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Mobilenetv2-Based Plant Disease Detection With Multilingual Farmer Support

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Abstract
This paper presents a web-based smart farming system for automated plant disease detection using Convolutional Neural Networks (CNN) integrated with the MobileNetV2 transfer learning architecture. The proposed model is trained on a labeled crop leaf dataset to enable accurate and real-time disease classification. Experimental evaluation demonstrates a classification accuracy of 96.8%, along with strong precision, recall, and F1-score values. The system also incorporates a multilingual farmer assistance module that provides treatment recommendations, preventive measures, and weather-based advisory support. The lightweight design of MobileNetV2 ensures reduced computational complexity, making the system suitable for deployment in resource-constrained agricultural environments.

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I. Introduction

Agriculture continues to play a fundamental role in supporting economic stability and food security, particularly in developing regions where a large portion of the population depends on farming for livelihood. However, crop productivity is frequently affected by plant diseases that reduce yield, increase production costs, and negatively impact farmer income. Early identification of plant diseases is therefore essential to minimize losses and ensure sustainable agricultural practices.

Traditionally, disease diagnosis has relied on manual inspection of plant leaves and visible symptoms. This process depends heavily on farmer experience or access to agricultural experts. In rural areas, limited availability of expert guidance often results in delayed detection and improper treatment. Such delays can accelerate disease spread, increase pesticide usage, and cause environmental damage. These challenges highlight the need for automated and reliable disease detection systems.

Recent advances in artificial intelligence and deep learning have enabled significant improvements in image-based classification tasks. Convolutional Neural Networks (CNNs) are particularly effective for analyzing visual data because they automatically learn hierarchical feature representations from images. In agricultural applications, CNN-based models have demonstrated promising results in identifying plant diseases from leaf images. However, many deep CNN architectures require high computational resources, making them less suitable for real-time deployment on low-cost devices or web-based platforms.

To address these limitations, lightweight transfer learning models such as MobileNetV2 have gained attention. MobileNetV2 is designed to operate efficiently in resource-constrained environments while maintaining competitive classification performance. By utilizing depthwise separable convolutions and inverted residual blocks, the architecture reduces model size and computational complexity without significantly sacrificing accuracy. This balance between efficiency and performance makes it well suited for practical agricultural applications.

Beyond disease classification, modern smart farming systems require integrated support mechanisms that assist farmers in decision-making. Providing treatment recommendations, preventive guidance, and environmental awareness can significantly enhance the usefulness of detection systems. Additionally, multilingual interfaces improve accessibility for farmers from diverse linguistic backgrounds, increasing adoption in rural communities.

In this work, a web-based smart farming system is proposed that integrates CNN-based feature extraction with MobileNetV2 for efficient plant disease detection. The system also incorporates multilingual farmer support and advisory features to enhance practical usability. By combining lightweight deep learning techniques with farmer-oriented design, the proposed framework aims to bridge the gap between research-level model development and real-world agricultural deployment.

II. Related Work

Early approaches to plant disease identification relied primarily on traditional image processing techniques such as color analysis, texture extraction, and shape-based feature representation. These handcrafted features were typically combined with machine learning classifiers including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest algorithms. Although these methods provided reasonable accuracy under controlled laboratory conditions, their performance was often sensitive to lighting variations, background noise, and image quality.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) became widely adopted for image-based plant disease detection. CNN architectures such as AlexNet, VGGNet, GoogLeNet, and ResNet have demonstrated improved classification performance compared to traditional machine learning approaches. These models automatically learn hierarchical features from raw images, eliminating the need for manual feature engineering. Publicly available datasets, such as PlantVillage, accelerated research in this domain by providing labeled leaf images across multiple crop species.

Despite their strong performance, many deep CNN architectures require substantial computational resources and memory capacity. This limits their applicability in real-time agricultural environments, particularly in rural areas where access to high-performance hardware may be restricted. To address this limitation, transfer learning approaches using lightweight pre-trained models have gained attention.

