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Optimized Machine Learning System for Identifying Plant Diseases

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Abstract: Plant diseases pose significant threats to agriculture, adversely affecting both crop yield and quality. This study offers a comprehensive overview of plant pathology, examining various types of diseases, their causative agents, and the intricate interactions between plants and pathogens. This study explored the integration of advanced deep learning and machine learning techniques. A dataset of plant leaf diseases, sourced from an online repository, was augmented with additional data featuring 11 West African plant species. The dataset underwent rigorous preprocessing to ensure compatibility with machine learning models. This study employed the ResNet50 Convolutional Neural Network (CNN) for feature extraction and XGBoost for classification, achieving a remarkable accuracy of 98.81% in differentiating between healthy and diseased plant leaves. The performance of the developed model was evaluated using key metrics, including accuracy, precision, recall, F1-score, confusion matrix, and ROC curve, and was found to outperform existing models in terms of accuracy. Furthermore, the model was successfully integrated into a mobile application, demonstrating efficient performance. This approach presents a scalable solution for precision agriculture, enhancing crop health management and boosting agricultural productivity.

Keywords: Feature Extraction, XGBoost, ResNet50, hybrid, mobile application.

I. Introduction

Food security is a pressing global issue, influenced by multiple factors including climate change [1], the decline in pollinators [2], and plant diseases [3]. Among these, plant diseases pose a significant threat not only to global food security but also to the livelihoods of smallholder farmers, who are particularly vulnerable to disruptions in crop health. In the developing world, smallholder farmers contribute over 80% of agricultural production [4] and commonly experience yield losses exceeding 50% due to pests and diseases [5]. Moreover, approximately 50% of the world's hungry population resides in smallholder farming households [6], underscoring their vulnerability to pathogen-induced food supply disruptions. To address the growing food demands of a projected 9.1 billion people by 2050, agricultural productivity must increase by up to 70% [7]. Plant diseases significantly impact crop yield and quality, with studies indicating that they can reduce yields by 20–40% [7]. These diseases contribute to an annual global loss of 10–16% in crop harvests, costing an estimated US$220 billion [7]. Plant diseases, characterized by physiological abnormalities, manifest in various symptoms including wilting, leaf spots, powdery mildew, galls, and dryness. Symptoms such as wilting result from a loss of turgor pressure, while spots and powdery mildew reflect fungal infections. Galls represent abnormal growths on plant parts, and dryness may signal fungal attacks. Traditional plant disease management strategies heavily rely on chemical pesticides, with 78–79% of applications exceeding the necessary amount without considering plant needs or disease prevalence [7]. Excessive pesticide use can lead to the emergence of resistant pest species and contribute to the shifting timing and occurrence of diseases due to climate change [7]. Therefore, systems that precisely detect disease locations and target pesticide application are essential to minimize unnecessary chemical use. Historically, disease detection was supported by agricultural extension services and local plant clinics. With increasing internet penetration and mobile phone usage, online resources and mobile-based tools have become prominent in disease diagnosis [8]. Despite these advancements, detection often relies on experienced plant pathologists, which is limited by the availability of specialists and the time-consuming nature of their diagnosis.

Current machine learning (ML) techniques for plant disease detection involve feature extraction and classification from images, focusing on attributes like color, texture, and shape. While these methods have been effective in detecting diseases such as leaf blotch, powdery mildew, and rust, they face limitations in identifying subtle symptoms and early-stage diseases and struggle with complex, high-resolution images [9][10][11]. Recent advances in deep learning (DL) techniques, such as convolutional neural networks (CNNs) and deep belief networks (DBNs), have shown promise for plant disease detection [12][13]. These methods learn the underlying features of images to detect subtle disease symptoms that traditional methods might miss [14][15][16]. DL models excel with complex and high-resolution images but require large labeled datasets and significant computational resources, which can be a limitation [17]. Despite the potential of ML and DL approaches, most research has focused on specific diseases or plant species, and there is a need for more publicly available datasets for model training and evaluation. The development of generalizable and robust models for diverse plant species and diseases is essential. Until recently, comprehensive datasets of diseased and healthy plant images were scarce, highlighting the need for more accessible and extensive datasets to improve plant

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disease management. This study aims to address this gap by developing a plant disease detection system using a hybrid machine learning approach, thereby creating an efficient system for accurate plant disease detection. The dataset used for training will be enhanced by incorporating additional data from 11 indigenous West African plants, broadening the model's applicability and improving its effectiveness.

