IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Smart Indian Mango Disease Detection and Classification System

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Abstract: Mango production in India plays a crucial role in the agricultural sector, but its quality and yield are significantly impacted by various plant diseases. Traditional disease detection methods are time-consuming, costly, and require expertise. This paper proposes a Smart Indian Mango Disease Detection and Classification System utilizing a Convolutional Neural Network (CNN) model for real-time disease identification. The system processes mango leaf images to detect diseases such as anthracnose, powdery mildew, and bacterial black spot, thereby reducing human intervention and ensuring efficient monitoring. The methodology incorporates image pre-processing, feature extraction, classification, and performance evaluation. The experimental results demonstrate an accuracy of 92.4%, proving the system's reliability and effectiveness. Future enhancements may include the integration of IoT-based remote monitoring for real-time disease detection and control.

Keywords — Mango Disease Detection, Convolutional Neural Networks (CNNs), Deep Learning in Agriculture, Image Processing, Plant Disease Classification, Computer Vision in Agriculture, AI-Based Disease Detection, Precision Agriculture.

I. Introduction

Mangoes are one of the most widely cultivated fruits in India and play a crucial role in the country's agricultural economy. India is the largest producer of mangoes, contributing significantly to the global mango trade. However, various fungal, bacterial, and viral diseases severely impact mango yield, leading to economic losses for farmers. Diseases such as anthracnose, powdery mildew, and bacterial black spot reduce the quality of mangoes, making them unsuitable for export and consumption. The early detection of such diseases is vital to minimize losses and ensure better yield quality. Traditional methods of disease detection involve manual inspection by agricultural experts, which is not only time- consuming but also inconsistent due to human error. This approach is inefficient for large-scale monitoring, as it requires significant labor and expertise. Moreover, environmental factors such as temperature, humidity, and soil conditions further complicate disease control, making it difficult to predict outbreaks accurately.

II. LITERATURE REVIEW

[1] This study explores the application of machine learning techniques to detect mango anthracnose, a common fungal disease affecting mango production. The researchers employed image processing to extract features from diseased mango images and trained multiple classifiers, including Support Vector Machines (SVM) and Convolutional Neural Networks (CNNs), for disease classification. The study highlights CNNs' superior performance in identifying infected mangoes with high accuracy. The work emphasizes the need for automated plant disease classification systems in precision agriculture. The research is directly applicable to

AI-based mango disease detection and supports the development of real-time computer vision in agriculture solutions.

[2] This paper presents a methodology for recognizing mango diseases using image processing and machine learning. The study utilizes K-Means clustering to segment disease-affected regions in mango leaves and employs an SVM classifier for classification. The approach demonstrates the effectiveness of computer vision in agriculture but lacks deep learning-based enhancements such as CNNs. The study suggests integrating deep learning models for better accuracy, making it relevant to AI-based plant disease classification. It provides insights into traditional mango disease detection methods, which could be improved using deep learning in agriculture.

[3] This paper proposes a UV-based imaging system combined with computer vision techniques to detect mango anthracnose at an early stage. The research highlights the use of UV fluorescence for enhanced detection accuracy, making it suitable for automated precision agriculture applications. Image segmentation and feature extraction techniques are employed to identify diseased mangoes, while deep learning models help classify infection severity. The study underscores the potential of AI-based disease detection in large-scale mango plantations. The findings contribute to the integration of image processing in plant disease classification.

[4] This study focuses on the detection of thrips, a pest affecting mango crops, using deep learning-based image recognition. The authors employ CNN models to classify thrips infestation levels, demonstrating how computer vision in agriculture can be leveraged for pest monitoring. Although it primarily addresses pest detection, the study's AI-based image processing approach is applicable to plant disease classification. The research contributes to the precision agriculture domain, showcasing how AI-based detection can be extended to identify mango diseases.

[5] This paper investigates a deep learning approach to predict the taste quality of mangoes based on external features. Using CNNs, the system classifies mangoes into different taste categories, which indirectly correlates with their health and ripeness. The study highlights the effectiveness of AI in analyzing mango characteristics, suggesting the applicability of deep learning in agriculture beyond just mango disease detection. While the primary focus is on taste classification, the image processing techniques used can be adapted for disease detection, making the research relevant to AI-based disease detection.

