1639) demonstrates the efficiency of the learning configurations, particularly the Adam optimiser with a learning rate of 1e-4.

Practical implications and mobile integration

The implementation of the model trained onto an application for mobile devices optimised with TensorFlow Lite shows great practical utility. Users may diagnose Castor leaf issues in real time using smartphone cameras, allowing for early illness identification and actionable solutions. The app's interactive interface (Figures 5 and 6) offers a smooth user experience, with options for retaking photographs, uploading from the gallery, saving findings locally, and sharing via messaging platforms. This offline functionality, made possible by local on-device processing, allows accessibility even in places with restricted internet connectivity.

The smartphone application's real-time testing proved its usefulness by correctly diagnosing sick leaves and providing practical treatment advice. This practical deployment bridges the gap between cutting-edge research and field applications, giving farmers a dependable tool for early disease identification and optimal crop management.

Conclusion

This paper provides a MobileNet-based deep learning model for real-time Castor leaf disease classification that is both accurate and efficient. The model had an overall accuracy of 96.6%, with consistently good precision, recall, and F1-scores in all six classes. Its success can be credited to an excellent dataset collection approach, sophisticated data preprocessing techniques, and the application of transfer learning to capitalise on pre-trained ImageNet weights. By adding real-world environmental variables during dataset collection and improving generalisation through data augmentation, the model displays good performance and is well-suited for deployment across varied agricultural settings.

The model developed was successfully incorporated into a mobile-based application that was optimised with TensorFlow Lite, resulting in lightweight and flawless performance on mobile devices. This practical deployment enables real-time disease identification and actionable advice, giving farmers a critical tool for prompt intervention and plant care management. Future work will entail expanding the dataset to cover more diseases, optimising the model for real-world circumstances, and improving the mobile app's user experience. This study provides the groundwork for AI-powered agricultural technologies that solve issues in dealing with plant diseases and contribute to practices that are environmentally friendly.

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