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Early Detection of Papaya and Mango Fruit Diseases Using Deep Learning

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Abstract: *Crop yield and fruit quality are both impacted by plant diseases, which are a serious threat to agricultural productivity. The commercially significant fruit crops papaya (Carica papaya L.) and mango (Mangifera indica) are particularly vulnerable to bacterial, viral, and fungal infections. Manual visual inspection, which is frequently laborious, subjective, and reliant on expert knowledge, is the foundation of traditional disease diagnosis. This research proposes a deep learning-based framework for automated disease classification utilizing fruit photos in order to overcome these constraints.*

EfficientNetB0's outstanding classification performance and processing efficiency make it the foundation of the suggested solution. Anthracnose, Black Spot, Ring Spot, Phytophthora, Powdery Mildew, and Healthy Papaya are the six classes in the papaya dataset; Alternaria, Anthracnose, Black Mould Rot, Stem End Rot, and Healthy Mango are the five classes in the mango dataset. To improve model resilience and generalization, image preprocessing methods like scaling, normalization, and data augmentation are used before training.

The algorithm automatically extracts disease-specific features and conducts multi-class classification of fruit samples that are both healthy and infected using transfer learning. By lowering crop losses and promoting precision agriculture, the suggested framework seeks to offer an accurate, scalable, and economical approach for early disease identification. Additionally, the approach might help farmers and agricultural specialists make prompt judgements on disease control, which would increase crop sustainability and output.

Keywords: *EfficientNetB0, deep learning, transfer learning, mango disease classification, papaya disease classification, plant disease detection, computer vision, precision agriculture.*

I. INTRODUCTION

One of the most significant industries supporting both economic growth and global food security is agriculture. Millions of farmers' livelihoods and the availability of food supplies globally are directly impacted by the production and quality of agricultural crops. Mango (Mangifera indica) and papaya (Carica papaya L.) are two of the many fruit crops that are extensively grown in tropical and subtropical countries because of their high nutritional value, therapeutic qualities, and commercial demand. These fruits are widely consumed in both home and foreign markets, and they make a substantial contribution to agricultural economies.

Mango and papaya crops are extremely susceptible to a variety of illnesses that impact fruit quality, productivity, and market value despite their economic significance. Under ideal environmental circumstances, diseases like Anthracnose, Black Spot, Ring Spot, Phytophthora, Powdery Mildew, Alternaria, Black Mould Rot, and Stem End Rot can spread quickly. These diseases have the potential to seriously harm crops if they are not identified in a timely manner. This could result in significant financial losses for farmers and lower agricultural output overall.

Farmers or agricultural specialists have historically used eye inspection to identify diseases. Manual diagnosis is frequently subjective, time-consuming, and reliant on the observer's experience, despite being commonly used. Inappropriate treatment choices and improper diagnoses can also result from similar visual signs across many diseases. Additionally, early disease detection is difficult in rural and isolated areas due to the scarcity of agricultural experts. These drawbacks make automated and trustworthy illness detection systems essential.

Agricultural disease surveillance has changed as a result of recent developments in computer vision, machine learning, and artificial intelligence. Specifically, Deep Learning methods have shown impressive results in tasks involving object detection and image classification. Convolutional Neural Networks (CNNs) are ideal for plant disease detection applications because they automatically learn hierarchical visual characteristics and do not require manual feature extraction.

Efficient Net's balanced scaling technique, which simultaneously optimizes network depth, width, and resolution, has drawn a lot of interest among contemporary deep learning architectures. EfficientNetB0 is appropriate for real-world agricultural applications where computational resources may be scarce since it offers good classification accuracy while keeping minimal computational complexity. Effective identification of illness symptoms across several fruit categories is made possible by its capacity to extract discriminative visual information from photos.