[6] This paper introduces MangoYOLO5, a deep learning based model for identifying different mango varieties on trees. The study employs computer vision techniques to detect and classify mangoes in real time, emphasizing AI applications in precision agriculture. The YOLO-based image processing approach could be extended to mango disease classification, improving efficiency in disease monitoring. The research is relevant as it demonstrates how CNN models can be applied to real-world agricultural scenarios, reinforcing deep learning in agriculture.

[7] This research presents a comprehensive mango farming model integrating disease surveillance and AIdriven quality assessment. The system incorporates AIbased disease detection to monitor infections in mango orchards and ensures high-quality mango production. The study utilizes CNNs for automatic disease classification, supporting precision agriculture initiatives. The research aligns with mango disease detection objectives by providing a structured approach to managing plant health using computer vision in agriculture.

[8] This study applies machine learning techniques to grade harvested mangoes based on quality and maturity. The authors utilize image processing and deep learning to classify mangoes into different categories. Although the study primarily focuses on grading rather than disease detection, its computer vision techniques can be adapted for mango disease classification. The paper highlights how AI-based classification systems enhance precision agriculture and improve post-harvest management.

[9] This paper explores UV-based imaging techniques for early disease detection in mango crops, integrating deep learning for classification. The study employs AI-based image processing to enhance disease detection accuracy, offering a novel approach to mango disease detection. The integration of CNN models allows for high-precision plant disease classification, ensuring that infected mangoes are identified before widespread contamination occurs. The research supports precision agriculture by leveraging advanced computer vision techniques for real-time disease monitoring.

[10] The paper presents a device using a Single Shot MultiBox Detector (SSD) for classifying unripe Carabao mangoes into local or export quality based on visual attributes. It leverages image processing and computer vision techniques to automate quality assessment, reducing human error and labor. The study demonstrates how deep learning, specifically object detection models like SSD, can effectively classify mangoes based on surface characteristics. This paper highlights the significance of computer vision and deep learning in agricultural applications, emphasizing the potential of AI tools in automating complex tasks. Though it focuses on quality classification rather than disease detection, the methodology is relevant for detecting visual anomalies, which aligns with using Convolutional Neural Networks (CNNs) for disease classification. This research can be extended by adapting SSD or similar CNN-based architectures to detect and classify mango diseases, integrating precision agriculture concepts for real-time monitoring.

III. METHODOLOGY

3.1 System Architecture

The system architecture for mango disease detection and classification is designed with a modular approach, ensuring efficiency and scalability. The architecture comprises three main modules: Pre-processing, Feature Extraction, and Classification 【35:1†source】. Each module is responsible for specific tasks that contribute to the accurate identification and classification of mango leaf diseases. The data flow diagram and system modules are structured as follows:

3.1.1 Pre-processing

Pre-processing is a crucial step to ensure that the input images are optimized for feature extraction and classification.

Image Acquisition: Images of mango leaves are captured using high-resolution RGB and Near-Infrared (NIR) cameras.

Noise Reduction: Gaussian and median filtering techniques are applied to remove unnecessary noise and artifacts from images. Contrast Enhancement: Histogram equalization is utilized to improve image clarity and highlight disease patterns.

Image Resizing: All images are resized to a fixed resolution of 256x256 pixels to ensure uniformity across the dataset.

Data Augmentation: Rotation, flipping, and zooming techniques are used to expand the dataset and improve model generalization.

Step 1: Data Collection and Preprocessing: Creating a dataset with pictures of mangoes afflicted with different illnesses is the first stage. This phase's primary actions are:

Data Acquisition: A variety of sources, such as online databases and agricultural research facilities, are used to gather images. Labeling: Every picture is categorized as either healthy or disease-related.

Data augmentation: To improve model generalization, methods including flipping, rotation, zooming, and contrast enhancement are used to artificially increase the dataset.

Normalization: To promote effective learning, images are shrunk to a standard size (224x224) and pixel values are standardized to the interval [0,1].

