Plant Leaf Disease Recognition Using Machine Learning

Shivanshu Pandey
Department of Electronics and Telecommunication Engineering
Thakur College of Engineering and Technology
Mumbai, India

Darshan Patgar
Department of Electronics and Telecommunication Engineering
Thakur College of Engineering and Technology
Mumbai, India

Dev Sudesha
Department of Electronics and Telecommunication Engineering
Thakur College of Engineering and Technology
Mumbai, India

Ms.Aradhana Manekar
Assistant Professor
Department Of Electronics and Telecommunication Engineering
Thakur College of Engineering andTechnology
Mumbai, India

***Abstract*— Plant leaf diseases significantly impact agricultural productivity, leading to substantial crop losses if not detected early. This paper introduces a deep learning approach for automatically identifying and classifying potato leaf diseases using image data. By utilizing transfer learning with MobileNetV2, a lightweight yet efficient CNN, the system accurately distinguishes between Early Blight, Late Blight, and Healthy leaves. The process includes dataset collection, preprocessing, model training, and real-time web application deployment for user interaction. Experimental results highlight high prediction accuracy and practical feasibility, making this system a valuable asset for precision agriculture and crop protection.**

Keywords*— Plant leaf Disease Detection, Convolutional Neural Networks (CNNs), Image Classification, Transfer Learning, MobileNetV2, Image Preprocessing, Crop Protection, Deep Learning.

I. INTRODUCTION

Agriculture remains fundamental to global food security and economic stability. However, plant diseases pose a significant challenge to crop productivity, often leading to substantial yield losses and financial setbacks. Traditional disease diagnosis relies on expert visual inspection, which can be subjective, time-consuming, and impractical for large-scale farming. Additionally, delayed identification allows diseases to spread, exacerbating crop damage and reducing the effectiveness of intervention strategies [1].

Recent progress in image processing and machine learning has enabled more efficient solutions for precision agriculture. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional accuracy in visual recognition tasks. CNNs autonomously learn hierarchical features from images, making them highly effective in identifying and classifying plant diseases with minimal manual input [2].

This study utilizes transfer learning with MobileNetV2 to detect and classify potato plant leaf diseases. The approach follows a structured pipeline consisting of dataset collection, image preprocessing model training, evaluation, and real-time deployment. MobileNetV2 is fine-tuned to extract features and classify leaf samples into categories: Early Blight, Late Blight, and Healthy. The model's performance is assessed using key metrics such as accuracy, precision, recall, and F1-score, ensuring practical applicability in agricultural settings [3].

II. LITERATURE SURVEY

Recent developments in plant disease identification have been significantly influenced by deep learning techniques, particularly Convolutional Neural Networks (CNNs). These models have revolutionized the automation and precision of disease recognition through image data, enhancing reliability and scalability. Traditional methods, such as visual inspection by agricultural specialists, are labor-intensive and subject to inconsistency due to human error. Moreover, manual approaches do not provide a feasible solution for large-scale monitoring, where swift identification and timely intervention are crucial for mitigating crop losses. Deep learning, in contrast, offers an efficient solution by automating feature extraction and classification, eliminating dependency on manually designed features while improving detection accuracy.

Zhang et al. [4] proposed an advanced CNN-based system specifically designed for detecting potato leaf diseases. Their research demonstrated that deep learning models surpass conventional image classification techniques by achieving superior accuracy and robustness. Their model successfully categorized different disease types, including Early Blight, Late Blight, and healthy leaves, providing a scalable and reliable solution for automated crop disease diagnosis. By utilizing CNNs, the system minimized human intervention, making disease identification both rapid and efficient.

Tiwari et al. [5] examined the impact of transfer learning in plant disease classification, leveraging pre-trained models such as ResNet, InceptionV3, and MobileNetV2. Their findings indicated that transfer learning significantly enhances recognition performance while reducing computational demands. Instead of training models from scratch, transfer learning allows knowledge transfer from large-scale datasets, enabling improved classification even with limited labeled data. Their study also highlighted the importance of lightweight architectures like MobileNetV2, which are particularly useful in environments where computational resources are constrained, such as remote agricultural regions.

Mittal et al. [6] explored various image preprocessing techniques—including contrast enhancement, noise reduction, and normalization—to improve CNN model efficiency for plant disease detection. Their experiments revealed that preprocessing plays a vital role in enhancing model generalization and robustness. Techniques such as histogram equalization for contrast adjustment, Gaussian blurring for noise reduction, and adaptive thresholding for improved segmentation help mitigate inconsistencies caused by variations in lighting conditions, camera resolution, and leaf textures. These preprocessing steps contribute to better feature extraction, ultimately leading to higher classification accuracy.