This study proposes a deep learning-based framework for automatically classifying papaya and mango illnesses from fruit photos. Anthracnose, Black Spot, Ring Spot, Phytophthora, Powdery Mildew, and Healthy Papaya are the six classes that make up the papaya dataset. Similarly, Alternaria, Anthracnose, Black Mould Rot, Stem End Rot, and Healthy Mango are the five classes found in the mango dataset. Image preprocessing methods including scaling, normalization, and data augmentation are used before to training in order to enhance model performance and generalization capacity.

This work's main goal is to create a precise and effective disease classification system that can differentiate between fruit samples that are healthy and those that are contaminated. The suggested system seeks to promote early disease detection, lower crop losses, and help farmers make wise crop management decisions by utilizing EfficientNetB0 and transfer learning approaches. By offering a scalable and automated method for diagnosing plant diseases, the developed technology can support intelligent farming techniques and precision agriculture.

II. LITERATURE REVIEW

Y. Hasan et al. (2026) developed a mobile-based CNN framework for detecting papaya diseases, pests, and fruit maturity. The model achieved 92.5% accuracy and enabled real-time diagnosis on handheld devices [1].

R. Angrakh, R. Shete, A. Dasgupta, and S. Deshmukh (2026) proposed a deep learning framework for mango fruit and leaf disease detection using transfer learning with VGG16 and ResNet50. An ensemble model combining both architectures achieved an accuracy of 94%, outperforming traditional machine learning approaches [2].

R. Gani et al. (2025) developed PapayaNet, an attention-guided lightweight CNN for papaya disease classification. The proposed model classified six papaya leaf conditions and achieved an accuracy of approximately 93%, demonstrating its suitability for practical agricultural applications [3].

S. S. Shetty et al. (2024) proposed a papaya disease classification system using YOLOv9c. Trained on 3,000 images of eight disease classes, the model achieved an accuracy of 89% [4]. M. Parmar and S. Degadwala (2024) utilized Vision Transformers (ViTs) for papaya disease identification. Their model achieved 91% accuracy, outperforming several traditional CNN architectures [5].

G. Dwivedi et al. (2024) developed a Simple Neural Network (SNN) using a pre-trained MobileNetV2 architecture for the automated detection of apple and mango fruit and leaf diseases. By implementing pixel scaling normalization and data augmentation to prevent initial overfitting, their transfer learning framework achieved a robust 95% classification accuracy [6].

L. Marlinda, M. Fatchan, W. Widiyawati, F. Aziz, and W. Indrarti (2021) proposed a mango fruit segmentation approach using the Fuzzy C-Means (FCM) clustering algorithm. The method improved mango ripeness classification through image segmentation and achieved an accuracy of 87% [7].

M. Hossen et al. (2021) introduced a machine vision-based papaya disease recognition framework using deep learning techniques. The CNN model was trained on preprocessed papaya disease images and achieved approximately 92% accuracy, demonstrating the effectiveness of automated disease diagnosis [8].

M. Habib et al. (2020) developed an online machine vision-based expert system for papaya disease recognition. The system employed image preprocessing techniques such as bicubic interpolation, histogram equalization, and Lab color space conversion, followed by k-means clustering and Support Vector Machine (SVM) classification. The proposed approach achieved an overall accuracy of 90.15% [9].

M. Hossen et al. (2020) proposed a deep learning-based papaya disease classification system using Convolutional Neural Networks (CNN) implemented through the Keras API. The model utilized 200×200 RGB images and multiple convolutional and pooling layers for feature extraction. Experimental results demonstrated an average classification accuracy of 91% [10].