II. Literature Review

[18] developed a hybrid model combining CNN with a recurrent neural network (RNN) for plant disease detection. Their work involved preprocessing images to enhance features, followed by feature extraction using CNNs and temporal pattern recognition with RNNs. This approach achieved an accuracy of 93% in detecting diseases such as powdery mildew and rust. The primary limitation noted was the computational expense associated with training the hybrid model, making it less accessible for resource-constrained environments. [19] utilized a deep belief network (DBN) for plant disease detection. Their methodology focused on training the DBN to learn hierarchical features from leaf images, which were then used for classification. The DBN model achieved an accuracy of 89% in detecting diseases like leaf spot and downy mildew. A key limitation was the need for extensive labeled data for training the DBN, which may not be available for all plant types. [20] employed a support vector machine (SVM) combined with texture and color features for plant disease detection. Their methodology involved extracting texture and color features from leaf images and training an SVM classifier. The study showed that the SVM model could effectively differentiate between healthy and diseased plants, achieving an accuracy of 90%. However, the study faced limitations in handling high-resolution images and subtle disease symptoms. [21] explored the use of an ensemble learning approach for plant disease classification. They combined multiple machine learning models, including decision trees, random forests, and gradient boosting, to improve classification performance. The ensemble approach achieved an accuracy of 91% in detecting diseases like blight and leaf curl. Nonetheless, the study highlighted the challenge of managing computational resources and integrating multiple models efficiently. [22] proposed a novel approach using a combination of CNN and transfer learning for plant disease detection. They utilized pre-trained CNN models and fine-tuned them on a dataset of plant leaf images. This method achieved an accuracy of 94% and reduced the need for extensive labeled data. However, the study noted that transfer learning might not be as effective for very specific or rare plant diseases.

[23] utilized a CNN with attention mechanisms to enhance the detection of plant diseases. Their methodology involved incorporating attention layers into the CNN to focus on relevant features in leaf images, improving detection accuracy. The model performed well on a variety of plant diseases, achieving an accuracy of 92%, but faced limitations in terms of computational complexity and the need for a substantial amount of training data. [24] employed a hybrid model combining CNN with a decision tree classifier for plant disease detection. Their approach involved using CNN for feature extraction and a decision tree for classification. This model showed improved performance in detecting diseases such as leaf rust and blight, with an accuracy of 91% compared to traditional methods. The limitation of this study was the increased complexity of combining two different models, which required careful tuning and validation. [25] developed a deep learning-based system for plant disease detection using CNNs. Their work involved training a CNN model on a large dataset of plant leaf images to classify diseases. The results showed high accuracy rates of 95%, but the study acknowledged limitations in the need for large-scale annotated datasets and the computational cost of training deep learning models. [26] proposed an approach using a CNN combined with data augmentation techniques for plant disease detection. Their methodology involved training a CNN model on augmented leaf images to enhance model robustness. They achieved high accuracy of 96% in detecting diseases such as tomato early blight and late blight. However, the study faced challenges with the computational resources required for extensive data augmentation and model training. [27] utilized a combination of CNNs and transfer learning to detect plant diseases from images. They applied transfer learning with pre-trained CNN models, such as VGG16 and ResNet, and fine-tuned them on a specific dataset of plant leaves. Their results indicated improved accuracy of 92% in detecting various plant diseases, but the study highlighted limitations in the need for large amounts of labeled data and the computational cost of fine-tuning. [28] developed a deep learning framework that integrated CNNs with feature fusion techniques for plant disease detection. Their approach involved fusing features extracted from multiple layers of CNNs to improve disease classification accuracy. The model showed high performance with an accuracy of 93% in identifying diseases like leaf spot and blight. A limitation noted was the increased complexity in feature fusion and model interpretation.