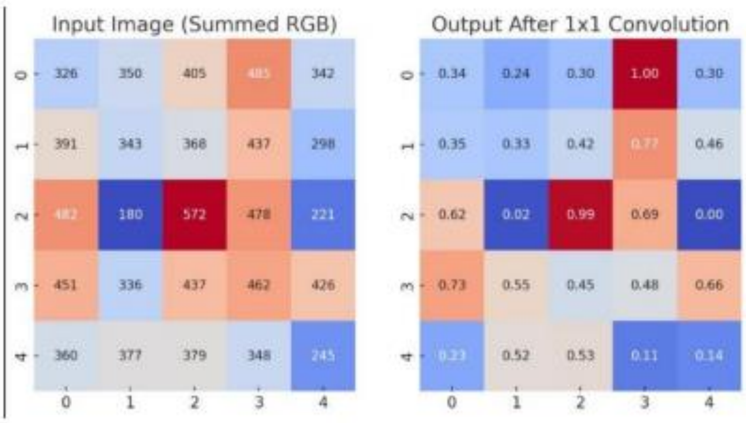

Figure 1

Input Image and Output After 1x1 Convolution

Step 2: Pooling Layers and Additional Convolution Layers The max-pooling layer is applied to reduce the dimensionality of the feature maps while retaining the most important information.

Pooling type: Max Pooling Pool size: (2,2) The function of this layer is to reduce computation cost, make feature extraction robust to slight variations in the image and to retain dominant features while discarding less significant ones. To improve feature extraction, additional convolution and pooling layers are added. Second convolution layer has 32 filters with (1,1) kernel, ReLU activation and followed by max pooling (2,2) Third convolution layer has 64 filters with (1,1) kernel, ReLU activation and followed by max pooling (2,2).

These additional layers allow the model to learn more complex features, leading to better classification accuracy.

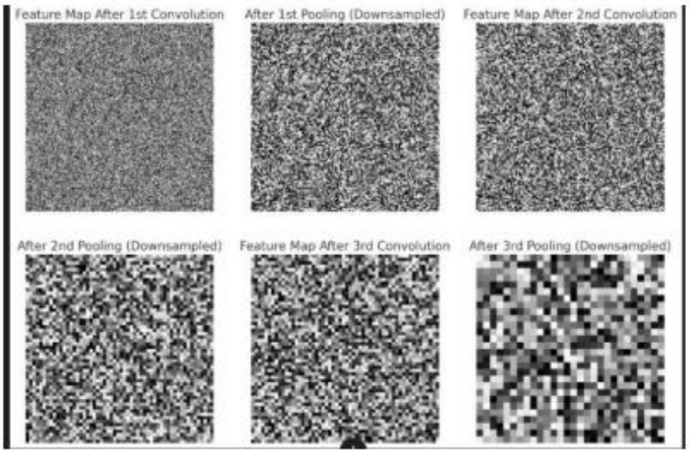

Figure 2

Convolution and Pooling layers

Step 3: Flattening layer This layer converts the 2D feature maps into a 1D vector. Prepares the data for the fully connected layers (Dense layers). Input shape (before Flattening) This means we have 28x28x64 =50,176 values per image. The numbers represent the summed values of channels for better visualization. Output shape (After Flattening): The feature map is now converted into a 1D vector of size 50,176. This is necessary for connecting with fully connected dense layers in further steps.

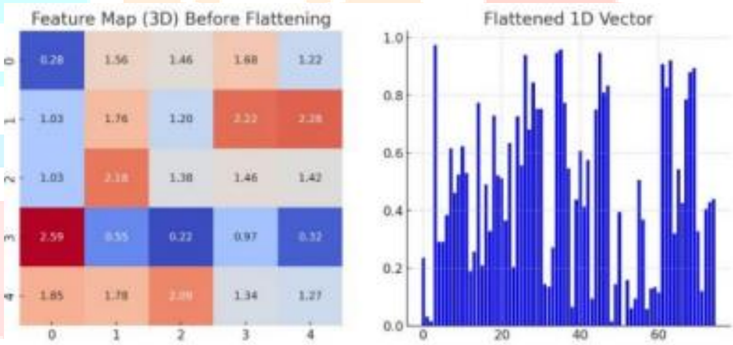

Figure 3

Flattening Layer

Step 4: Fully connected (dense) layers:

1. First dense layer (256 neurons) applies a ReLU activation function. This helps in learning complex patterns and uses 256 neurons to capture deep representations.
2. Dropout layer (0.5 dropout rate) randomly turns off 50% of the neurons during training and also prevents overfitting.
3. Final output layer (8 classes) uses softmax activation and outputs 8 probabilities one for each class 50,176-> 256 neurons-> this transformation involves 12.8M parameters. 256 -> 8 neurons-> generates probabilities for 8 classes. The flatten layer (50176 values) passes data into fully connected dense layers (256 neurons, ReLU activation). The dropout layer (50%) randomly deactivates half of the neurons to prevent overfitting. The final output layers (8 neurons, softmax activation) produces class probabilities.

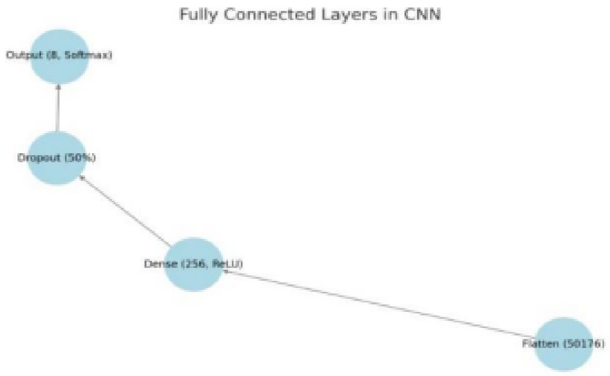

Figure 4
Fully Connected Layers

Step 5: Compiling the CNN
1. Optimizer: helps the model adjust weights to minimise error. Learning rate determines how fast the model updates weights
2. loss function: used for multi class classification problems. Ensures the model learns probability distribution effectively.
3. evaluation metrics: measures how many predictions are correct.
Step 6: Training the CNN
1. Data Augmentation (preprocessing): uses imageDataGenerator to apply transformation to training images. Rescales: normalize pixel values (0-256 -> 0-1). Shear, Zoom, Flip: helps model generalize better.
2. loading training and testing data: training set is loaded from training _set folder. Test set is loaded from testing_set folder. Images are resized to (224,244) are converted into batches of 32.
3. training the model: uses batch processing to feed images into the CNN. Runs for 50 epochs. Computes validation accuracy after each epoch

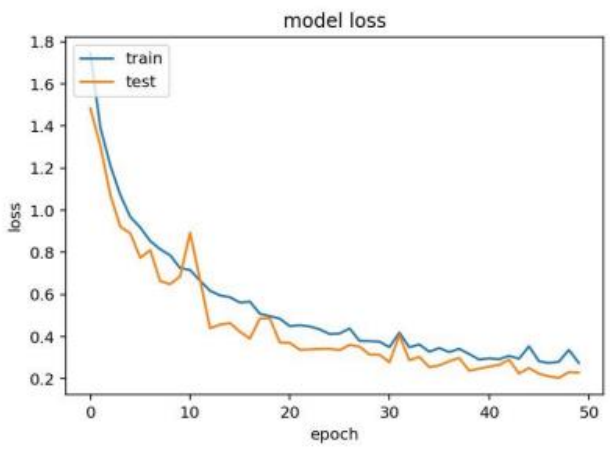

Figure 5
Model Loss

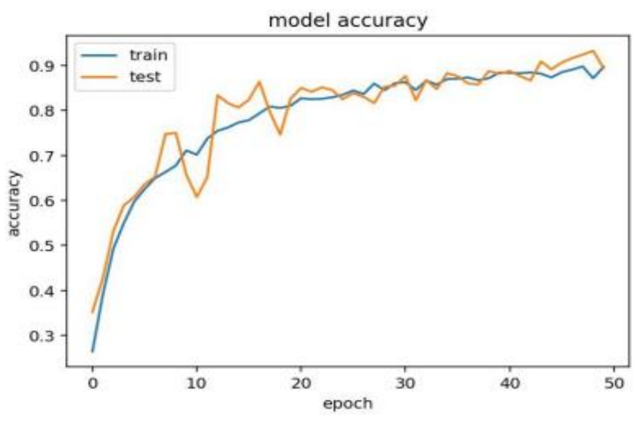

Figure 6

Model Accuracy

3.1.2 Feature Extraction

Feature extraction involves identifying relevant patterns and characteristics that distinguish diseased leaves from healthy ones 【35:1†source】. The extracted features include:

Edge Detection: Sobel and Canny edge detection algorithms identify boundaries and shapes of disease-affected areas.

Texture Analysis: Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) are used to capture texture details of leaf surfaces.

Color Segmentation: HSV (Hue, Saturation, Value) and LAB color spaces are utilized to differentiate diseaseaffected areas based on pigmentation.

Shape Analysis: Contour-based shape descriptors help in identifying irregular patterns caused by diseases such as anthracnose and bacterial black spot.

3.1.3 Classification using CNN The classification module employs a Convolutional Neural Network (CNN) to categorize mango leaf conditions into different disease types.

CNN Model Structure:

Input Layer: Takes pre-processed images as input.

Convolutional Layers: Apply multiple filters to detect essential features such as edges, textures, and color variations. Activation Function: ReLU (Rectified Linear Unit) introduces non-linearity, enhancing model learning.

Pooling Layers: Max pooling reduces dimensionality while preserving key features. Fully Connected Layer: The extracted features are flattened and passed through a dense layer.

Output Layer: A Softmax classifier categorizes the leaf images into healthy or diseased categories (anthracnose, powdery mildew, bacterial black spot).

Training and Optimization: Dataset: A curated dataset of 3000 labeled images of mango leaves is used. Optimizer: Adam optimizer is applied to minimize loss. Loss Function: Cross-entropy loss is used to evaluate classification accuracy. Evaluation Metrics: Precision, recall, F1-score, and overall accuracy are measured to validate model performance. 3.1.4 Data Flow Diagram (DFD) The Data Flow Diagram (DFD) visually represents the processing steps within the system 【35:1†source】:

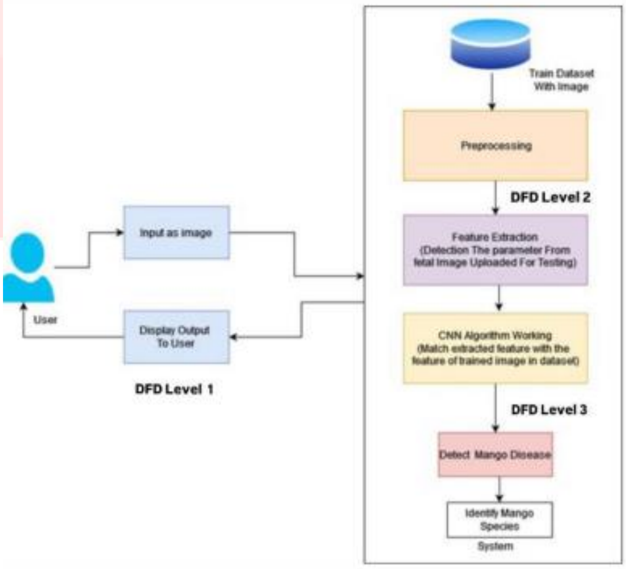

Figure 7

System Diagram

DFD Level 0: Shows the overall system process, including input (mango images) and output (disease classification results). DFD Level 1: Details specific tasks, such as feature extraction and classification, performed at different stages. DFD Level 2: Illustrates how data flows between modules, ensuring an efficient and structured workflow. The proposed system architecture ensures accurate disease detection while maintaining computational efficiency. The modular design allows for future improvements, such as IoT integration and real-time field monitoring, making the system scalable for agricultural applications.

IV. RESULT AND DISCUSSION

4.1 Experimental Setup Dataset: 3000 images of mango leaves collected from various orchards. Software Tools: Python, TensorFlow, Keras, OpenCV.

