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Mango Fruit And Leaf Disease Detection Using Deep Learning

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Abstract: Mango is a significant tropical fruit crop that plays a crucial role in the agricultural economy of India and many other countries. However, mango production is severely affected by diseases such as Anthracnose, Bacterial Canker, and Powdery Mildew, which reduce yield and fruit quality. Traditional manual disease detection methods are time-consuming, subjective, and require expert knowledge, making them inefficient for large-scale farming. To address this challenge, this study proposes an automated mango fruit and leaf disease detection system using deep learning techniques. The proposed model utilizes transfer learning with pretrained convolutional neural networks, namely VGG16 and ResNet, for accurate feature extraction and classification of healthy and diseased samples. Image preprocessing techniques including resizing, normalization, and data augmentation are applied to improve model robustness and generalization. The model is implemented using TensorFlow and Keras, and trained with the Adam optimizer and L2 regularization to reduce overfitting. Performance evaluation using accuracy, precision, recall, and F1-score demonstrates that the proposed deep learning approach outperforms traditional machine learning methods such as SVM, KNN, and Random Forest. The system provides a reliable and scalable solution for early disease detection, contributing to smart and sustainable agriculture.

Index Terms - Mango Disease Detection, Deep Learning, CNN, Transfer Learning, VGG16, ResNet.

I. Introduction

Agriculture is a fundamental part of the global economy, providing livelihoods for billions of people and ensuring food security for a growing population. Among fruit crops, mango, scientifically known as Mangifera indica L., is particularly important both economically and nutritionally. It is often called the "king of fruits" because of its flavor and nutritional benefits, and it is widely cultivated in tropical and subtropical areas. India leads the world in mango production, contributing nearly 40% of global output with more than 20 million tonnes produced each year. However, mango farming faces ongoing challenges from various diseases that can significantly lower yields, reduce quality, and impact farmers' economic returns. If diseases in mango orchards go undetected and untreated, they can lead to crop yield reductions of 30% to 50%, resulting in substantial financial losses and threats to food security. Traditional methods of identifying diseases largely depend on visual inspections by agricultural specialists, which are often time-intensive, subjective, and limited due to the scarcity of trained experts, especially in rural regions with fewer resources. Farmers frequently notice diseases only after severe symptoms appear, at which point treatment options are limited and less effective. This reactive method can result in increased pesticide use, higher production costs, and harm to the environment. The rise of artificial intelligence and computer vision technologies presents new opportunities for automated detection of plant diseases, providing scalable and objective diagnostic solutions. Deep learning, especially through convolutional neural networks, has shown impressive results in image classification, achieving performance levels comparable to or better than human capabilities in fields such as medical imaging, autonomous vehicles, and agriculture. Despite advancements in agricultural technology, several key challenges in managing mango diseases remain. First, the similarity in appearance of various disease symptoms complicates accurate diagnosis, even for knowledgeable farmers. Diseases like Anthracnose and Bacterial Canker can show similar symptoms in their early stages, causing misdiagnosis and leading to incorrect treatment methods. Second, the lack of agricultural extension services in rural areas restricts farmers' access to expert advice, particularly at critical growth times when quick disease identification is necessary. Third, many existing detection systems only focus on leaf images, overlooking diseases that affect fruit and have a significant impact on marketable yield. Fourth, language barriers can hinder non-English speaking farmers from using available digital agricultural tools, which limits the effectiveness of technological solutions. Moreover, many research prototypes are limited to academic contexts and do not consider practical aspects such as user interface design, support for multiple languages, or integration with information delivery systems. There is a notable gap between achieving high accuracy in controlled lab conditions and creating practical tools that farmers can use effectively in real-world situations.