[29] proposed a novel approach combining CNNs with a long short-term memory (LSTM) network for plant disease detection. Their methodology involved using CNNs for feature extraction and LSTMs for sequence modeling to improve disease detection over time. The results demonstrated improved accuracy of 94% in detecting plant diseases, but the study encountered limitations related to the need for sequential data and increased model complexity. [30] explored the use of machine learning techniques, including SVM and k-nearest neighbors (KNN), for detecting plant diseases from image data. They compared the performance of these algorithms in classifying plant diseases and found that SVM achieved higher accuracy of 89% compared to KNN. The study's limitations included difficulty in handling high-dimensional data and the need for feature engineering. [31] employed a deep learning approach using a hybrid CNN and attention mechanism for plant disease detection. Their methodology involved integrating attention mechanisms into CNNs to focus on important features in leaf images, enhancing disease classification accuracy. The study achieved promising results with an accuracy of 92% but faced challenges with the increased computational demands and the need for a large annotated dataset. [32] investigated the use of ensemble learning techniques for plant disease detection. They combined various machine learning models, including random forests, gradient boosting, and neural networks, to

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improve classification performance. The ensemble approach demonstrated high accuracy of 93% in detecting multiple plant diseases, but the study highlighted challenges related to model integration and computational resources.

III. Material and Methods

This section outlines the materials and methods used to develop a system for detecting plant diseases, as illustrated in Figure 1. The process begins with the collection of datasets containing images of plant leaves showing various symptoms of different diseases. The collected data then undergoes preprocessing procedures aimed at ensuring data quality and enhancing the effectiveness of the training process. This preprocessing involves resizing images, normalizing pixel values, and applying data augmentation techniques. A transfer learning algorithm, specifically ResNet50, is applied to the preprocessed data to extract features from the images. ResNet50 is used due to its ability to leverage pre-trained weights and efficiently capture complex image features. Following feature extraction, a gradient boosting machine, the XGBoost model, is trained using the extracted features. This model generates the plant disease detection system. The effectiveness of the XGBoost model is assessed through various performance metrics to evaluate its accuracy and robustness. The trained model is then integrated into a mobile app. The entire implementation process is carried out using the machine learning toolbox available within the Python environment, with additional support from libraries such as Pandas, NumPy, and Scikit-learn (sklearn). The app is developed using Android Studio and Flutter to provide a user-friendly interface for plant disease detection. To validate the methodology, a comparative analysis is performed, comparing the performance of the developed model with other approaches to ensure its efficacy and reliability.

Data Collection

The dataset utilized in this study was sourced from Roboflow, an online repository. It consists of a total of 52,446 images of diseased and non-diseased plant leaves, which are divided into training, testing, and validation sets. The images are organized into 38 distinct classes representing 14 different plant species.

To augment the dataset, an additional set of images featuring 11 indigenous West African plants, captured with smartphone cameras, was incorporated. This augmentation expanded the dataset to include 25 plant species, resulting in a total of 64 different classes. The updated dataset now contains 61,459 images, which are divided into 43,021 training images, 9,218 testing images, and 9,218 validation images. Table 1 provides a detailed list of the classes included in the updated dataset.

Table 1. List of classes in the Updated dataset.

S/N	Plant	Classes
1	Aloe Vera	Aloe Vera Healthy, Aloe Vera Leaf Rot, Aloe Vera Leaf Rust
2	Apple	Apple Healthy, Apple Black Rot, Apple Cedar Rust, Apple Cloudy Spot, Apple Scab, Apple Worm
3	Blueberry	Blueberry Healthy, Blueberry Mummy Berry
4	Banana	Banana Healthy, Banana Bacterial Wilt, Banana Black Sigatoka
5	Cherry	Cherry Healthy, Cherry Bacterial Canker, Cherry Powdery Mildew, Cherry Shot Hole
6	Corn	Corn Healthy, Corn Common Rust, Corn Northern Leaf Blight, Corn Southern Leaf Blight, Corn Stewart's Wilt
7	Coffee	Coffee Healthy, Coffee Cercospora Leaf Spot, Coffee Leaf Rust, Coffee Red Spider Mite
8	Grape	Grape Healthy, Grape Black Rot, Grape Esca, Grape Leaf Blight, Grape Leaf Spot, Grape Powdery Mildew, Grape Red Blotch
9	Peach	Peach Healthy, Peach Bacterial Spot, Peach Brown Rot, Peach Leaf Curl, Peach Powdery Mildew, Peach Rust
10	Pepper	Pepper Healthy, Pepper Bacterial Spot, Pepper Phytophthora Blight, Pepper Leaf Curl Virus
11	Potato	Potato Healthy, Potato Early Blight, Potato Late Blight, Potato Leaf Roll Virus, Potato Black Leg
12	Strawberry	Strawberry Healthy, Strawberry Leaf Spot, Strawberry Powdery Mildew, Strawberry Root Rot
13	Healthy Leaf	Healthy Leaf Blight, Healthy Red Leaf Spot, Healthy Red Scab
14	Tomato	Tomato Healthy, Tomato Bacterial Spot, Tomato Early Blight, Tomato Late Blight, Tomato Leaf Mold, Tomato Septoria Leaf Spot, Tomato Spider Mites, Tomato Yellow Leaf Curl Virus
15	Wheat	Wheat Healthy, Wheat Leaf Rust
16	Cassava	Cassava Healthy, Cassava Mosaic Disease, Cassava Brown Streak Disease