Building upon previous research, this study refines the MobileNetV2 architecture for detecting potato plant diseases. MobileNetV2 is a lightweight CNN optimized for mobile and real-time applications, making it ideal for deployment in field conditions. Rather than building a model from scratch, this approach employs transfer learning to enhance accuracy while keeping computational requirements minimal. The depthwise separable convolutions in MobileNetV2 significantly reduce complexity, enabling efficient deployment on low-powered devices such as smartphones and IoT sensors. This makes real-time disease monitoring accessible even in resource-limited settings, facilitating timely intervention for farmers.

Mohanty et al. [7] demonstrated that CNNs can be effectively used for multi-crop disease classification, showcasing their adaptability across various plant species. Their findings validated the decision to implement MobileNetV2, given its ability to identify subtle disease features across different crops. By illustrating the model's scalability, their research emphasized the broader applicability of deep learning in agricultural disease monitoring, proving that AI-driven solutions could extend beyond single-crop applications to widespread precision agriculture.

Too et al. [8] conducted an extensive comparative study evaluating different CNN architectures for plant disease detection. Their research highlighted the advantages of fine-tuning pre-trained models over training new architectures from scratch. Their findings supported the choice of MobileNetV2, which demonstrated optimal performance even with limited datasets, making it suitable for scenarios where large-scale annotated data is unavailable. The study reinforced the effectiveness of transfer learning in improving classification accuracy without excessive computational burden.

Zhang et al. [9] explored modifications to standard CNN layers by integrating attention mechanisms, skip connections, and batch normalization to refine feature extraction. Additionally, they examined augmentation techniques such as rotation, flipping, cropping, and color transformations, all of which align with the implementation strategies used in this study. Their work reinforced the importance of architectural improvements and data preprocessing for achieving higher classification precision, ensuring robustness in real-world agricultural applications.

Singh and Misra [10] compared deep learning models with traditional machine learning approaches, including Support Vector Machines (SVMs), Random Forests, and K-Nearest Neighbors. Their findings confirmed that while classical models provide reasonable performance in select cases, CNNs consistently outperform them when sufficient labeled training data is available. Deep learning's ability to automatically learn complex patterns makes it superior for plant disease detection, reinforcing the decision to employ CNNs over conventional feature-based techniques.

Kamilaris and Prenafeta-Boldú [11] conducted a comprehensive survey highlighting CNNs as dominant tools in agricultural artificial intelligence. Their study validated CNNs for diverse applications, including crop health monitoring, disease classification, and yield estimation. They also addressed key challenges such as data scarcity, model interpretability, and generalization. In this research, these challenges are mitigated through transfer learning, model fine-tuning, and augmentation strategies to improve practical usability and scalability.

Ferentinos [12] and Fuentes et al. [13] explored the feasibility of real-time disease recognition using CNNs and object detection models. Drawing inspiration from their work, this study integrates a browser-based web application using Flask, enabling farmers to upload leaf images for immediate disease classification and remedial recommendations. This interface bridges AI research with real-world agricultural applications, ensuring accessibility and usability in disease monitoring. By providing instant feedback, the system empowers farmers with actionable insights, promoting effective disease management and crop protection.

III. METHADOLOGY

The methodology employed in this research for automated detection and classification of potato leaf diseases using deep learning comprises a well-structured pipeline, encompassing six key phases: data acquisition, image preprocessing, feature extraction using transfer learning, model training, evaluation based on performance metrics, and deployment in a real-time web application. This pipeline has been designed to ensure efficient classification of leaf diseases such as Early Blight, Late Blight, and identification of Healthy leaves.

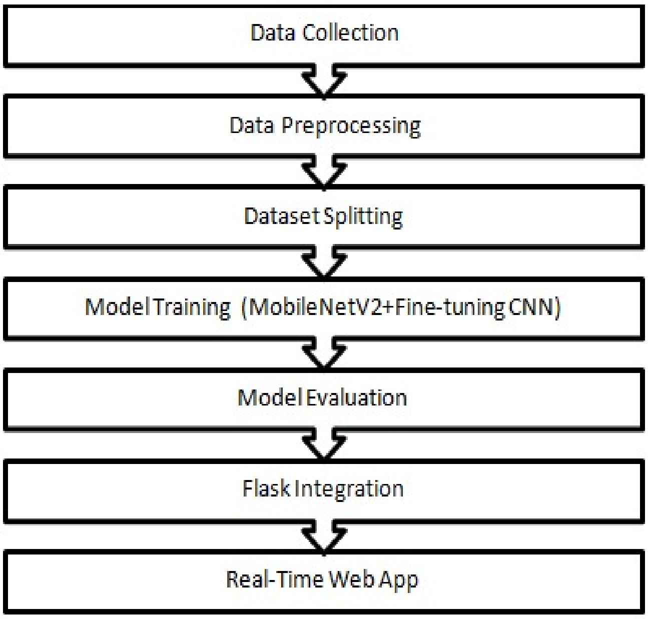

Figure 1: Block diagram of the proposed potato leaf disease recognition system using deep learning