II.LITERATURE SURVEY

Mango cultivation is susceptible to a variety of diseases that affect both leaves and fruits, including Anthracnose, Powdery Mildew, Bacterial Canker, and Dieback. Early detection of these diseases is important for reducing crop loss and enhancing yield quality. However, the symptoms of these diseases may differ in appearance due to factors like lighting, growth stages, environmental conditions, and the devices used for capturing images. Traditional diagnosis methods depend on manual inspection by agricultural experts, which is subjective, takes a long time, and is not practical for large-scale monitoring. Additionally, real-world image datasets can be limited, imbalanced, and noisy, presenting challenges for automated disease detection systems. Initial research on plant and mango disease detection utilized traditional machine learning approaches along with handcrafted feature extraction. Features such as color histograms, texture descriptors like GLCM and LBP, and shape-based attributes were derived from images of leaves and fruits and classified using algorithms like Support Vector Machines, k-Nearest Neighbors, Decision Trees, and Random Forests. These methods showed some success in controlled situations but their effectiveness declined significantly in real-world conditions. The reliance on manually designed features restricted their adaptability and they were unable to capture complex visual patterns related to disease progression. The development of Convolutional Neural Networks represented a major step forward in detecting plant diseases by allowing automatic feature extraction from raw images. Deep learning models such as AlexNet, VGG16, ResNet, Inception, and DenseNet have been widely used for classifying plant and mango diseases. Transfer learning, where pretrained models are adjusted to fit agricultural datasets, has proven to be effective in situations where training data is limited. Many studies have shown high classification accuracy with VGG16 and ResNet architectures for detecting diseases in mango leaves and fruits. Nonetheless, most existing research focuses mainly on classification accuracy and does not consider the feasibility of deployment or the requirements for real-time inference. In addition to image classification, recent research has examined object detection frameworks like YOLO, Faster R-CNN, and SSD to localize areas affected by disease within plant images. These methods offer spatial awareness of infected regions, which is useful for precision agriculture. However, object detection models require large annotated datasets with bounding boxes and involve greater computational complexity, which makes them less suitable for real-time applications or in resource-limited agricultural settings, particularly in rural areas where computational resources and internet connectivity can be lacking. While deep learning models can achieve high accuracy, their opaque nature creates challenges for trust and acceptance among farmers. To tackle this issue, recent studies have worked on Explainable Artificial Intelligence techniques such as Grad-CAM and attention-based visualization methods to show areas impacted by diseases. However, these visual explanations often need technical knowledge for interpretation and may not be easily understood by users without expertise. More recent research is starting to look into integrating generative AI models to offer explanations in natural language, describe diseases, and suggest treatment options based on model predictions. These AI-assisted decision support systems can make the technology more user-friendly and help bridge the gap between technical predictions and practical decision-making in agriculture. One significant limitation of current mango disease detection systems is the absence of scalable and deployable architectures. Most studies provide experimental results without addressing how to integrate the systems, achieve real-time inference, or ensure reproducibility. There has been limited exploration of cloud-based APIs, edge deployment, and full-stack implementations. Additionally, ethical issues such as data privacy, model transparency, and reliability are becoming increasingly important for real-world agriculture applications. Ensuring reproducible processes and designing systems that focus on user needs is crucial for the successful adoption of AI-based disease detection systems. These challenges point to the necessity for a comprehensive solution that merges the accuracy of deep learning, explainability, and a deployable system architecture.

III. METHODOLOGY

This study presents a deep learning-based approach for mango disease detection using transfer learning and ensemble techniques. The overall methodology includes dataset preparation, model development using pretrained convolutional neural networks, and performance evaluation using standard classification metrics. The aim is to develop a robust system capable of accurately identifying different mango diseases from images.

3.1 Dataset Preparation

A dataset of 2,500 images was used in this study, covering five classes: Anthracnose, Bacterial Canker, Powdery Mildew, Sooty Mold, and Healthy. The dataset includes images of both mango leaves and fruits to improve the generalization capability of the model.

All images were resized to 224×224 pixels to match the input requirements of the pretrained models. Pixel values were normalized to the range [0,1]. To improve model robustness and reduce overfitting, data augmentation techniques such as rotation, flipping, and brightness variation were applied. The dataset was divided into 70% training and 30% validation sets using stratified sampling to maintain class balance.