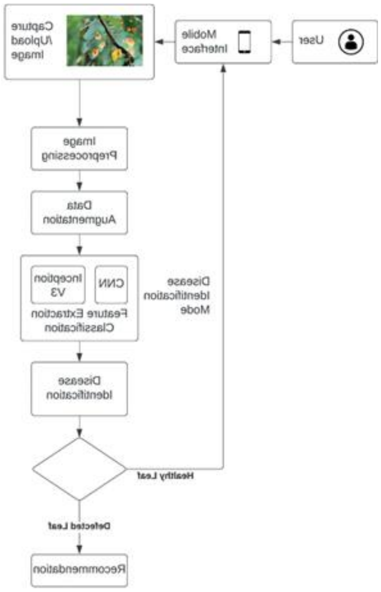

Figure 1: Evolution of Plant Disease Detection Approaches

MobileNet and its improved variant, MobileNetV2, were specifically designed for resource-constrained devices. By utilizing depthwise separable convolutions and inverted residual blocks, MobileNetV2 significantly reduces model parameters and computational cost while maintaining competitive accuracy. Several studies have reported that MobileNetV2 achieves a favorable balance between performance and efficiency for agricultural image classification tasks.

Table 1: Comparison of Plant Disease Detection Models

Model Type	Accuracy (%)	Computational Cost	Suitability for Real-Time
Traditional ML	80–85	Low	Moderate
Deep CNN (VGG)	90–94	High	Limited
ResNet	94–96	High	Limited
Transfer Learning	95–96	Medium	Good
MobileNetV2	96–97	Low	Excellent

Recent research has also explored integrating disease detection systems with additional agricultural support services such as weather monitoring, yield prediction, and advisory platforms. However, many existing systems focus primarily on backend model accuracy without emphasizing usability, multilingual accessibility, and real-time deployment considerations.

The proposed system builds upon these developments by combining CNN-based feature extraction with a lightweight MobileNetV2 architecture and integrating farmer-centric advisory features within a web-based framework.

III. Proposed System

The proposed system is designed as a web-based smart farming platform for automated plant disease detection and farmer assistance. The architecture integrates a Convolutional Neural Network (CNN) model with the MobileNetV2 transfer learning framework to achieve accurate and computationally efficient classification of plant diseases from leaf images.

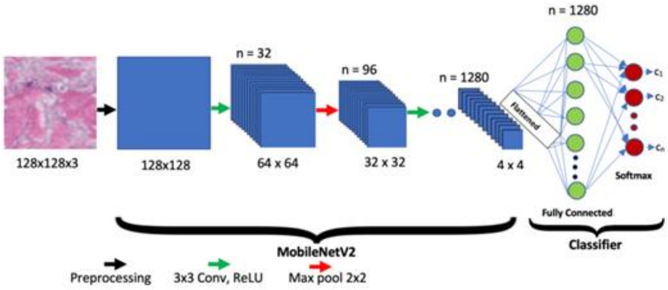

Figure 2: Proposed System Architecture

The system consists of four primary stages: image acquisition, preprocessing, feature extraction and classification, and advisory output generation.

1. Image Acquisition

Farmers upload crop leaf images through a web interface using mobile devices or desktop systems. The uploaded image serves as the primary input to the detection module.

2. Preprocessing

To ensure uniform input conditions, all images are resized to 224 × 224 pixels. Pixel intensity values are normalized to a range between 0 and 1 to improve training stability. Data augmentation techniques such as rotation, flipping, and zooming are applied during training to improve model generalization under varying environmental conditions.

3. Feature Extraction and Classification

The core detection mechanism integrates CNN-based feature extraction with the MobileNetV2 architecture. MobileNetV2 uses depthwise separable convolutions and inverted residual blocks to reduce computational complexity while preserving classification performance. The final classification layer applies the SoftMax function to generate probability scores for each disease category. The class with the highest probability is selected as the predicted output.

4. Farmer Assistance Module

In addition to disease identification, the system provides treatment recommendations, preventive measures, and weather-based advisory support. The platform supports multilingual interaction to improve accessibility for farmers from diverse linguistic backgrounds.