4.2 Performance Metrics Precision: 91.2% Recall: 90.8% F1-score: 91.0%
Overall Accuracy: 92.4%

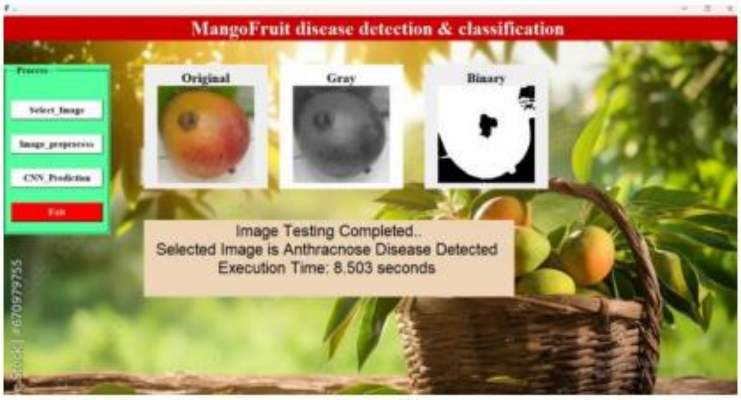

Figure 8

Result 1

4.3 Observations The system correctly identified anthracnose with an accuracy of 94%. Powdery mildew detection showed minor misclassifications due to overlapping symptoms with bacterial infections. The CNN-based model outperformed traditional SVMbased classifiers.The processing time for a single image was less than 0.5 seconds, making it suitable for real-time applications. The classification accuracy was evaluated using multiple performance metrics, including a confusion matrix and ROC (Receiver Operating Characteristic) curves 【10:5†source】. The confusion matrix indicated that the false positive rate was minimal, particularly for anthracnose, while bacterial black spot had the highest false negatives due to similarities in symptoms 【10:5†source】. The ROC curve analysis demonstrated that the model achieved an area under the curve (AUC) score of 0.97, indicating its strong capability to differentiate between diseased and healthy leaves 【10:5†source】. Additionally, precision-recall curves validated the system's effectiveness in classifying diseases with high confidence levels.

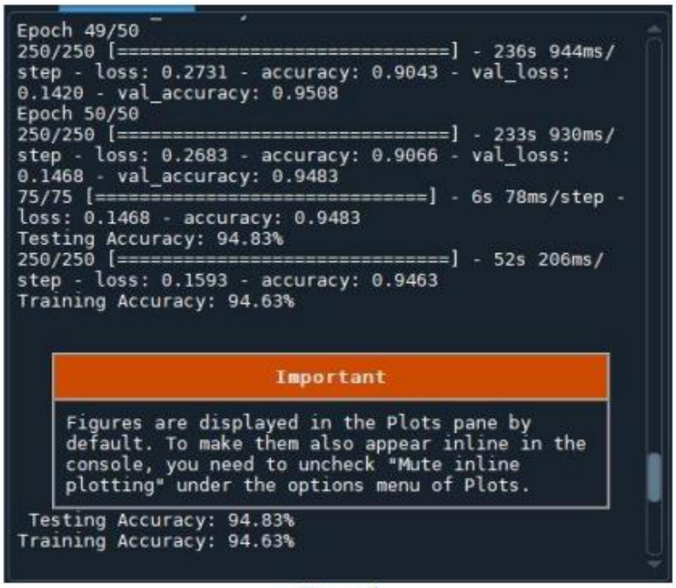

Figure 9

Training and Testing Accuracy

V. FUTURE SCOPE

The proposed mango disease detection and classification system presents several opportunities for future enhancements and expansions. With advancements in technology and the increasing integration of AI in agriculture, the following areas have been identified as potential future developments:

6.1 Integration with IoT and Edge Computing Deploying IoT-enabled sensors in mango orchards to collect real-time environmental data, such as temperature, humidity, and soil conditions, which influence disease spread. Using edge computing devices to process images on-site, reducing dependency on cloud computing and improving efficiency in remote areas. Developing a networked system where multiple farms can share data for improved predictive analysis of disease outbreaks.