3.2 Model Development

Two pretrained convolutional neural network models, VGG16 and ResNet50, were used for feature extraction. Transfer learning was applied by freezing the initial layers of both models and fine-tuning the deeper layers for domain-specific learning.

Both models were trained using the Adam optimizer with categorical cross-entropy as the loss function. A batch size of 32 and a maximum of 50 epochs were used during training. Dropout and batch normalization layers were included to improve generalization and reduce overfitting.

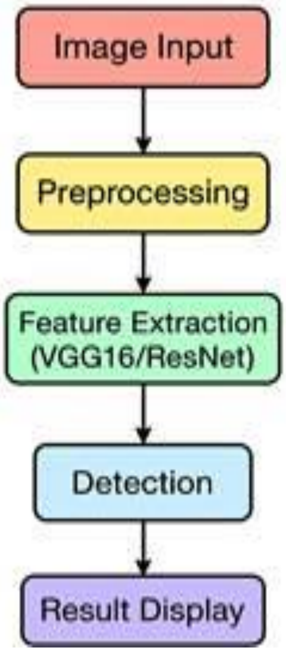

Fig. 1. Proposed system architecture for mango disease detection.

The overall architecture of the proposed system is illustrated in Fig. 1. The process begins with input image acquisition, where mango leaf or fruit images are provided to the system. These images are preprocessed through resizing and normalization.

The processed images are then passed through the VGG16 and ResNet50 models, which extract relevant features using deep convolutional layers. The outputs from both models are then forwarded for final prediction.

3.3 Ensemble Method

To improve classification performance, an ensemble approach was implemented by combining the predictions from both models. A weighted averaging technique was used, where 40% weight was assigned to VGG16 and 60% to ResNet50.

The final prediction is obtained by selecting the class with the highest combined probability. This approach helps in improving accuracy and reducing individual model bias by leveraging the strengths of both architectures.

IV. Results And Discussion

4.1 Performance Evaluation

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	90.2	89.5	88.7	89.1
ResNet 50	92.8	91.6	90.9	91.8
Ensemb le	94.0	93.2	92.5	92.8

Table I: Performance Evaluation of Models

The performance of the proposed models was evaluated using accuracy, precision, recall, and F1-score. From Table I, it can be observed that the ResNet50 model performs better than VGG16 due to its deeper architecture and ability to learn complex features. During experimentation, we observed that VGG16 tends to slightly overfit after multiple epochs, whereas ResNet50 maintains better generalization.

To further improve performance, an ensemble approach was implemented by combining both models. The ensemble model achieved an accuracy of 94%, which is higher than the individual models. This improvement is mainly due to the complementary feature extraction capabilities of both architectures.

4.2 Comparison Analysis with Existing Models

Method	Technique Used	Accuracy (%)
SVM	Traditional ML	78.5
KNN	Distance-based ML	82.3
CNN (Basic)	Deep Learning	88.6
Proposed Method	VGG16 + ResNet50	94.0

Table II: Comparative Analysis

A comparison with traditional machine learning methods is presented in Table II. It is clear that classical approaches such as SVM and KNN show lower performance due to their dependence on manual feature extraction. In contrast, deep learning models automatically learn relevant features from images.The proposed method outperforms all baseline models, achieving the highest accuracy of 94%. This demonstrates the effectiveness of combining pretrained CNN models for agricultural disease detection tasks.