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17	Yam	Yam Healthy, Yam Anthracnose, Yam Leaf Spot
18	Maize	Maize Healthy, Maize Leaf Blight, Maize Streak Virus
19	Cowpea	Cowpea Healthy, Cowpea Mosaic Virus, Cowpea Aphid-Borne Mosaic Virus
20	Groundnut	Groundnut Healthy, Groundnut Leaf Spot, Groundnut Web Blight
21	Okra	Okra Healthy, Okra Yellow Vein Mosaic Virus, Okra Anthracnose
22	Plantain	Plantain Healthy, Plantain Sigatoka Disease
23	Oil Palm	Oil Palm Healthy, Oil Palm Bunch Rot, Oil Palm Yellowing
24	Sorghum	Sorghum Healthy, Sorghum Ergot, Sorghum Rust
25	Taro	Taro Healthy, Taro Leaf Blight, Taro Colocasia Virus

Data Preprocessing

To prepare the dataset for training, several preprocessing steps are undertaken to ensure consistency and improve model performance. All images are resized to a standard size of 224x224 pixels to ensure uniformity across the dataset. After resizing, pixel values are scaled to a range between 0 and 1 by dividing them by 255, as pixel values are typically in the range of 0 to 255. This scaling helps normalize the data and speeds up model convergence. Additionally, data augmentation techniques are applied to enhance the training dataset. These techniques generate new variations of images through transformations such as rotation, flipping, scaling, and cropping, thereby increasing the variety of the dataset and improving the model's robustness and generalization capabilities.

Feature Extraction using Resnet50

ResNet50 is a deep convolutional neural network designed for image classification, renowned for its use of residual connections to facilitate training of very deep networks. It consists of 50 layers, including convolutional layers, residual blocks, and pooling layers.

In the feature extraction process, each plant leaf image is first resized and normalized before being fed into ResNet50. The image then undergoes a forward pass through the network, which includes 48 convolutional layers and 2 fully connected layers. As the image progresses through these layers, the convolutional layers and residual blocks extract hierarchical features from the image, capturing various levels of detail and patterns. The final output from the convolutional layers, just before the classification layer, is used as the feature vector. This vector represents the high-level features of the plant leaf image, providing a compact representation of its visual content that can be used for further analysis or classification tasks.

