

# NisargaScan-Mobile Based Plant Disease Detection using Deep Learning

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## ABSTRACT

This paper presents a comprehensive mobile-based intelligent system for fruit plant disease detection and severity estimation by integrating deep learning and image processing techniques. Plant diseases significantly impact agricultural productivity, causing major economic losses and reduced crop quality, particularly in regions where timely expert diagnosis is not readily available. Conventional detection methods rely on manual inspection, which is labor-intensive, time-consuming, and prone to human error, highlighting the need for automated solutions. To address this, the proposed system utilizes the EfficientNetB3 convolutional neural network for accurate multi-class classification of plant leaf diseases across six fruit crops—apple, cherry, grape, orange, peach, and strawberry—using a dataset of 27,676 images with extensive preprocessing and data augmentation to improve robustness under varying conditions. In addition to classification, a color-based image segmentation technique in the HSV color space is employed to estimate disease severity by calculating the proportion of infected regions relative to the total leaf area. The system is deployed as a cross-platform mobile application developed using React Native, enabling users to capture or upload leaf images and receive real-time diagnostic results along with treatment recommendations, multi-language support for Hindi, English, and Marathi to enhance accessibility for a wider range of users, and PDF report generation with history tracking. Experimental results show that the proposed model achieves an accuracy of 99.42%, outperforming VGG16 and MobileNetV2 across key metrics such as precision, recall, and F1-score. Overall, the system provides a scalable and user-friendly solution for early disease detection and informed agricultural decision-making, with future work focused on improving robustness in real-world conditions and enabling offline deployment.

**Keywords** - Plant Disease Detection, Convolutional Neural Networks, Deep Learning, Mobile App Development

## I. INTRODUCTION

Agriculture plays a crucial role in the global economy and is especially significant in developing countries, where a substantial proportion of the population depends on farming for their livelihood. However, agricultural productivity is continuously challenged by various biotic and abiotic factors, among which plant diseases are one of the most detrimental. In the case of fruit crops, diseases can spread rapidly, leading to severe yield losses, deterioration in quality, and significant economic consequences for farmers as well as the agricultural supply chain. Traditional plant disease detection methods primarily rely on manual inspection and expert knowledge. While effective to some extent, these approaches are labor-intensive, time-consuming, and susceptible to human error. Moreover, their limited accessibility in rural and remote areas further constrains timely diagnosis. Delayed detection and treatment of plant diseases often result in the rapid progression of infections, thereby intensifying crop damage and losses. These limitations underscore the need for efficient, accurate, and scalable detection techniques. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have provided promising solutions for automated plant disease detection. Image-based analysis using Convolutional Neural Networks (CNNs) and related deep learning architectures has demonstrated high accuracy in classifying plant diseases from leaf images. Furthermore, techniques such as transfer learning, attention mechanisms, and generative models have been increasingly adopted to enhance model performance, particularly in scenarios with limited annotated datasets.

In addition, the emergence of mobile computing and cloud-based platforms has enabled real-time disease diagnosis in field conditions. These technologies facilitate the deployment of AI-powered applications that allow farmers to capture plant images and receive instant diagnostic feedback. Such integration supports timely intervention, improves decision-making, and contributes to more sustainable agricultural practices. This survey paper presents a comprehensive review of recent developments in plant disease detection using deep learning techniques. It analyzes key methodologies, model architectures, datasets, and deployment strategies, while also identifying existing challenges and research gaps. Furthermore, it highlights emerging trends and potential future directions in this rapidly evolving field.