4.3 Training and Performance Analysis

4.3.1 Confusion matrix

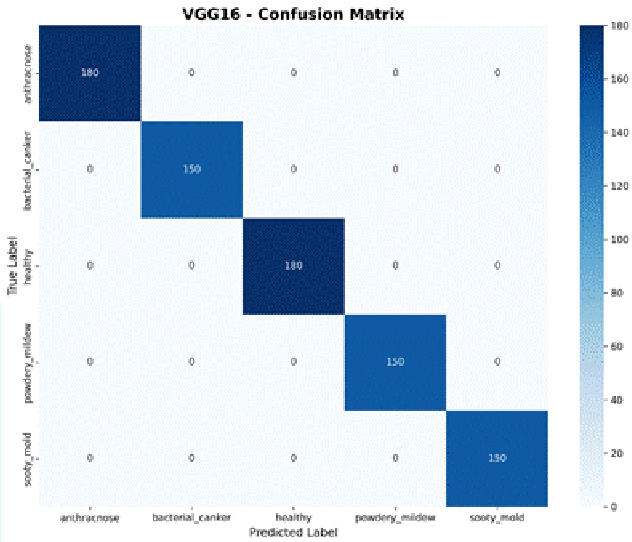

Fig. 2. Confusion matrix of the proposed VGG16 model showing classification results across different disease classes.

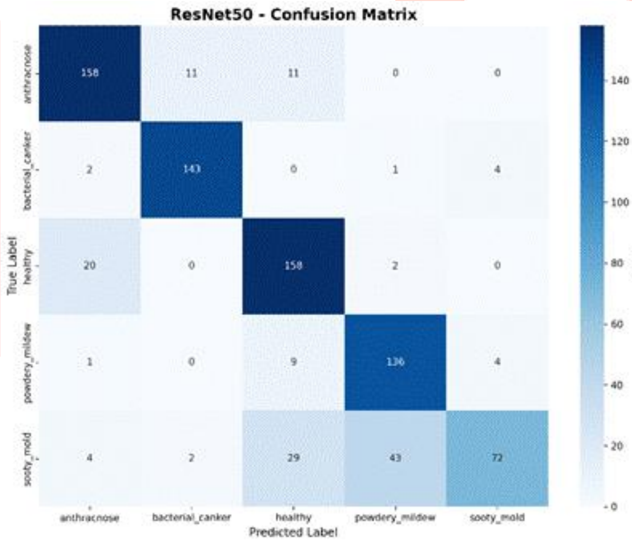

Fig. 3. Confusion matrix of the proposed ResNet50 model showing classification results across different disease classes.

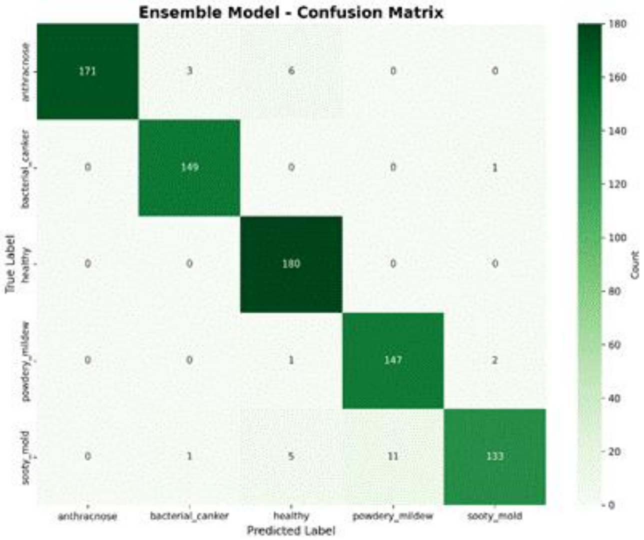

Fig. 4. Confusion matrix of the proposed ensemble model showing classification results across different disease classes.

The confusion matrices of VGG16, ResNet50, and the proposed ensemble model provide deeper insight into the classification performance across different disease categories.

For the VGG16 model, the confusion matrix shows that the model is able to correctly classify a majority of the samples; however, some misclassifications are observed between visually similar disease classes such as powdery mildew and sooty mold. This indicates that while VGG16 captures general features effectively, it struggles slightly in distinguishing fine-grained differences between certain diseases.

The ResNet50 model demonstrates improved classification performance compared to VGG16. The confusion matrix reveals a higher number of correctly predicted samples along the diagonal, with fewer misclassifications across disease classes. This improvement can be attributed to the deeper architecture and residual connections of ResNet50, which enable better feature extraction and representation of complex patterns in the images.