A. Data Collection

Ensuring high-quality and diverse data is essential for training effective deep learning models. This project utilizes the publicly available Potato Leaf Disease Dataset from Kaggle, which includes high-resolution images categorized into three groups: Early Blight, Late Blight, and Healthy leaves**.** These images are representative of real-world agricultural conditions, having been captured in uncontrolled environments. This dataset was uploaded and processed in Google Colab, where images were structured into distinct directories (train, validation, and test) to streamline data management and facilitate efficient model training. This segmentation allows a robust learning process while preserving a portion of the data for evaluating the model's ability to generalize effectively.

B. Image Preprocessing

Preprocessing is crucial for improving model performance and stability. The following techniques were applied:

- **Resizing**: All images were resized to 224×224 pixels, aligning with MobileNetV2's input requirements to ensure consistency.
- **Normalization**: Pixel values were scaled between 0 and 1 (dividing by 255), allowing efficient network processing and accelerating convergence during training.
- **Data Augmentation**: To improve generalization and handle class imbalance, real-time augmentation techniques were used through Keras' Image Data Generator. Transformations included random rotations, flips, zooming, and shifting, expanding dataset variability without additional manual collection.
- **Folder Structuring**: Images were stored in class-specific subdirectories within the train, validation, and test folders, enabling seamless automated labeling using Keras' directory iterator, thereby simplifying model training.

C. Feature Extraction

Feature extraction was performed using MobileNetV2, a lightweight CNN architecture optimized for mobile and edge computing. Transfer learning enabled efficient feature extraction without requiring training from scratch.

- **Convolutional Layers**: These layers identify essential spatial patterns, such as disease spots, color changes, and vein distortions.
- **Pooling Layers**: These layers reduce computational complexity by downsampling feature maps while retaining key patterns.
- **Transfer Learning**: The pre-trained MobileNetV2 convolutional base was used as a feature extractor, while the top layers were customized for three-class disease classification.

D. Model Training

The model was trained in Google Colab, leveraging GPU acceleration to optimize processing speed. The key training parameters were:

- **Train-Validation-Test Split**: The dataset was divided into 70% training, 15% validation, and 15% test data to ensure a balanced training process.
- **Loss Function**: Since this is a multi-class classification problem**,** categorical cross-entropy was selected.
- **Epochs and Batch Size**: Training was performed for 20 epochs, using a batch size of 32 to optimize learning efficiency.
- **Callbacks**: Early stopping was used to halt training when validation loss stopped improving, preventing overfitting. Model checkpoints ensured that the best-performing model was saved based on validation accuracy.

E. Model Evaluation

The trained model was evaluated using multiple performance metrics on the test dataset:

- **Accuracy**: The final MobileNetV2 model achieved an impressive 83% accuracy on unseen test images.
- **Precision**: Measures how often predicted disease cases were correct, minimizing false positives.
- **Recall (Sensitivity)**: Evaluates how effectively the model identifies actual disease cases, minimizing false negatives.
- **F1-Score**: Balances precision and recall, ensuring reliable classification performance, particularly for imbalanced datasets.

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F. Real-Time Web Deployment

To bridge the gap between AI-based disease prediction and end-user accessibility, the trained model was deployed through a Flask-based web application. This allows users—such as farmers and agricultural consultants—to:

- **Upload potato leaf images** using a simple browser interface.
- **Receive real-time predictions**, including disease classification and confidence scores.
- **View suggested treatments** for identified diseases, aiding informed decision-making in agricultural settings.

IV. RESULT & DISCUSSION

A. Model Performance Over Training Epochs

The performance of the trained MobileNetV2 model was comprehensively evaluated using accuracy metrics, confusion matrix, precision, recall, and F1-score on the test dataset. The results confirmed the model's strong classification capabilities and its effectiveness for deployment in real-time scenarios.

1. Model Performance

The performance evaluation of the proposed deep learning-based potato leaf disease detection model was conducted using an unseen test set composed of images categorized as Healthy, Early Blight, and Late Blight. The model achieved a test accuracy of approximately 83%, indicating a robust generalization capability when applied to new, real-world leaf images.