## II. LITERATURE REVIEW

Manual monitoring of plant health is inefficient and error-prone. The proposed mobile-based system employed a lightweight Convolutional Neural Network (CNN) for disease detection, achieving an accuracy of 92%. The mobile application was developed using React Native, integrated with a Flask backend for inference. Images of leaves were captured and transmitted to the backend for classification into healthy or diseased categories. Severity estimation was carried out using classical image processing techniques through OpenCV and NumPy. The system enabled real-time field diagnosis and displayed disease severity on the app interface. It reduced dependence on manual inspection and provided a low-cost, portable solution suitable for farmers in remote regions where rapid decision-making is essential.[1]

A comprehensive study conducted a systematic literature review covering 176 research papers on AI-based plant disease detection. The review analyzed both laboratory and in-field datasets, identifying gaps such as lack of standard evaluation metrics and limited generalization due to small datasets. The paper summarized key classification approaches, including cognitive CNNs, attention mechanisms, and transfer learning strategies. It emphasized that localization and segmentation techniques remain underdeveloped and represent major bottlenecks in real-world application. The review concluded by suggesting the need for benchmark datasets, standardized performance indicators, and robust models capable of adapting to real-world agricultural variability for improved AI-driven disease detection in plants.[2]

The research focused on the detection of rice plant diseases using deep learning methods. A CNN model based on DenseNet architecture was implemented to identify four major rice diseases. The dataset consisted of labeled images collected under controlled conditions. The model achieved 99.45% accuracy, outperforming traditional manual inspection methods. Despite its high accuracy, the system lacked testing under diverse field environments and provided no interpretability tools to explain predictions. The authors recommended extending the approach to include explainable AI components and multi-disease classification to improve reliability and transparency in practical agricultural deployments.[3]

A hybrid machine learning approach was developed for cotton disease detection to improve crop health monitoring and yield prediction. The model combined Random Forest, Support Vector Machine (SVM), and Ensemble techniques for accurate classification of diseased and healthy leaves. Image preprocessing included segmentation and color feature extraction. Although the approach mainly focused on binary classification, it demonstrated strong performance for cotton-specific diseases. The hybrid ensemble improved stability and detection accuracy compared to individual classifiers. The study contributed to a visual and practical disease detection mechanism that can be used for early prevention and yield optimization in cotton farming environments.[4]

A deep learning model employing EfficientNetB0 architecture was proposed for classifying 38 plant diseases with high precision. The system achieved an overall accuracy of 99.69%. To address the interpretability issue of deep models, the authors integrated Explainable Artificial Intelligence (XAI) using LIME to visualize and interpret model predictions. This approach enabled end-users to understand which parts of the leaf image contributed most to the classification outcome. Although computationally intensive, the model proved reliable in providing accurate and explainable results. The integration of XAI improved user trust and offered valuable insight into the decision-making process of the neural network.[5]

The study presented a comparative analysis of machine learning and deep learning algorithms for plant disease classification and object detection. A total of 65 classification and 14 detection methods were reviewed and benchmarked using the PlantDoc dataset. Results indicated that while deep learning models achieved high accuracy in controlled environments, they struggled under field conditions due to dataset bias. Most models were found to be dataset-specific and lacked robustness in uncontrolled lighting and background conditions. The paper highlighted the importance of real-world validation and proposed standardized evaluation methods for future research to develop generalized models adaptable to various crops and field conditions.[6]

A lightweight 2D CNN architecture named “Plant Disease Classifier” was developed for dual-crop disease detection in cotton and tomato plants. The model supported 14 classes, including 12 diseased and 2 healthy categories. Designed specifically for Android platforms, the CNN achieved an accuracy of 97.36% and an AUC of 99.9%, with an average inference time of 4.84 milliseconds. Grad-CAM visualization was used to provide interpretability by highlighting disease regions on the leaf images. The model’s small size and fast execution made it well-suited for mobile deployment. However, scalability beyond dual crops remained a limitation, requiring future enhancement for multi-crop support and adaptability.[7]

A deep learning framework using stepwise transfer learning was developed to address dataset imbalance in plant disease detection. The system utilized a MobileNet-based CNN to achieve high performance while maintaining low computational requirements. Stepwise fine-tuning improved convergence and reduced the risk of negative transfer common in traditional transfer learning. The model achieved 99.69% accuracy on the PlantVillage dataset and 99% on a pepper dataset. Training time and hardware requirements were significantly reduced. The proposed architecture demonstrated the feasibility of deploying deep learning solutions on mobile and edge devices for real-time agricultural disease monitoring in resource-constrained environments.[8]