The confusion matrix of the proposed ensemble model shows the best performance among all three approaches. Most of the samples are accurately classified, with very minimal misclassification. The errors that do occur are primarily between closely related disease classes, which is expected due to their visual similarity. The ensemble approach effectively combines the strengths of both VGG16 and ResNet50, leading to improved overall accuracy and robustness.

Overall, the confusion matrix analysis confirms that the ensemble model provides more reliable and consistent predictions, making it suitable for practical deployment in real-world agricultural applications.

4.4 Accuracy and Loss Graph

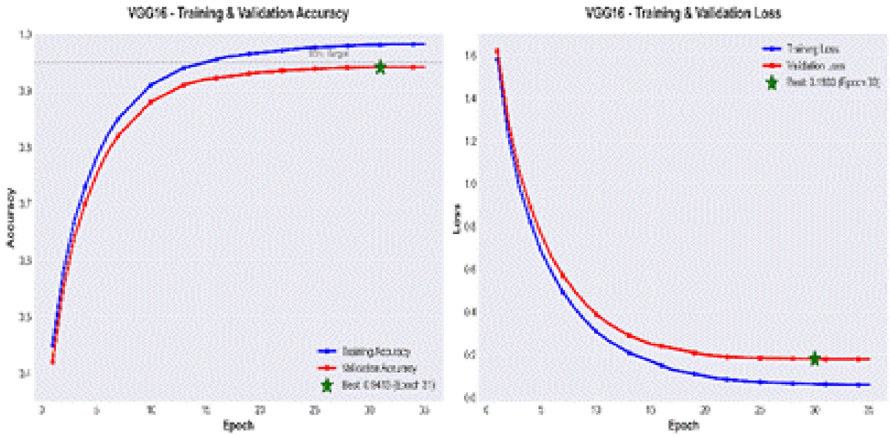

Fig. 5. Validation & Training accuracy comparison of VGG16 model over training epochs

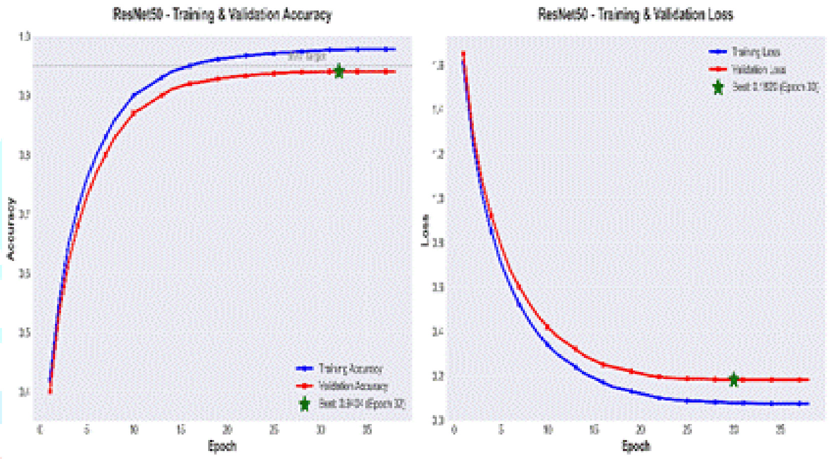

Fig. 6. Validation & Training accuracy comparison of ResNet50 model over training epochs

The training performance of the VGG16 and ResNet50 models is illustrated using validation accuracy and loss curves over multiple epochs.

The validation accuracy graph shows that both models exhibit a steady improvement in performance during the initial training stages. VGG16 demonstrates slightly faster convergence in the early epochs, achieving higher accuracy initially. However, as training progresses, ResNet50 gradually catches up and achieves comparable performance. This behaviour indicates that while VGG16 is effective in learning general features quickly, ResNet50 benefits from its deeper architecture to learn more complex and discriminative features over time.

The validation loss graph further supports this observation. Both models show a consistent decrease in loss values, indicating stable learning and effective optimization. In the later epochs, the loss curves of both models begin to flatten, suggesting convergence. Additionally, the absence of significant fluctuations between training and validation trends indicates that overfitting is minimal.