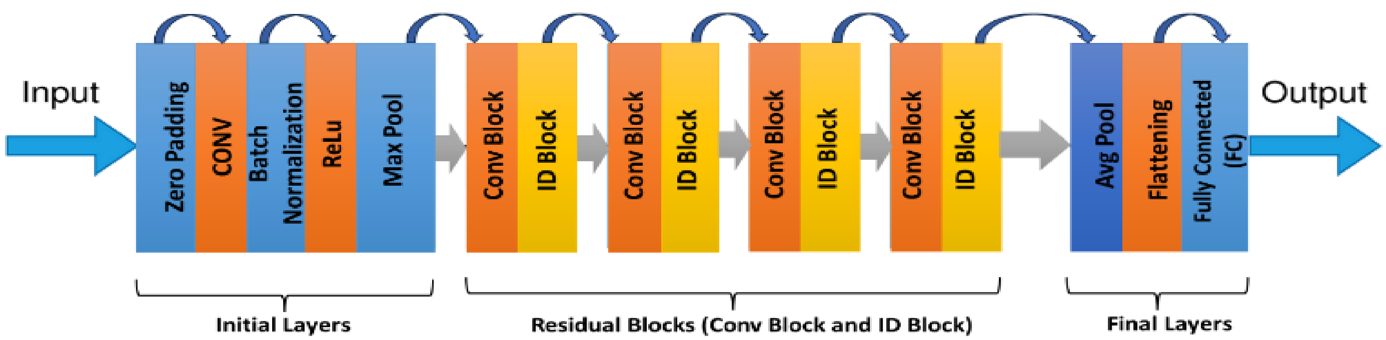

Fig. 1. Architecture of ResNet50

Training of the XGBoost Model

After processing all plant disease images through ResNet50, a collection of feature vectors was obtained, each representing a specific plant leaf image. These feature vectors summarize the visual content of the images, capturing essential information about whether a leaf is diseased or healthy. The next step is to divide the feature dataset into training and testing sets. The training set, which consists of feature vectors and their corresponding labels (diseased or healthy), is used to train the XGBoost model. XGBoost is a powerful machine learning algorithm renowned for its efficiency and predictive performance. It builds an ensemble of decision trees through boosting, a process where trees are added sequentially to correct errors made by previous trees. The XGBoost algorithm learns to identify patterns and relationships between the features and the labels by iteratively constructing and refining decision trees to minimize classification errors. It adjusts its parameters based on the training data to enhance accuracy. Once the XGBoost model is trained using the feature vectors from the training set, its performance is evaluated with the testing

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set. This set, which also contains feature vectors and their true labels, is used to assess how well the model generalizes to new, unseen plant leaf images.

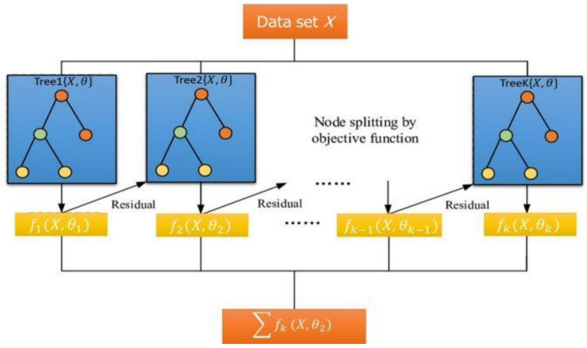

Fig. 2. Architecture of XGBoost

IV. Results

After applying the ResNet-50 architecture for feature extraction and using these features to train the XGBoost algorithm, the model's performance was rigorously evaluated using several metrics, including accuracy, precision, recall, specificity, F1-score, confusion matrix, and ROC curve, as summarized in Table 2. Accuracy represents the proportion of correct predictions out of all predictions made by the model. Precision measures the ratio of true positive leaf disease detections to the total number of instances predicted as diseased, reflecting the quality of positive predictions. Recall assesses the model's ability to detect actual cases of leaf disease. The F1-score provides a balanced measure by taking both precision and recall into account, serving as the harmonic mean of these two metrics.

Fig. 3 and 4 illustrate the model’s performance, with Fig. 3 depicting the training and validation accuracy, and Fig. 4 showing the training and validation loss.

Table 2. Training Reports of the models

Algorithm	Accuracy	Precision	Recall	F1-score
XGBoost	98.81%	0.98	1.0	0.99

Fig. 3. Training and Validation Accuracy

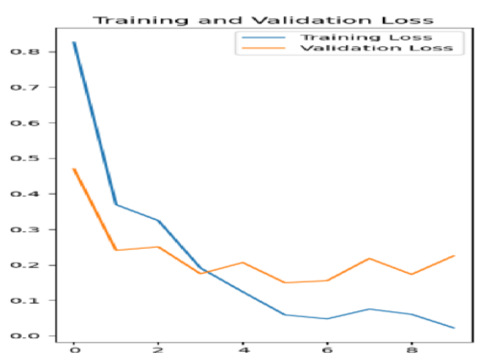

Fig. 4. Training and Validation Loss

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Fig. 5 shows the Confusion Matrix of the model, providing a detailed table that provides insights into the true positives, true negatives, false positives, and false negatives. Fig. 6 depicts ROC curve which plots the true positive rate against the false positive rate at various threshold settings.