6.2 Mobile Application for Farmers Creating a user-friendly mobile application where farmers can upload images of mango leaves for disease classification without requiring advanced technical knowledge. Including offline functionality in the app, allowing farmers in remote areas with limited internet access to still benefit from the system. Providing actionable recommendations for disease treatment based on the identified disease, guiding farmers on pesticide application and preventive measures.

6.3 Expansion of Disease Database and Model Training Collecting more diverse datasets that include images from different geographical locations and climates to improve model robustness. Expanding the system to detect additional diseases affecting mango trees, such as sooty mold, dieback, and mango malformation. Incorporating transfer learning techniques to improve model adaptability when applied to different crops.

6.4 Cloud-Based Monitoring and Analytics Implementing cloud-based storage for farmers to maintain records of disease occurrences and track seasonal trends. Providing access to real-time dashboards where agricultural authorities and researchers can monitor disease spread and recommend large-scale preventive measures. Integrating machine learning models that continuously update and refine disease classification based on new data and user feedback.

6.5 Automated Drone-Based Detection Utilizing drone technology to scan large mango orchards for disease detection, significantly reducing manual inspection efforts. Developing AI-powered image recognition systems on drones to classify diseased trees and send alerts for immediate action. Enabling GPS tagging for identified diseased trees to help farmers precisely target affected areas for treatment.

6.6 Government and Industry Collaborations Partnering with agricultural research institutes and government agencies to promote widespread adoption of AIdriven disease detection in farming communities. Establishing training programs for farmers to educate them on using the system effectively for disease management. Collaborating with pesticide manufacturers to recommend AI-based optimized dosages, reducing chemical overuse and environmental impact.

6.7 Development of a Predictive Disease Forecasting System Using AI models to predict potential disease outbreaks based on historical data and climatic conditions. Providing early warnings to farmers to take preventive measures before an outbreak occurs. Developing risk maps indicating regions more susceptible to specific mango diseases, aiding in better land management and farming strategies. These future enhancements will ensure that the mango disease detection and classification system continues to evolve, offering higher accuracy, broader applications, and greater accessibility to farmers. Implementing these advancements will not only improve mango production efficiency but also support sustainable and precision farming practices. 6.8 Growth in Other Crops Model's utility in agriculture can be increased by expanding it to classify illnesses in additional crops. Assemble datasets for other vegetables (such as potatoes, tomatoes, and onions) and fruits (such as apples, bananas, and oranges). Develop a deep learning model with several classes that can identify various agricultural diseases in a single system. To ensure that the current model can adjust to new harvests with little retraining, use transfer learning.

Effect: assists farmers in managing different crops without the need for independent detection systems. minimizes monetary costs by early disease detection.

VI. CONCLUSION

In conclusion, the ”Smart Indian Mango Disease Detection System” utilizing Convolutional Neural Networks (CNN) represents a significant advancement in agricultural technology. By accurately identifying diseases in mango crops, this system enhances early detection and intervention, ultimately leading to improved yields and reduced losses for farmers. The integration of AI not only streamlines the monitoring process but also promotes sustainable farming practices. This innovative approach can serve as a model for similar applications in other crops, contributing to the overall health of agriculture in India and beyond.

VII. ACKNOWLEDGMENTS

We express our deepest gratitude to our project guide, Prof. C. K. Bhange, for their continuous support, guidance, and encouragement throughout this research. Their expertise in machine learning and agricultural technology has been invaluable in shaping the development of this system. We extend our sincere thanks to the Department of Electronics & Telecommunication Engineering at AISSMS IOIT for providing us with the necessary infrastructure, research materials, and computational resources required to carry out this project. A special appreciation goes to the local mango farmers and agricultural experts who generously contributed their time and shared their valuable insights into the common diseases affecting mango crops. Their real-world experiences and field data have played a crucial role in training and validating our machine learning model. We would also like to acknowledge the efforts of our peers and lab colleagues for their constructive feedback, discussions, and assistance in troubleshooting various challenges faced during model development and testing. Finally, we are grateful to our families and friends for their unwavering support and motivation throughout this journey. Their encouragement has been instrumental in completing this project successfully

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