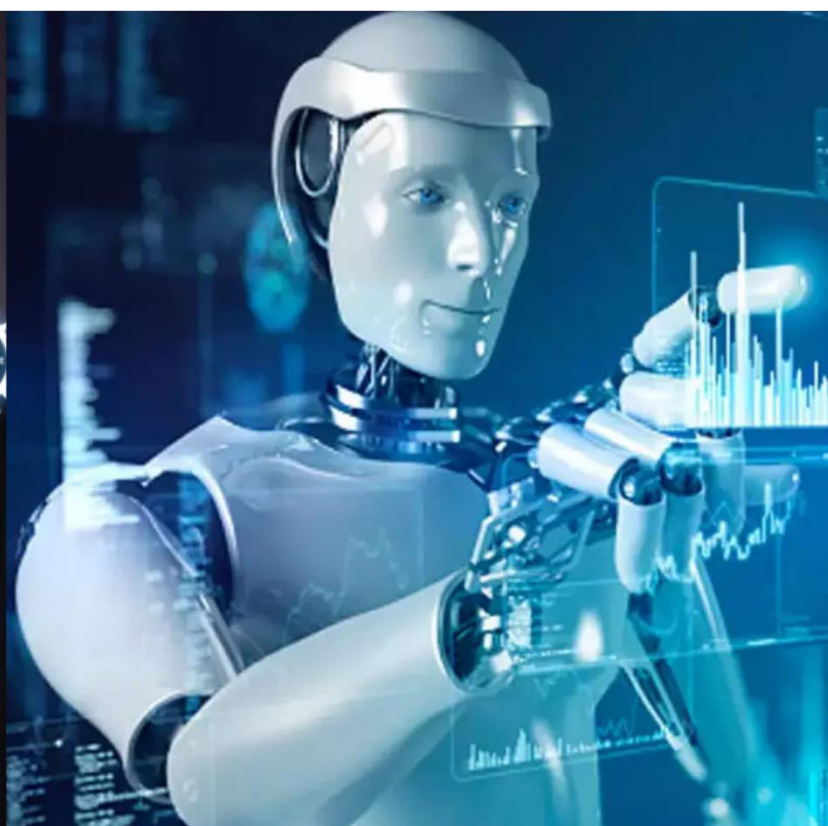




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AI-Based Disease Identification in Horticultural Plants

Santhosha P¹, Chetan B², Kiran Kumar K M³, Sharath B G⁴, Dhanush G Gowda⁵

¹ Assistant Professor, Department of Artificial Intelligence and Machine Learning, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India

^{2,3,4,5} U.G. Student, Department of Artificial Intelligence and Machine Learning, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India

ABSTRACT: Plant diseases significantly reduce crop productivity and lead to major economic losses for farmers. Early and accurate diagnosis is essential for effective treatment and prevention. This project presents a MobileNetV2-based system for the automatic detection of four major crop diseases: Mango Anthracnose, Banana Sigatoka Leaf Spot, Potato Early Blight, and Tomato Early Blight. The proposed system takes an image of a diseased leaf as input, processes it using a trained MobileNetV2 model, and predicts the disease with a confidence score. Additionally, the system estimates disease severity, recommends appropriate fertilizers and pesticides, and provides preventive measures to assist farmers in managing plant health. The model is trained using a custom dataset collected from publicly available image resources and augmented to improve accuracy. A web-based user interface developed using HuggingFace allows easy interaction, enabling users to upload leaf images and receive instant diagnosis. The system demonstrated promising accuracy during testing and provides a scalable foundation for detecting additional plant diseases. The project aims to support smart agriculture by offering an intelligent, affordable, and accessible solution for disease management.

KEYWORDS: MobileNetV2, Deep Learning, Smart Agriculture, HuggingFace, Web Deployment.

I.INTRODUCTION

Agriculture holds a central position in the Indian economy, contributing significantly to the nation's GDP and supporting the livelihood of millions of farmers. Ensuring healthy crop production is essential for food security, economic stability, and sustainable agricultural practices. However, plant diseases continue to be a major threat to crop productivity worldwide. These diseases, caused by fungi, bacteria, or viruses, often spread rapidly and remain unnoticed until the damage becomes severe. This results in substantial yield loss, quality degradation, and financial setbacks for farmers.

With the increasing availability of smartphones and affordable digital cameras, image-based diagnosis has emerged as a promising solution. The rapid advancement of machine learning (ML) and deep learning (DL) has further revolutionized this field, enabling automated disease detection with high accuracy from simple leaf images.

Deep learning models such as Convolutional Neural Networks (CNNs) and transfer learning architectures like MobileNetV2, ResNet, and VGG have demonstrated exceptional capabilities in extracting meaningful features from plant images. These models can learn complex patterns, textures, and disease-specific characteristics with minimal human intervention.