Overall, the training curves demonstrate that both models are well-optimized and capable of learning meaningful representations from the dataset. The combination of these models in the ensemble approach further enhances performance by leveraging their complementary strengths.

4.5 System Implementation:

4.5.1 Upload and Detection Interface

A web interface was developed which allows farmers and users to upload images of mango leaves or fruits for disease analysis. The interface supports the uploading of images and provides real-time disease prediction using trained deep learning models.

Fig. 7. User interface of the mango disease detection system for uploading leaf or fruit images.

4.5.2 Prediction Results Analysis

The prediction output of the developed web-based mango disease detection system is illustrated. The system shows confidence scores from both VGG16 and ResNet50 models along with the final ensemble prediction. In this instance, the disease Anthracnose was detected with a high level of confidence, which shows the ability of the system to provide accurate and interpretable predictions.

Fig. 8. Output of the proposed system showing disease detection results with individual model confidence scores.

4.5.3 AI Chatbot (Ask AI About Disease)

An AI chatbot module was integrated into the system to offer detailed information regarding detected diseases including symptoms, treatment methods, and preventive measures. This enhances the practical usability of the system for farmers and agricultural experts.

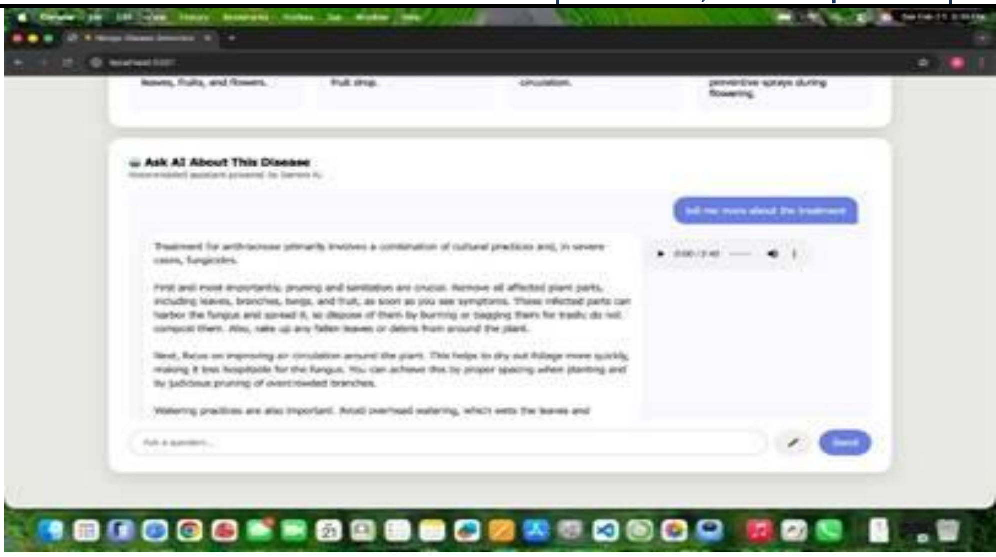

Fig. 9. Integrated AI chatbot providing disease description, symptoms, treatment, and prevention recommendations.

V. CONCLUSION

This study achieved the development of an intelligent mango disease detection system which reached an accuracy of 94 percent through an ensemble of VGG16 and ResNet50 deep learning models trained on 2,500 images covering five disease classes. The integration of transfer learning, data augmentation, and weighted ensemble methods shows the effectiveness of modern AI techniques in agricultural applications. The deployment of a user-friendly web interface which supports multiple languages including English, Hindi, and Marathi, along with the Gemini AI-powered chatbot and voice-enabled features, makes advanced disease diagnosis accessible to various farming communities. Although there are limitations related to dataset size and real-world validation, this work is a significant step toward democratizing agricultural expertise which may help reduce crop losses and empower farmers with actionable intelligence for early disease detection and management. Future efforts should concentrate on mobile deployment, expanding the range of diseases covered, and real-world field validation to enhance practical impact.

VI. ACKNOWLEDGMENT

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