III. METHODOLOGY

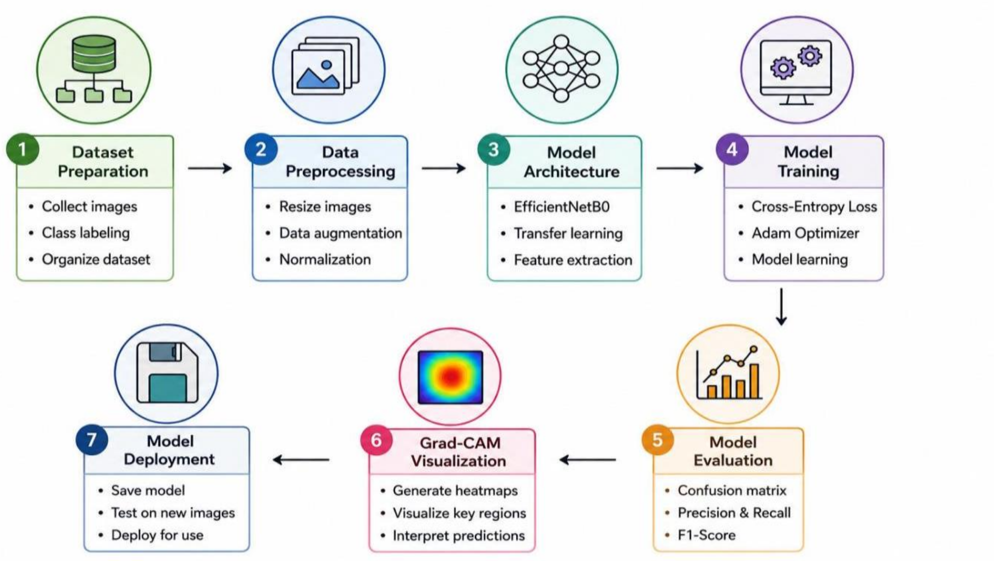

Figure 3.1: Overall Workflow

Figure 3.1 shows the classification system used for papaya and mango fruit diseases. Dataset preparation, picture preprocessing, EfficientNet-B0 feature extraction with transfer learning, model training, performance assessment, Grad-CAM visualization, and deployment for automated illness identification comprise the workflow.

a) Dataset Preparation

Images of papaya and mango fruits are gathered from many sources at this stage and divided into classes for diseases and health. Every picture is appropriately labeled and arranged into distinct folders. To guarantee appropriate model learning and evaluation, the dataset is subsequently split into training, validation, and testing sets.