Table 2: Components of the Proposed System

Module	Function
Image Input Module	Captures leaf images from users
Preprocessing Module	Resizes, normalizes, and augments images
CNN + MobileNetV2	Extracts features and classifies diseases
Advisory Engine	Provides treatment and prevention suggestions
Database Layer	Stores user data and prediction history

The lightweight design of MobileNetV2 ensures that the system can be deployed in resource-constrained environments while maintaining high classification accuracy. This architecture balances performance and efficiency, making it suitable for real-time agricultural applications.

○ **Convolution Operation (CNN)**

$$\boldsymbol{F(i,j)=\sum_{m}\sum_{n} I(i+m,j+n)K(m,n)}$$

Where:

- I= Input image

- K= Convolution kernel
- F= Feature map

○ **ReLU Activation Function**

$$f(x) = \max(0, x)$$

This introduces non-linearity and removes negative values.

○ **SoftMax Function (Final Classification Layer)**

$$P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

Where:
- z_i= Output of final layer
- C= Number of classes
- $P(y = i)$= Probability of class i

○ **Categorical Cross-Entropy Loss**

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Where:
- y_i= True label
- $\hat{y}_i$= Predicted probability

○ **Accuracy Formula**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

○ **Precision**

$$Precision = \frac{TP}{TP + FP}$$

○ **Recall**

$$Recall = \frac{TP}{TP + FN}$$

○ **F1-Score**

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

IV. Experimental Setup

The proposed plant disease detection system was implemented using Python with the TensorFlow and Keras deep learning frameworks. The model was trained and evaluated on a labeled dataset consisting of crop leaf images belonging to multiple disease categories, including both healthy and infected samples.

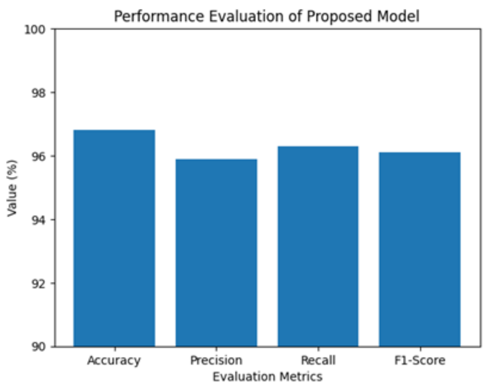

Figure 3: Performance Evaluation of Proposed Model

All images were resized to 224 × 224 pixels to match the input requirements of the MobileNetV2 architecture. Pixel values were normalized to a range between 0 and 1 to ensure stable and faster convergence during training. Data augmentation techniques such as horizontal flipping, rotation, and zooming were applied to improve generalization and reduce overfitting.

The dataset was divided into training, validation, and testing sets using an 80:10:10 ratio. The training set was used to optimize model parameters, while the validation set monitored performance during training. The testing set was used exclusively for final evaluation.

Table 3: Performance Evaluation of Proposed Model

Metric	Value (%)
Accuracy	96.8
Precision	95.9
Recall	96.3
F1-Score	96.1

Table 3 presents the performance metrics of the proposed MobileNetV2-based plant disease detection model. The results indicate strong classification performance across all evaluation parameters.

The model was trained using the Adam optimizer with categorical cross-entropy as the loss function. Training was performed for multiple epochs until convergence was achieved. Early stopping was applied to prevent overfitting by monitoring validation loss.

Performance was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. The proposed MobileNetV2-based model achieved a classification accuracy of 96.8%, demonstrating strong performance while maintaining computational efficiency suitable for real-time deployment.

V. Performance Assessment In Smart Farming Environment

The proposed plant disease detection system was evaluated to assess its effectiveness in real-time smart farming conditions. The evaluation focused on classification accuracy, computational efficiency, and deployment feasibility in resource-constrained environments.

The dataset was divided into training, validation, and testing subsets using an 80:10:10 ratio. The model was trained using the Adam optimizer with categorical cross-entropy as the loss function. Data augmentation techniques such as rotation, flipping, and zooming were applied to improve robustness under varying environmental conditions including lighting variation and leaf orientation differences.