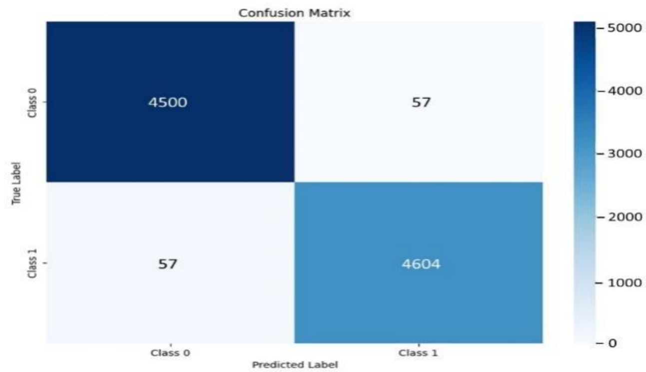

Fig. 5. Confusion matrix of the XGBoost

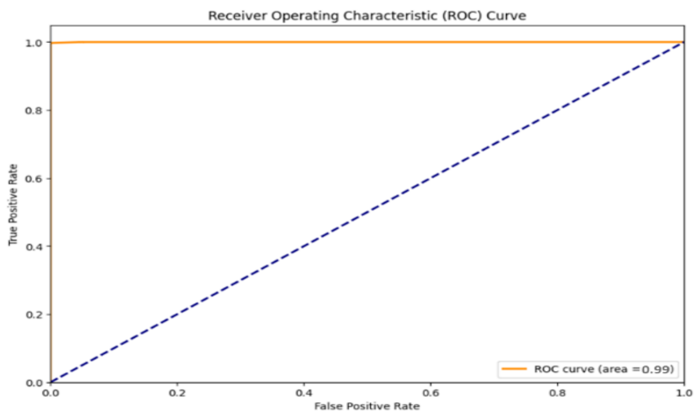

Fig. 6. ROC of the XGBoost

Table 3. Comparative analysis of results with other techniques

Authors	Technique	Accuracy
[18]	Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN)	93%
[19]	Deep Belief Network (DBN)	89%
[21]	Decision Trees, Random Forest, and Gradient Boosting	91%
[22]	Convolutional Neural Networks (CNN) and Transfer Learning	94%
[27]	Convolutional Neural Networks (CNN), VGG16 and ResNet	92%
[29]	CNN and Long Short Term Memory (LSTM)	94%
New model	ResNet50 and XGBoost	98.8%

The Table 3 compared the performance of the existing techniques with the new model for plant disease detection. In the comparative assessment, the new model for plant disease detection was compared with other pre-existing models. The outcomes indicated that newly developed model attained a superior detection accuracy.

System Implementation

The system implementation involved using Python and Flutter. After training and evaluating the model, it was exported to TensorFlow Lite (TFLite), which is optimized for mobile deployment. The mobile user interface was developed using Flutter, and the TFLite model was integrated into the app. The mobile app is designed to capture images of plant leaves and display the results, including the name of the detected disease and any relevant suggestions.

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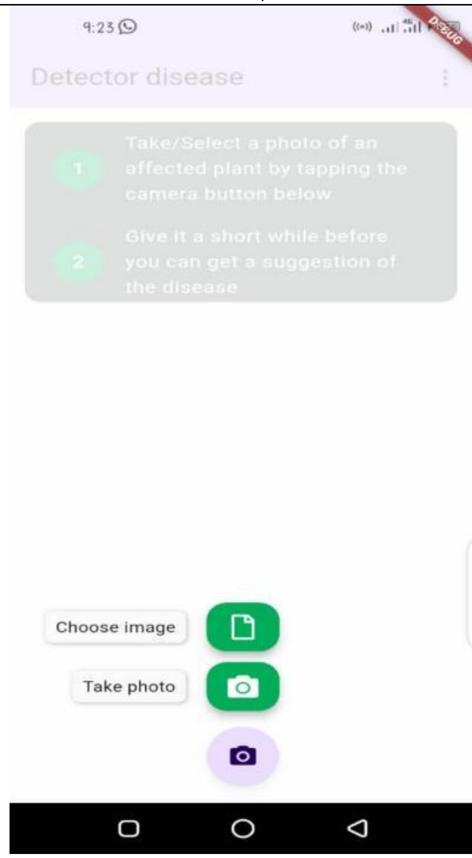

Fig. 7. Upload image and Take photo Screen

Fig. 7 displays the mobile app screen, where users can either upload images of plant leaves directly from the gallery or take new photos for disease detection. Fig 8 illustrates a prompt asking whether the uploaded image should be saved. After the image upload, the integrated model processes the image to detect plant diseases, as shown in Figure 9.