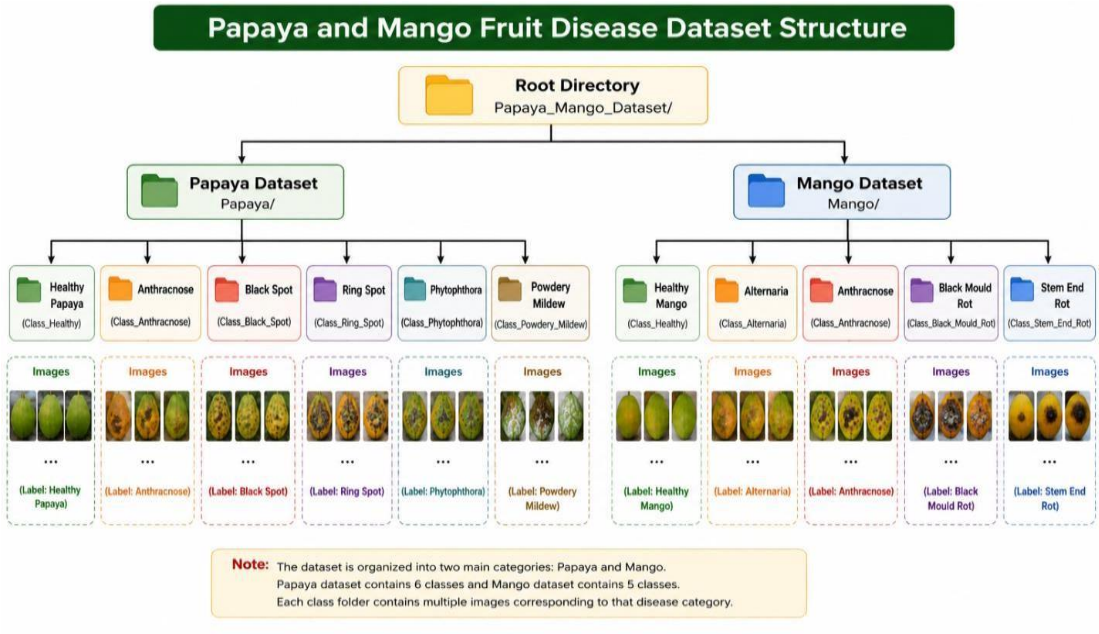

Figure 3.2: Papaya and Mango Fruit Disease Dataset Structure

b) Data Preprocessing

The deep learning model is fed the gathered images after they have undergone preprocessing. Every image is scaled to meet EfficientNet-B0's input size requirement of 224 × 224 pixels. Rotation, flipping, zooming, and brightness adjustment are examples of data augmentation techniques used to decrease overfitting and promote dataset diversity. Lastly, pixel values are normalized to increase model convergence and training efficiency.

c) Model Architecture (EfficientNet-B0 with Transfer Learning

The system makes use of EfficientNet-B0, a cutting-edge Convolutional Neural Network (CNN) that uses compound scaling to strike a compromise between accuracy and computing economy. By loading weights that have already been trained on the ImageNet dataset, transfer learning is employed in place of training from scratch. While deeper layers collect papaya fruit traits particular to disease, the first layers extract low-level data including edges, textures, and color patterns.

EfficientNet-B0's initial classification layer is eliminated and substituted with:

Layer of Global Average Pooling

- Dropout Layer, which lessens overfitting
- Dense (Completely Integrated) Layer
- Softmax Output Layer for the classification of diseases

The model can effectively learn pertinent illness features thanks to this architecture, which also requires less training samples and processing resources.

d) Model Training

The Cross-Entropy Loss function is used to train the model on the preprocessed images. To reduce classification mistakes, the Adam Optimizer uses back propagation to adjust network settings. Until the model performs at its best on the validation dataset, training is done over several epochs.

e) Model Appraisal

Unseen test photos are used to evaluate the training model. Confusion Matrix, Precision, Recall, and F1-Score are used to gauge performance. These metrics offer a thorough evaluation of the model's capacity to correctly categorize papaya fruit illnesses.

f) Visualization with Grad-CAM

Gradient-weighted Class Activation Mapping (Grad-CAM) is used to enhance interpretability. It produces heatmaps that show the areas of the image that have the biggest impact on the model's predictions. This aids in confirming that the model concentrates on disease-affected regions rather than unrelated background characteristics.

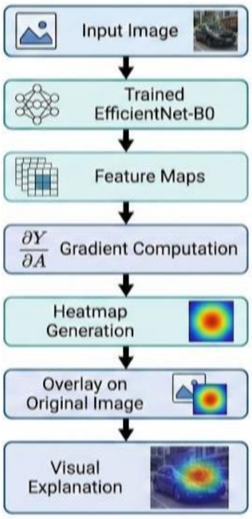

Figure 3.3: Grad-CAM Process

g) Model Deployment

The trained model is saved and put to use for real-world applications following a successful evaluation. Before being sent to the model for prediction, fresh papaya fruit photos go through the same preprocessing procedures. For real-time disease detection, the deployed system can be incorporated into mobile applications, web applications, or agricultural decision-support systems.

IV. RESULTS AND DISCUSSION

The system utilizes the EfficientNetB0 model for the classification of papaya and mango fruit diseases. The model was trained and evaluated using multiple disease categories and healthy fruit samples. Performance was assessed using accuracy and loss curves, confusion matrix analysis, and standard evaluation metrics.

a) Accuracy Analysis

The training and validation accuracy curves show a steady improvement throughout the training process. The validation accuracy remains close to the training accuracy, indicating good generalization capability and minimal overfitting.

Key Observations:

- Continuous improvement in classification accuracy.
- Stable learning behavior during training.
- High validation accuracy demonstrates effective disease recognition.