A novel CNN model incorporating inception and residual blocks was designed for plant disease identification with reduced computational complexity. The architecture used depthwise separable convolutions to lower the number

of trainable parameters while retaining high accuracy. The model achieved 99.66% accuracy on rice datasets, 99.39% on PlantVillage, and 76.59% on cassava datasets. Experimental evaluations showed improved performance for lightweight applications suitable for low-power hardware. Although accuracy declined in highly variable field data, the study demonstrated how optimized CNN structures can enable efficient and scalable plant disease detection on portable and embedded systems for on-field diagnosis.[9]

The research focused on developing real-time plant disease datasets and testing deep learning models under realistic conditions. The authors created three large-scale datasets for rice, wheat, and maize crops, capturing different growth stages and complex environmental backgrounds. A proposed MRW-CNN model and eight fine-tuned architectures were evaluated on these datasets. The models successfully detected diseases across multiple severity stages and field scenarios. The inclusion of real-world noise and illumination variations improved model adaptability. This study highlighted the necessity of authentic, field-collected datasets to enhance the robustness and reliability of deep learning-based plant disease detection systems for agricultural deployment.[10]

An efficient deep learning architecture named YR2S was proposed for detecting and classifying plant leaf diseases with high accuracy. The model combined YOLOv7 for real-time object detection, PCFAN for advanced feature aggregation, and ShuffleNetV2 for lightweight computation. Red Fox Optimization was applied to refine segmentation and improve classification accuracy. The system achieved 99.69% overall accuracy and effectively detected small and densely clustered disease spots. The design reduced the number of parameters and improved inference speed, making it suitable for real-time applications. The model demonstrated superior efficiency compared to conventional deep learning architectures while maintaining precision and robustness in disease detection.[11]

### III. METHODOLOGY

The proposed Plant Disease Detection System follows a modular and systematic approach, consisting of data collection and preprocessing, deep learning-based model development, severity estimation using image processing, mobile application integration, and report generation.

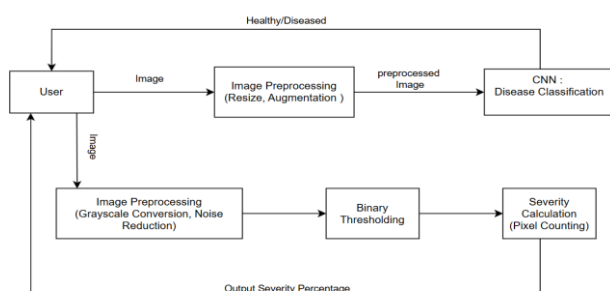


Figure 1. Block diagram of proposed system

#### A. Data Collection and Preprocessing:

A comprehensive dataset of plant leaf images was collected from the publicly available **New Plant Diseases Dataset** on Kaggle, provided by Samir Bhattarai. The dataset comprises both healthy and diseased samples across multiple fruit crops. To ensure compatibility with the deep learning model, all images were resized to  $300 \times 300$  pixels, corresponding to the input requirements of the EfficientNetB3 architecture. Pixel intensities were normalized to improve convergence during training. Additionally, data augmentation techniques such as rotation, horizontal and vertical flipping, zooming, and brightness adjustment were applied to enhance model generalization and robustness against variations in lighting conditions, orientations, and backgrounds commonly encountered in real-world agricultural environments.

#### B. Dataset Description (List of Plants and Diseases):

The dataset used in this study consists of multiple plant species along with their corresponding diseases and healthy conditions, forming a multi-class classification problem. Each class represents a specific plant–disease combination or a healthy leaf category.

A total of six plant species are included, namely apple, cherry, grape, orange, peach, and strawberry. For each plant, common diseases are considered along with healthy samples to ensure effective learning and accurate classification. The inclusion of healthy classes enables the model to distinguish between infected and non-infected leaves.