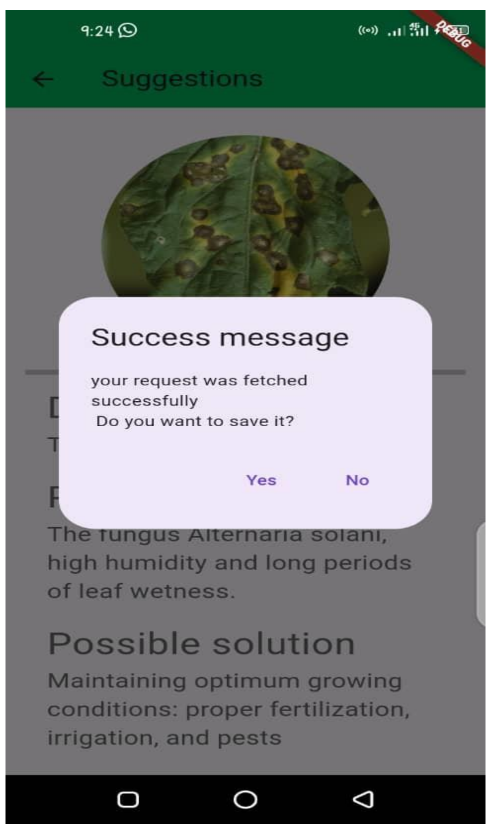

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Fig. 8. Screen displays whether you want to save the image or not

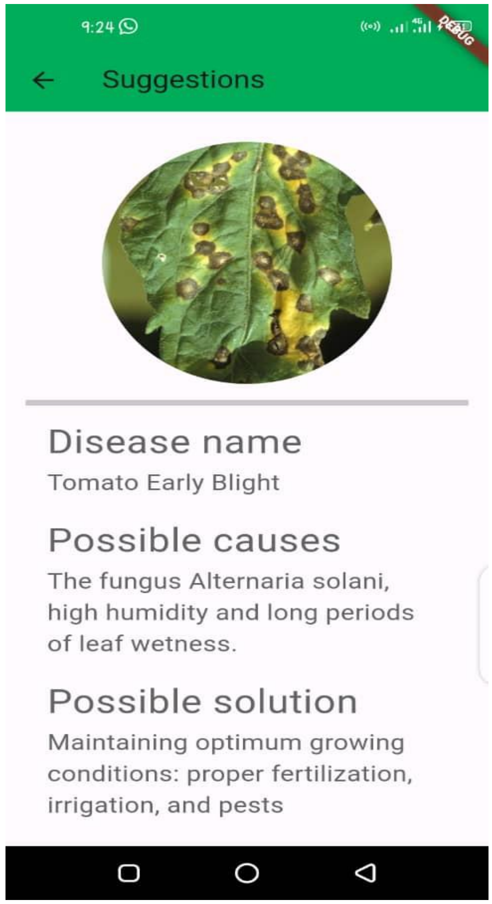

Fig. 9. Screen showing diseases name, possible causes and solutions

V. Discussion

The study effectively demonstrates the integration of machine learning (ML) techniques, particularly CNN and XGBoost, in the detection and classification of plant diseases. The adoption of ResNet50 for feature extraction significantly enhances the model's ability to capture complex patterns within the image data, which is crucial for accurately identifying disease symptoms. The model achieved an impressive accuracy of 98.81%, indicating a high level of precision and recall in identifying diseased versus healthy plant leaves. Comparing the developed model with existing models indicated that the model attained a high accuracy. However, this study distinguishes itself by successfully integrating ResNet50 with XGBoost, which not only improves the model's performance but also optimizes it for mobile deployment via TensorFlow Lite. The model was effectively integrated into a mobile system, demonstrating its practical application in real-world scenarios.

VI. Conclusion

This study presents a hybrid approach to plant disease detection using advanced ML techniques, particularly ResNet50 and XGBoost. The high accuracy and precision achieved demonstrate the potential of these techniques in improving agricultural productivity by enabling early and accurate detection of plant diseases. The successful deployment of the model on a mobile platform further underscores its practicality for real-world applications, especially in regions where traditional disease detection methods are not readily available.

Recommendation

Future research should aim to broaden the dataset by including a greater diversity of plant species and diseases, particularly those from under-represented regions like Africa and Southeast Asia. To improve practical applications, integrating the model with Internet of Things (IoT) devices, such as smart cameras and sensors, could enable real-time monitoring and disease detection. This would help farmers receive timely information to reduce crop losses. Additionally, providing training and educational resources for end-users, especially smallholder farmers, is essential to ensure effective use of the technology.

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