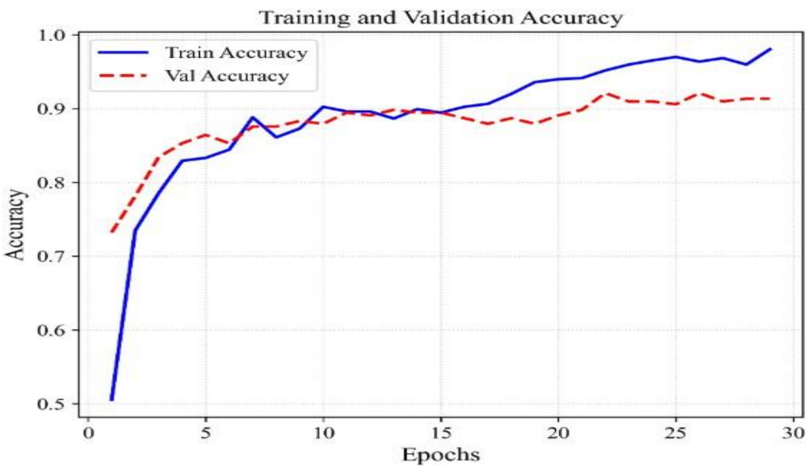

Figure 4.1: Training and Validation Accuracy

b) Loss Analysis

The loss curves exhibit a consistent downward trend, indicating successful optimization of model parameters. The close alignment between training and validation loss confirms stable convergence and reliable performance.

Key Observations:

- Training loss decreases steadily.
- Validation loss follows a similar trend.
- Minimal overfitting observed.

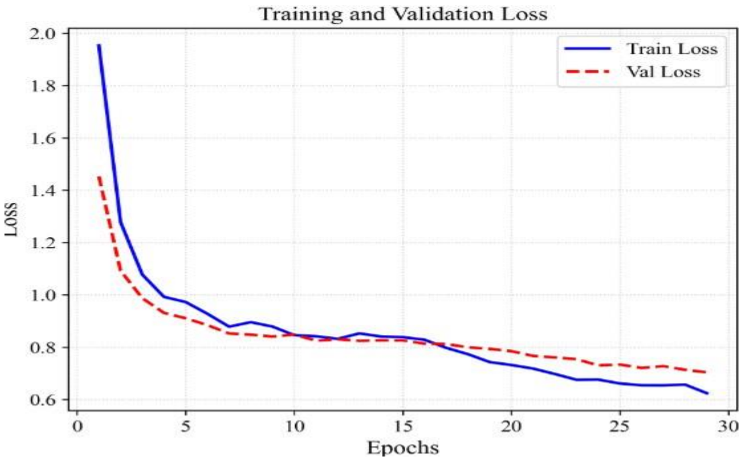

Figure 4.2: Training and Validation Loss

c) Confusion Matrix Analysis

The confusion matrix demonstrates strong classification performance across different fruit disease classes. Most samples are correctly classified, as indicated by the dominant diagonal values. Only a few misclassifications occur among visually similar diseases.

Key Observations:

- High correct classification rate.
- Low confusion between disease categories.
- Effective multi-class disease recognition.