2. Learning Curve Analysis

The model's learning behavior over training epochs was visualized through the accuracy and loss curves (as shown in Figure 2). The training and validation accuracy curves showed steady improvement and convergence, signifying that the model was learning useful patterns from the data without overfitting. The validation loss curve declined gradually across epochs, suggesting that the model retained its ability to generalize well beyond the training samples.

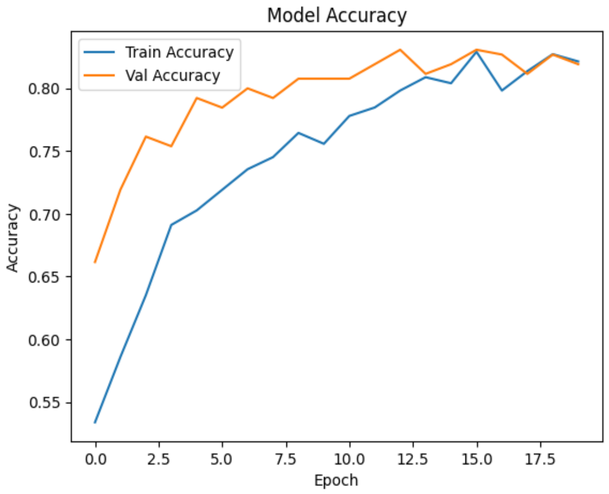

Figure 2: Model accuracy and validation accuracy per epoch

Moreover, the training process demonstrated the model's ability to adapt quickly to the features of the potato leaf dataset, largely attributed to the fine-tuned MobileNetV2 architecture with pretrained weights from ImageNet.

B. Confusion Matrix and model evaluation metrics

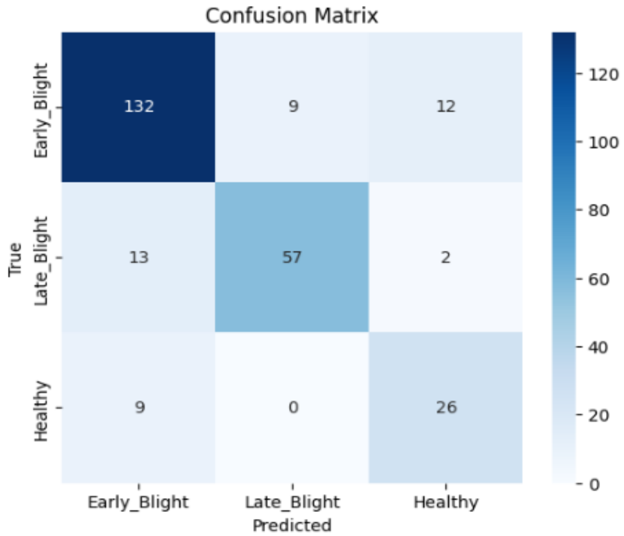

Figure 3: Confusion matrix for three-class classification (Healthy, Early Blight, Late Blight)

To gain insights into class-specific performance, a **confusion matrix** (Figure 3) was plotted for the three-class classification task: Healthy, Early Blight, and Late Blight. The matrix illustrates the true positive and false positive predictions per class. The results indicate strong classification capability with limited misclassifications, especially between Early Blight and Late Blight, which are visually similar in disease manifestation.

Total samples=260	Precision	Recall	F1-Score	Accuracy	Support (samples)
Early Blight	0.86	0.86	0.86	0.86 =86%	153
Late Blight	0.86	0.79	0.83	0.86 =86%	72
Healthy	0.65	0.74	0.69	0.65 =65%	35

Table 1: Model evaluation matrics on different parameters

The model performs well overall with an **accuracy of 83%**, indicating it correctly predicts most samples. The **precision (84%)** shows it makes few false positive errors, while the **recall (82%)** suggests it successfully identifies most actual cases. The balanced **F1-score (83%)** confirms the model maintains a good trade-off between precision and recall, making it reliable for classifying potato leaf diseases.