In the context of this project, the focus is on identifying four major plant diseases:

- Mango Anthracnose
- Banana Sigatoka Leaf Spot
- Potato Early Blight
- Tomato Early Blight

These diseases are widespread across tropical agricultural regions and significantly impact the productivity of their respective crops.

To make the solution practical and accessible, the trained model is converted into a TensorFlow Lite (TFLite) format, allowing for lightweight deployment. The prediction interface is implemented using Gradio, and the complete system is deployed on HuggingFace Spaces, enabling instant disease detection from any device with an internet connection. Thus, this project combines deep learning, mobile-friendly model optimization, and real-time deployment to present a complete end-to-end solution for plant disease diagnosis.

II.PROBLEM STATEMENT

Plant disease diagnosis is difficult for farmers because leaf symptoms often look similar across different crops and disease stages, leading to incorrect or delayed identification. Traditional methods depend on expert observation, which is not always available in rural agricultural areas, causing farmers to lose critical time before taking corrective action. This project builds a deep-learning-based crop disease detection system using MobileNetV2 that can identify Anthracnose in Mango, Sigatoka Leaf Spot in Banana, Koleroga in Arecanut, and Early Blight in Tomato from leaf images. The model provides fast, reliable predictions supported by clear confidence scores, and a lightweight TFLite version enables deployment on the web. This ensures early detection, consistent diagnosis, and practical assistance for farmers, ultimately improving crop health and reducing economic losses.

III.METHODOLOGY

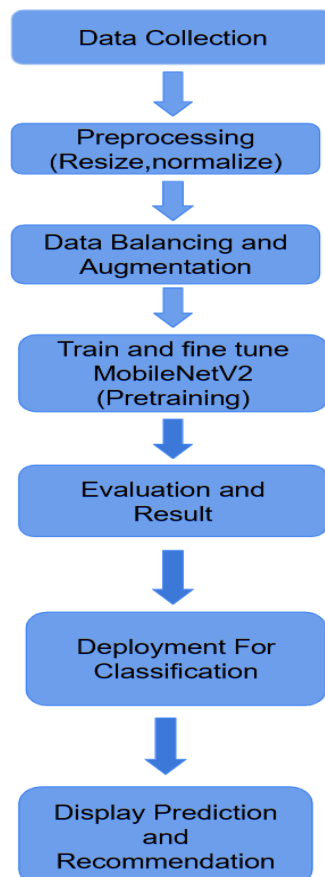


Figure 1: Methodology Diagram for AI Based Disease Identification In Horticultural Plants

1.1 Data Collection:

Images of plant leaves affected by different diseases are gathered from online sources to build the dataset.

1.2 Preprocessing (Resize, Normalize):

All images are resized to a fixed dimension and pixel values are normalized to prepare them for model training

1.3 Data Balancing and Augmentation:

Image augmentation (rotation, zoom, flip, brightness) is applied to increase dataset size and balance class distribution

1.4 Train and Fine-Tune MobileNetV2 (Pretraining):

A pretrained MobileNetV2 model is used and fine-tuned on the custom leaf dataset to achieve high accuracy.

1.5 Evaluation and Result:

The trained model is tested on unseen images to measure accuracy, loss, and prediction performance.

1.6 Deployment for Classification:

The trained model is exported to TFLite and integrated into a Gradio interface for real-time inference

1.7 Display Prediction and Recommendation:

The system predicts the disease, shows confidence, severity estimation, and provides fertilizer/pesticide recommendations

IV.RESULTS AND DISCUSSION

To ensure that the Crop Disease Detection System performs reliably across different plant species, image types, and real-world variations, a multi-level testing strategy was implemented. The following tests were used to evaluate system behaviour, accuracy, and deployment performance.

4.1. Functional Testing

- **Image Input Handling** – Checked support for image formats (.jpg, .png, .jpeg, .jif) and verified auto-preprocessing (resize, normalize, convert to array).
- **Model Prediction Output** – Ensured correct classification of four diseases: Mango Anthracnose, Banana Sigatoka, Arecanut Koleroga, and Tomato Early Blight.
- **Error Handling** – Tested invalid formats, corrupt images, and confirmed the system gives safe fallback messages.
- **Gradio Frontend** – Verified image upload works and displays the predicted disease, confidence score, and optional Grad-CAM heatmap.
- **Model & TFLite Loading** – Confirmed the TFLite model loads properly and produces predictions consistent with the original .h5 model.