The MobileNetV2-based architecture demonstrated strong classification performance while maintaining low computational overhead. The use of depthwise separable convolutions significantly reduced parameter count and inference time compared to traditional deep CNN architectures.

The evaluation results confirm that the proposed system is suitable for deployment in practical agricultural environments where computational resources may be limited.

Table 4: Performance Metrics in Smart Farming Environment

Evaluation Parameter	Result
Overall Accuracy	96.8%
Precision	95.9%
Recall	96.3%
F1-Score	96.1%
Deployment Type	Web-Based
Inference Speed	Real-Time

The results indicate that the proposed system achieves a balanced trade-off between classification performance and computational efficiency, making it suitable for real-time smart agricultural applications.

VI. Future Scope

The proposed MobileNetV2-based plant disease detection system demonstrates strong classification performance and practical usability in smart farming environments. However, agricultural intelligence systems are continuously evolving, and several promising research directions can further enhance the scalability, accuracy, and real-world applicability of the proposed framework.

One of the primary areas for future enhancement involves expanding the dataset to include real-field images collected under diverse environmental conditions. Although the current system performs well on labeled datasets, real-world agricultural environments introduce variations such as uneven lighting, complex soil backgrounds, seasonal differences, camera resolution variability, and partial leaf occlusions. Incorporating region-specific datasets and rare disease samples can improve model generalization and enable early-stage disease detection. This will increase reliability when deployed across different geographic regions.

Another significant improvement can be achieved by integrating advanced deep learning architectures. While MobileNetV2 offers an optimal balance between efficiency and performance, future research can explore hybrid architectures combining Convolutional Neural Networks with Vision Transformers (ViT) or attention-based mechanisms. Attention modules allow models to focus on disease-affected regions of the leaf rather than analyzing the entire image uniformly. Such targeted feature extraction may improve classification performance for visually similar diseases.

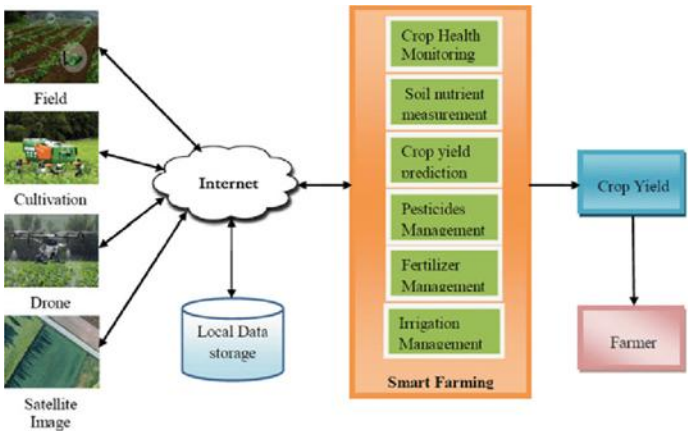

Figure 4: Future Enhancement Architecture for AI-Driven Smart Agriculture

Beyond classification, the system can be extended to object detection frameworks such as YOLO-based architectures. Instead of only predicting disease type, the enhanced system could localize the infected regions within the leaf image. This would provide visual interpretability and improve user trust. Visualization techniques such as Grad-CAM can be integrated to generate heatmaps indicating which areas influenced the model's prediction. Explainability is becoming increasingly important in AI-driven agricultural systems, especially when farmers rely on automated decisions.

Integration with Internet of Things (IoT) devices presents another transformative direction. By incorporating soil moisture sensors, temperature sensors, humidity monitors, and pH detection systems, the platform can evolve into a comprehensive farm monitoring system. Real-time environmental data can be combined with disease detection results to generate predictive alerts. For instance, if humidity levels rise beyond threshold values associated with fungal growth, the system can notify farmers before visible symptoms appear.