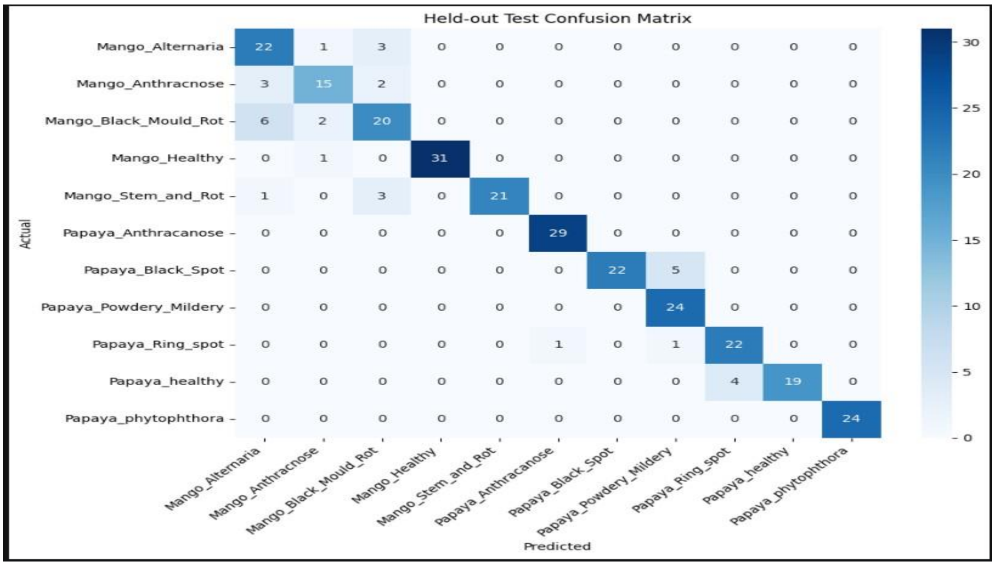

Figure 4.3: Confusion Matrix

d) System Implementation and Output Screens

To evaluate the performance of the proposed Papaya & Mango Guard AI system, a web-based interface was developed for disease detection. The complete workflow includes image upload, disease analysis, and result generation. The corresponding output screens are shown in Figures 4.4, 4.5, and 4.6.

Step 1: User Interface

The developed system provides a simple and user-friendly interface for papaya and mango disease detection. Users can easily access the disease diagnosis module through the web application.

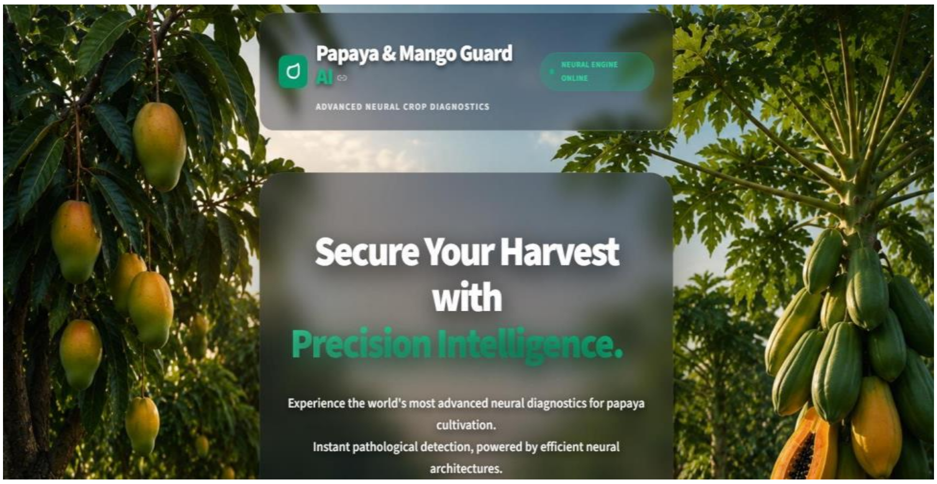

Figure 4.4: User Interface

Step 2: Image Upload

The user uploads a fruit image using the drag-and-drop area or the Browse Files option. The selected image is successfully loaded into the system for analysis.