4.2. Performance Testing

- **Different Image Qualities** – Tested high/low resolution, mobile camera images, low-light, and overexposed photos.
- **Noise & Distortion** – Checked model performance on blurry, cropped, and background-cluttered leaf images.
- **Augmented vs Non-Augmented** – Verified generalization on rotated, zoomed, and flipped images.
- **Deployment Performance** – Measured prediction speed on HuggingFace (0.4 - 1.2 sec per image) and confirmed smooth UI response multiple uploads.

4.3. Real-Time Testing

- **Unseen Real Leaf Images** – Tested farm and online photos with poor lighting, soil/water patches, and irregular leaf shapes to check real-world accuracy.
- **Consistency Testing** – Repeated predictions to verify stable outputs, consistent confidence scores, and session-to-session repeatability.
- **User Interaction Testing** – Ensured Gradio UI was easy to use and validated smooth drag-and-drop/upload functionality.

4.4. Accuracy Testing

- **Precision** – Checks how accurate the model's positive predictions are for each disease.
- **Recall** – Measures how well the model detects all diseased leaf images in each class.
- **F1-Score** – Balances precision and recall, especially useful for imbalanced classes.
- **Confusion Matrix** – Shows misclassifications and detects bias toward classes with more images.
- **Training & Validation Graphs** – Accuracy and loss curves confirmed stable learning, no overfitting, and effective augmentation + fine-tuning.



Figure 2: Disease Detected in Uploaded Photo

V.CONCLUSION

The proposed Crop Disease Detection System effectively identifies major leaf diseases in Mango, Banana, Arecanut, and Tomato using deep learning and transfer learning, particularly through MobileNetV2 supported by data augmentation, preprocessing, and fine-tuning to achieve strong evaluation performance. Deployed via TFLite and a Gradio-based HuggingFace web interface, the model provides an accessible, user-friendly platform that enables instant image-based disease classification, making it suitable even for low-resource and mobile environments. While it does not replace agricultural experts, the system offers a fast, efficient, and cost-effective preliminary diagnosis tool that can reduce crop losses, enhance productivity, and serve as an important component of modern precision agriculture—with potential for further improvement to increase its value as a decision-support system.

REFERENCES

- [1] S. Too, S. Yujian, L. Njuki, and J. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease recognition," *Computers and Electronics in Agriculture*, vol. 173, p. 105394, 2020. <https://doi.org/10.1016/j.compag.2020.105394>
- [2] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep Neural Networks-based recognition of plant diseases by leaf image classification," *Computational Intelligence and Neuroscience*, vol. 2016, 2016. <https://doi.org/10.1155/2016/3289801>
- [3] A. K. Das, M. Mishra, and S. Routray, "Detection of plant leaf diseases using MobileNet-based transfer learning approach," *Materials Today: Proceedings*, vol. 49, pp. 2847–2853, 2022. <https://doi.org/10.1016/j.matpr.2021.07.433>
- [4] S. Koirala, K. Walsh, Z. Wang, and D. McCarthy, "Deep learning for real-time fruit detection and orchard yield estimation using YOLO networks," *Journal of Field Robotics*, vol. 36, no. 7, pp. 1080–1100, 2019. <https://doi.org/10.1002/rob.21876>
- [5] P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018. <https://doi.org/10.1016/j.compag.2018.01.009>
- [6] N. Dhaka, S. Meena, P. Mittal et al., "A deep learning-based transfer learning method for plant leaf disease detection and classification," *Machine Learning with Applications*, vol. 10, p. 100384, 2022. <https://doi.org/10.1016/j.mlwa.2022.100384>

- [7] K. Islam, T. Dinh, and K. Wahid, "Automated system for plant disease detection using deep transfer learning," EAI Endorsed Transactions on Scalable Information Systems, vol. 8, no. 32, 2021. <https://doi.org/10.4108/eai.13-7-2018.159622>
- [8] V. Singh and A. Misra, "Detection of plant leaf diseases using deep convolutional neural networks," International Journal of Applied Engineering Research, vol. 11, no. 6, pp. 441–446, 2016. https://www.ripublication.com/ijaer16/ijaerv11n6_19.pdf
- [9] Y. Cao, L. Zhang, and X. Guo, "Attention-based deep learning model for agricultural disease detection," Sensors, vol. 22, no. 4, p. 1512, 2022. <https://doi.org/10.3390/s22041512>
- [10] S. Alaba, J. R. Lord, and T. Abiodun, "Lightweight CNN architectures for crop disease detection on mobile devices," IEEE Access, vol. 10, pp. 74162–74173, 2022. <https://doi.org/10.1109/ACCESS.2022.3188614>
- [11] G. Barman and B. Chanda, "Impact of transfer learning and data augmentation for plant leaf disease classification using MobileNetV2," Neural Processing Letters, vol. 55, pp. 10827–10846, 2023. <https://doi.org/10.1007/s11063-023-11218-z>



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