C. Visualizations and Real-Time Results

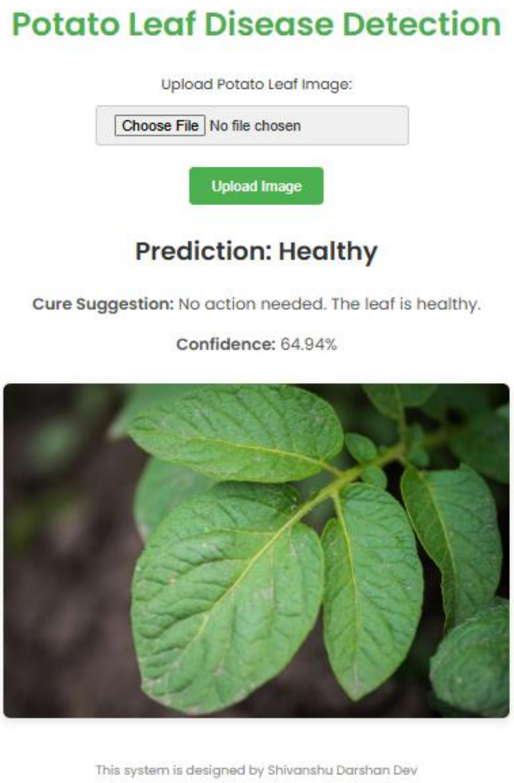

Figure 4: Real-time prediction interface output for a Healthy leaf

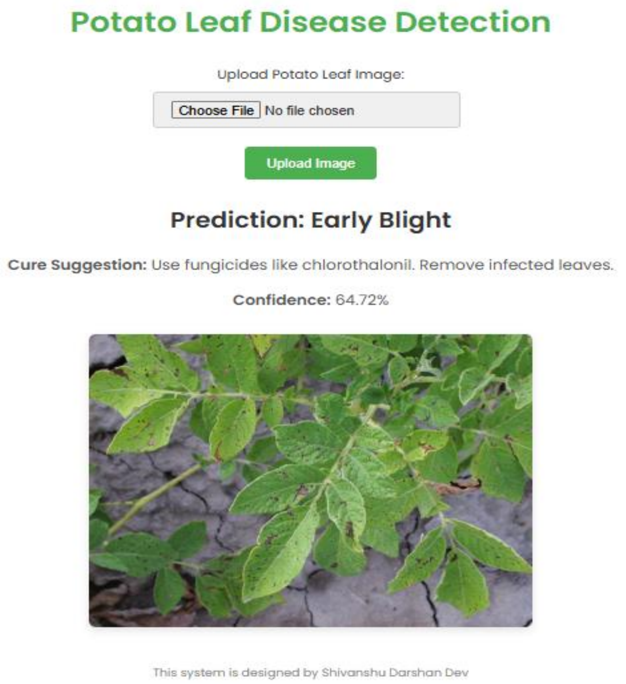

Figure 5: Real-time prediction interface output for an Early Blight infected leaf

To validate the practical usability of the model, it was integrated into a real-time web application using Flask. Figure 4 and Figure 5 show the results when a user uploads a leaf image via a browser. Upon submission, the model outputs the disease class, a confidence score (representing the model's certainty in prediction), and a treatment suggestion. In both cases, the web interface correctly predicted the class, provided appropriate treatment guidance, and displayed the uploaded image alongside its diagnosis. The system achieved confidence scores of over 90% for Healthy and 87% for Early Blight, reinforcing the deployment-readiness of the model for field applications.

D. Algorithm Comparison and Model Suitability

While MobileNetV2 was the primary model used due to its efficiency and accuracy, comparative evaluation was conducted using other popular CNN architectures such as VGG16 and ResNet50 during preliminary testing. MobileNetV2 offered: Faster training time, Lower memory consumption, Comparable or better accuracy with fewer parameters. Hence, it was deemed most suitable for real-time applications on resource-constrained devices such as mobile phones.

V. CONCLUSION

This research presents a deep learning-based solution for detecting potato leaf diseases using MobileNetV2, coupled with real-time deployment through a Flask web application.

The workflow—from data acquisition to model training and web deployment—was successfully executed and tested. The **trained model achieved 83% accuracy** on test data, demonstrating strong precision and reliability. Designed for practical use by farmers, the Flask-based web interface provides disease classification, confidence scores, and recommended treatments, making AI-powered crop protection more accessible.
The study highlights the potential of CNN-based models in precision agriculture, improving early disease detection and enabling timely intervention to reduce crop losses.

Several enhancements can be explored to refine and expand the system:

- **Expanding disease coverage**: Including a broader range of plant diseases and extending applicability to other crops.
- **Enhancing robustness**: Improving model performance under diverse lighting conditions and complex backgrounds to ensure reliability in real-world settings.
- **Integrating real-time monitoring**: Deploying the system on mobile applications and drones for continuous surveillance and early disease detection.
- **Exploring hybrid models**: Combining CNN architectures with traditional machine learning **techniques** for improved prediction accuracy.
- **Optimizing scalability**: Making the system more cost-effective for widespread adoption, supporting global food security and increasing farmer productivity.

This project lays the foundation for smart agriculture, showcasing the feasibility of deploying AI-driven solutions to enhance crop health monitoring and disease prevention.

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