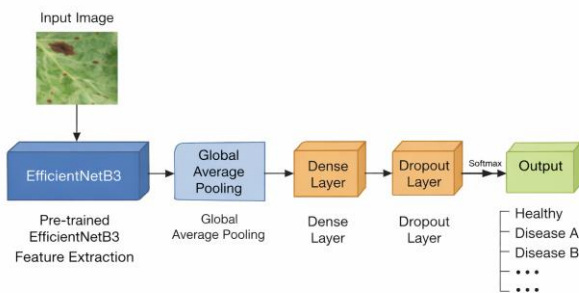
The dataset includes diseases characterized by visible symptoms such as spots, discoloration, and lesions. The dataset comprises a total of 27,676 images distributed across all classes. Table 1 presents the list of plant species and their associated diseases/conditions used in this study.

Plant	Diseases/Conditions
Apple	Apple Scab, Black Rot, Cedar Apple Rust, Healthy
Cherry	Healthy, Powdery Mildew
Grape	Esca (Black Measles), Healthy, Black Rot, Leaf Blight (Isariopsis Leaf Spot)
Orange	Huanglongbing (Citrus Greening)
Peach	Bacterial Spot, Healthy
Strawberry	Healthy, Leaf Scorch

**Table 1. Plants and Diseases in the Dataset**

### B. Model Development using EfficientNetB3:

The **EfficientNetB3** architecture was utilized as the base Convolutional Neural Network (CNN) for feature extraction due to its optimal balance between accuracy and computational efficiency. The pre-trained top classification layers were removed and replaced with a custom classification head tailored to the target disease classes. The model was trained using the **categorical cross-entropy loss function** and optimized using the **Adam optimizer**.



**Figure 2. Architecture of the proposed CNN model for plant disease classification.**

Transfer learning was employed to leverage pre-trained weights, thereby improving performance on limited datasets and reducing training time. The final model is capable of accurately classifying input leaf images into multiple disease categories or identifying them as healthy.

#### Evaluation Metrics :

- $Precision = \frac{TP}{TP + FP}$
- $Recall = \frac{TP}{TP + FN}$
- $F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

### C. Severity Estimation using Image Processing:

To quantify the extent of infection on plant leaves, a color-based image segmentation approach is employed to estimate disease severity. The method computes the proportion of infected regions relative to the total leaf area.

The proposed system utilizes a **color-based image segmentation approach** to quantify disease severity in plant leaves. HSV-based **color thresholding segmentation** is employed due to its robustness against illumination variations and its ability to effectively separate color components.

In this method, segmentation is performed using predefined color ranges in the HSV (Hue, Saturation, Value) color space along with thresholding techniques (e.g., cv2.inRange in OpenCV). This enables precise extraction of both healthy and diseased regions.

**Leaf Region Extraction:** The input image is first converted from the RGB color space to HSV color space. This transformation enhances color discrimination, making it easier to isolate the leaf from the background.

- A green color threshold is applied to identify the healthy leaf region.
- The resulting binary mask represents the total leaf area.
- Morphological operations, such as opening and closing, are applied to:
  - Remove noise
  - Fill small holes
  - Improve mask continuity

**Diseased Region Detection:** To detect infected areas, multiple color thresholds corresponding to visible disease symptoms are defined:

- **Yellow regions** → Early-stage infection
- **Brown regions** → Moderate infection
- **Black regions** → Severe infection

Each region is extracted using predefined HSV ranges. Additionally, grayscale thresholding may be applied to enhance darker infected regions. The individual masks are then combined using logical operations to generate a unified disease mask.

$$Severity (\%) = \frac{Number\ of\ Diseased\ Pixels}{Total\ Leaf\ Pixels} * 100$$

Based on the computed percentage, the severity is categorized into four levels:

- Mild: < 10%
- Moderate: 10% – 30%
- Severe: 30% – 60%
- Very Severe: > 60%



**Figure 3. Severity Estimation of Apple Leaf Infected with Black Rot**

The figure 3 illustrates the process of estimating severity of black rot disease in an apple leaf using image segmentation. The original image shows a leaf exhibiting typical symptoms of black rot, such as brown and dark necrotic spots distributed across the surface. The leaf mask isolates the leaf from the background, ensuring that only the relevant region is analyzed. The disease mask then identifies the infected portions of the leaf by highlighting the affected areas based on color differences. In the final overlay image, these diseased regions are marked in red on

the original leaf, providing a clear visual representation of infection spread. The computed severity value of **17.89%** indicates the proportion of the leaf area affected by black rot, demonstrating how segmentation can be used for quantitative disease assessment.