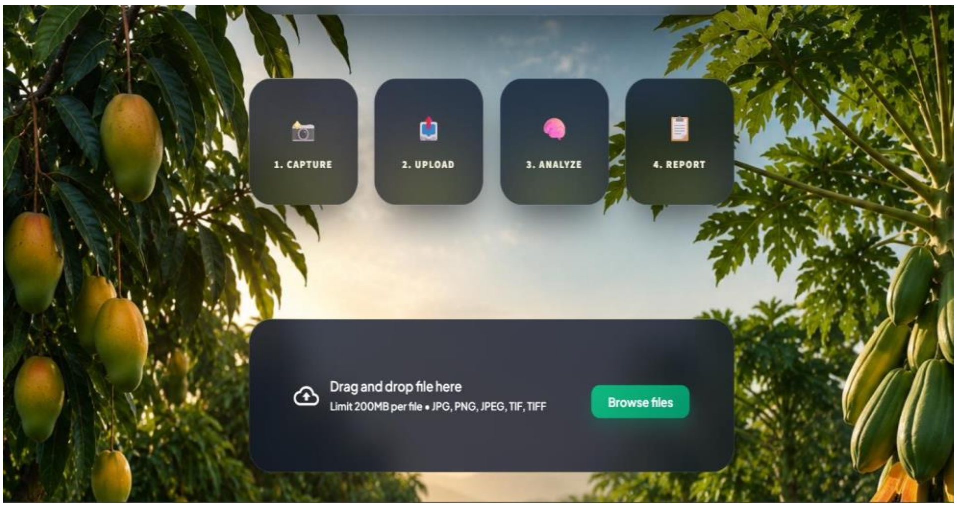

Figure 4.5: Image Upload Process

Step 3: Disease Detection Result

After image processing, the CNN model predicts the disease and displays the result along with the confidence score. In the sample result, the system detected Anthracnose Disease with an accuracy of 97.77%.

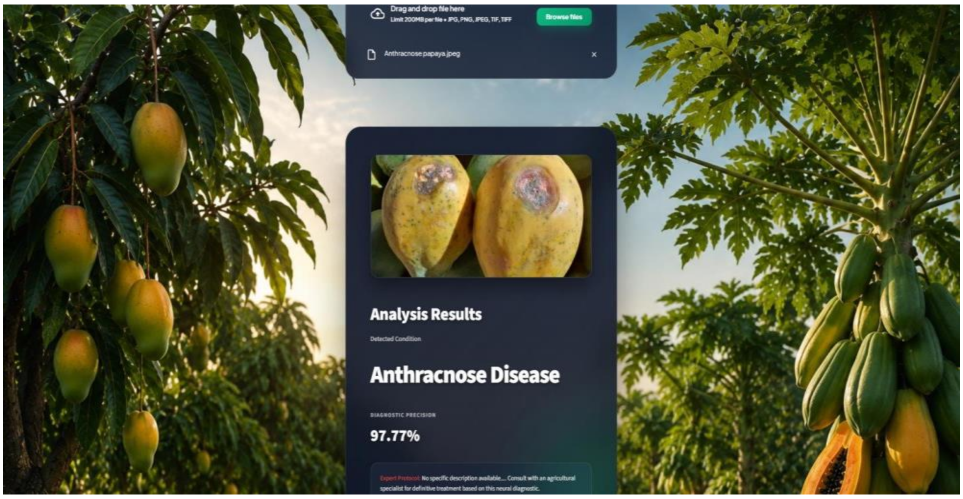

Figure 4.6: Disease Detection Result

e) Sample Prediction Results

Several sample predictions generated by the developed system are shown in Figure 5.4. The model successfully identifies various papaya & mango diseases, including Anthracnose Disease, Black Spot Disease, Stem and Rot Disease, Black Mould Rot Disease, Powdery Mildew Disease, Phytophthora Disease, and Ring Spot Disease, with confidence scores exceeding 90% in most cases.

The prediction results demonstrate the capability of the EfficientNetB0 model to accurately classify both healthy and infected papaya fruits under varying visual conditions.