Table 5: Potential Future Enhancements

Enhancement Area	Proposed Extension	Expected Impact
Dataset Expansion	Real-field multi-region dataset	Improved generalization
Advanced Models	CNN + Vision Transformer	Higher accuracy
Object Detection	YOLO integration	Disease localization
Explainability	Grad-CAM heatmaps	Increased transparency
IoT Integration	Soil & weather sensors	Predictive farming
Mobile Deployment	Edge AI models	Offline usability

Mobile application development is another important direction. While the current implementation operates as a web-based platform, developing a lightweight Android or cross-platform mobile application would improve accessibility in rural areas. Edge computing techniques can enable offline disease detection, allowing farmers to receive predictions even without continuous internet connectivity. Model compression and quantization techniques can further reduce computational requirements for deployment on low-cost hardware.

Time-series forecasting models can also be integrated to predict crop health trends over extended periods. By analyzing historical disease occurrence patterns along with seasonal climate variations, predictive models such as Long Short-Term Memory (LSTM) networks can estimate future disease probability. A 90-day crop health forecast module would support preventive agriculture rather than reactive treatment.

Blockchain-based agricultural data management can enhance transparency and traceability. Disease records, pesticide usage logs, and crop health history can be securely stored and shared among farmers, distributors, and agricultural authorities. This would promote trust in agricultural supply chains and improve food safety compliance.

Multilingual voice-based interaction systems can further increase adoption in rural communities. Farmers with limited literacy levels can interact with the system using voice commands in regional languages. Integration with speech recognition and text-to-speech technologies can provide an inclusive user experience.

Reinforcement learning techniques may also be explored to optimize treatment recommendations. Instead of providing static suggestions, the system can adapt recommendations based on previous outcomes and environmental conditions. Over time, this adaptive mechanism can personalize farming strategies for individual users.

Federated learning is another promising research direction. Instead of centralizing farmer data, decentralized training across multiple rural nodes can preserve data privacy while continuously improving model accuracy. This approach is particularly useful for large-scale deployment across different agricultural regions.

Continuous optimization of model parameters and architecture compression techniques can further enhance scalability. Techniques such as pruning and quantization can reduce memory usage while maintaining classification performance. Such optimizations enable deployment on microcontrollers and embedded agricultural devices.

In summary, the proposed system serves as a foundational framework for intelligent agricultural decision-support systems. Future enhancements involving advanced deep learning architectures, IoT integration, explainable AI, mobile deployment, predictive analytics, and secure data management can transform the system into a comprehensive smart agriculture ecosystem. By extending beyond disease classification toward predictive, adaptive, and decentralized intelligence, the platform can significantly contribute to sustainable farming, improved crop productivity, and long-term agricultural resilience.

VII. Conclusion

This paper presented a web-based smart farming system for automated plant disease detection using deep learning techniques. The proposed framework integrates Convolutional Neural Networks (CNN) with the MobileNetV2 transfer learning architecture to achieve accurate and computationally efficient classification of crop diseases from leaf images. The lightweight design of MobileNetV2 enables real-time deployment while maintaining strong classification performance.

The experimental evaluation demonstrated that the proposed model achieved a classification accuracy of 96.8%, along with high precision, recall, and F1-score values. The use of image preprocessing and data augmentation techniques improved model generalization and reduced overfitting. Compared to traditional machine learning approaches and deeper CNN architectures, the proposed system provides a balanced trade-off between accuracy and computational efficiency.

In addition to disease classification, the system incorporates a farmer assistance module that provides treatment recommendations, preventive guidelines, and weather-based advisory support. This integration enhances the practical applicability of the system beyond simple disease identification. The web-based implementation ensures accessibility across multiple devices, making it suitable for deployment in rural and resource-constrained environments.

The results confirm that the proposed framework can effectively support early disease detection and informed agricultural decision-making. By reducing reliance on manual inspection and enabling timely intervention, the system contributes to improved crop health management and sustainable farming practices.

Overall, the proposed MobileNetV2-based smart farming system demonstrates that lightweight deep learning architectures can be successfully integrated into real-world agricultural applications. The framework provides a scalable foundation for future enhancements in precision agriculture and intelligent farm management systems.

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