#### D. Mobile Application Development:

A cross-platform mobile application was developed using React Native to ensure accessibility on both Android and iOS devices. The application enables users to capture images of plant leaves in real time or upload existing images from their device. The captured images are processed through the trained model, and the results including detected disease type, severity percentage, and recommended treatment or preventive measures are displayed on the user interface. This real-time diagnostic capability supports informed decision-making for farmers.

#### E. PDF Report Generation and History Tracking:

To facilitate record-keeping and longitudinal analysis, the system generates a **downloadable PDF report** for each prediction. The report includes the input leaf image, detected disease class, severity level, and recommended solutions. Additionally, a history tracking module stores previous analyses, allowing users to monitor disease progression over time and maintain a structured record of plant health. This feature enhances usability and supports data-driven agricultural practices.

### IV. RESULT AND DISCUSSION

#### A. Classification Performance

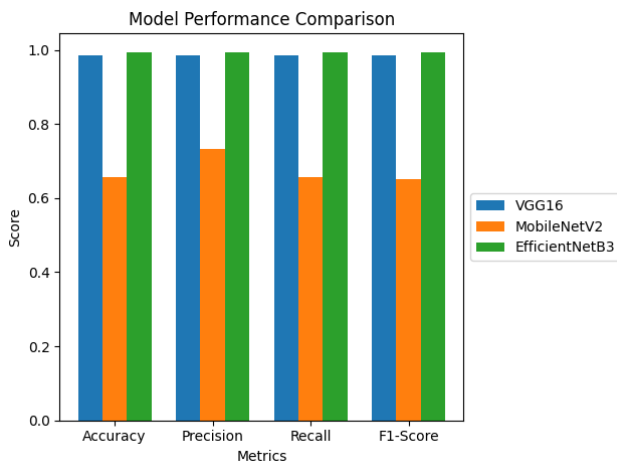


Figure 4. Comparison of model performance metrics

From the results, it is evident that **EfficientNetB3 outperforms both VGG16 and MobileNetV2** across all evaluation metrics. It achieves the highest accuracy of 99.42%, indicating superior classification capability for plant disease detection.

Model	Accuracy	Precision	Recall	F1-Score
VGG16	0.9853	0.9859	0.9853	0.9853
MobileNetV2	0.6557	0.7331	0.6557	0.6521
<b>EfficientNetB3</b>	<b>0.9942</b>	<b>0.9943</b>	<b>0.9942</b>	<b>0.9942</b>

Table 2. Model Comparison

The performance of VGG16 is also strong, with an accuracy of 98.53%, but it is slightly lower than EfficientNetB3. This can be attributed to VGG16's deeper architecture without optimized scaling, leading to higher computational cost and comparatively lower efficiency.

In contrast, MobileNetV2 shows significantly lower performance, with an accuracy of 65.56%. Although MobileNetV2 is designed for lightweight applications and faster inference, its reduced complexity limits its ability to capture intricate disease patterns in plant leaves.

The ROC-AUC score for EfficientNetB3 is nearly 1.0, indicating excellent separability between classes. Similarly, precision, recall, and F1-score values confirm that the model maintains a strong balance between false positives and false negatives.

The superior performance of EfficientNetB3 can be attributed to its compound scaling technique, which efficiently balances network depth, width, and resolution, enabling better feature extraction compared to traditional CNN architectures.