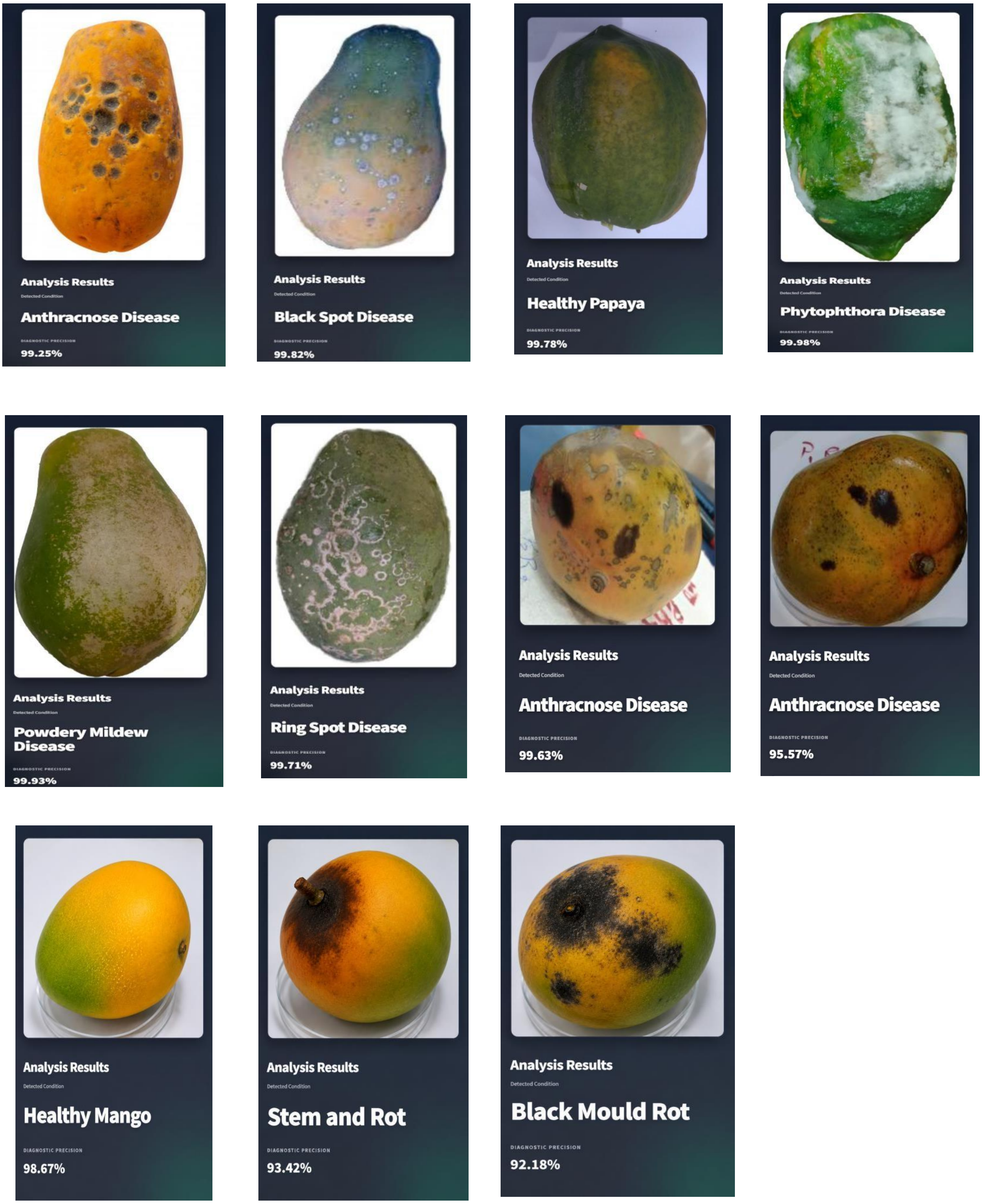

Figure 4.7 Sample Prediction Result

V.CONCLUSION AND FUTURE WORK

An EfficientNetB0-based deep learning framework for the automatic categorization of papaya and mango diseases was described in this study. To enhance model performance and generalization, transfer learning and data augmentation strategies were utilized. The suggested method attained an overall classification accuracy of about approximate (~ 92%) and successfully classified several disease types of both crops.

The experimental findings show how well EfficientNetB0 extracts disease-specific characteristics and correctly separate fruit samples that are healthy from those that are diseased. Grad-CAM's integration improved the model's interpretability even more by emphasizing the areas that influence categorization choices.

Future research can enhance the system by using more and more varied datasets gathered in actual agricultural settings. To further improve classification performance, other illness categories and sophisticated deep learning architectures should be investigated. Additionally, real-time disease diagnostics and precision agriculture techniques can be supported by deployment via mobile or web-based applications and interaction with IoT-enabled smart farming systems.

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