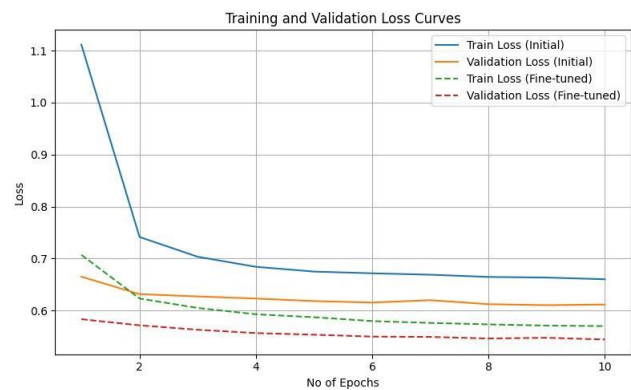


Figure 5. Training and validation loss curves for EfficientNetB3

The loss curves exhibit a consistent decrease throughout both the initial training and fine-tuning phases. During initial training, the training loss reduces markedly from above 1.1 to approximately 0.65, while the validation loss decreases more gradually, stabilizing near 0.61. This indicates effective learning with some room for improvement in generalization.

Fine-tuning further refines the model, as evidenced by lower starting losses and continued reduction in both training and validation loss, reaching approximately 0.57 and 0.54, respectively, by the final epoch. The validation loss remains closely aligned with or slightly below the training loss, suggesting minimal overfitting and enhanced model robustness.

These trends demonstrate that fine-tuning significantly improves the model's generalization capability, corroborating the superior classification performance observed in earlier evaluation metrics.

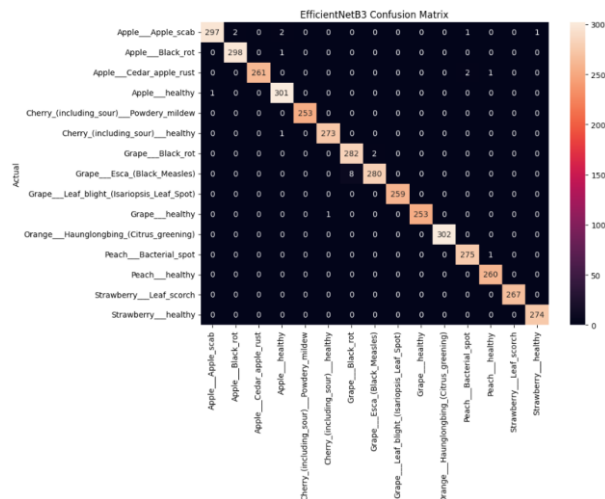


Figure 6. Confusion matrix for EfficientNetB3

The confusion matrix of the proposed EfficientNetB3 model is presented in Figure 3. It provides a detailed visualization of the classification performance across all plant disease categories. From the matrix, it is evident that the majority of predictions lie along the diagonal, indicating that most samples are correctly classified. This demonstrates the high accuracy and robustness of the proposed model. Only a few misclassifications are observed, primarily between visually similar disease classes such as different types of leaf spots and rust diseases. These minor errors can be attributed to the similarity in color, texture, and pattern of certain plant diseases.

The model achieves near-perfect classification for several classes, including healthy leaves and distinct disease categories such as Apple Scab, Grape Black Rot, and Orange Huanglongbing, where almost all samples are correctly predicted.

Overall, the confusion matrix confirms that the proposed EfficientNetB3 model is highly effective in distinguishing between multiple plant disease classes with minimal error.

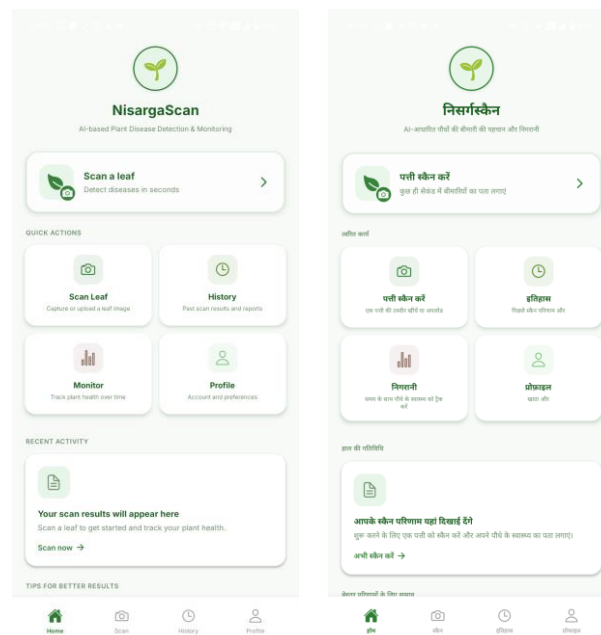
## B. Mobile App Performance And Usability

### Home Screen (Dashboard Interface)

The Home Screen of the NisargaScan application provides a simple and user-friendly interface for navigation. It includes the “Scan a Leaf” feature for quick disease detection and a Quick Actions section with options like Scan, History, Monitor, and Profile. A bottom navigation bar ensures smooth switching between modules, making the app easy to use.

### Multi-language Support

The system provides multi-language support for English, Hindi, and Marathi to ensure accessibility for a diverse group of users. It allows users to select their preferred language, and the interface dynamically updates all text and content accordingly. This improves user experience by making the application easier to understand and use, especially for regional users.



(a) English

(b) Hindi

Figure 7. App Home Page

### Prediction Result Screen (Disease Detection Output)

The Prediction Result screen presents the analysis of the scanned leaf image, including the detected disease name, severity percentage, and classification level. The structured layout ensures clear and quick understanding of results.

### Recommendation and Action Module

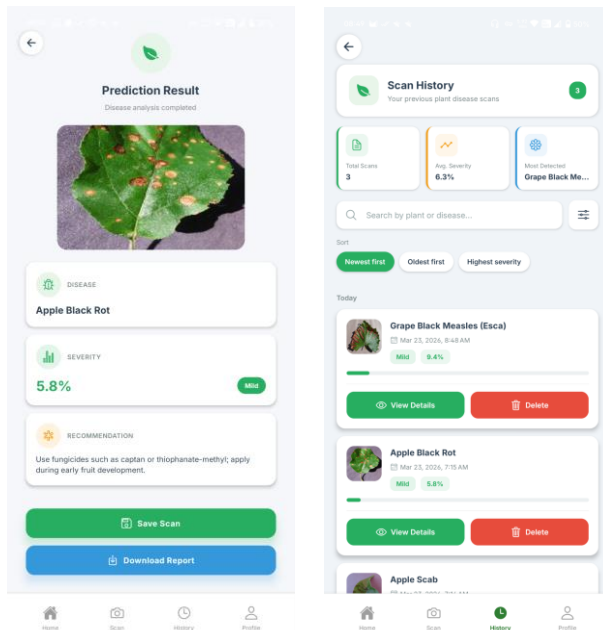
This module provides treatment suggestions based on the detected disease. It also allows users to save scan results and download a detailed report, making the system useful for practical decision-making.

### History and Report Management

The History module stores all previous scan results, allowing users to review past data and track disease progression. It also supports report downloading for proper record-keeping and analysis.

### Disease Progress Dashboard (Analytics Overview)

The Disease Progress Dashboard displays key plant health metrics such as latest severity, average severity, total scans, and overall health status. It also includes a current condition summary indicating disease trends, helping users quickly understand the plant's condition.



(a) Results Page

(b) History Page

**Figure 8. Results and History Pages**

## V. CONCLUSION

This study presents a mobile-based fruit plant disease detection and severity estimation system leveraging deep learning and image processing techniques. The core CNN model, EfficientNetB3, demonstrated superior classification performance with an accuracy of 99.42%, outperforming VGG16 and MobileNetV2 across all key metrics including precision, recall, and F1-score.

The system was implemented as a user-friendly mobile application using React Native, supported by a backend capable of real-time image processing. Users can easily capture or upload leaf images to receive immediate disease identification and severity assessment, facilitating timely and informed decisions in agricultural management.

Experimental results validate that the proposed system achieves an excellent balance between accuracy, computational efficiency, and practical usability. Compared to traditional methods, it offers faster diagnosis, greater accessibility, and enhanced support for farmers in the field.

Future work will focus on expanding disease class coverage, enhancing robustness under diverse environmental conditions, and enabling on-device inference for offline use.

Overall, this system provides an intelligent, accessible tool for plant health monitoring, contributing to improved agricultural productivity and sustainable farming practices.

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