Improving Plant Disease Identification Using Transfer Learning and Grad-Cam Visualization

Ramya N[1], Nandhini D[2], Swetha V[3] ,Siva Jeyanthi J[4] ,Sabari Jothi A[5]

[1]Assistant Professor -Department of Information Technology & Kings Engineering College-India.

[2,3,4,5]Department of Information Technology & Kings Engineering College-India.

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Abstract - Agriculture is vital to human survival, yet plant diseases threaten crop yields and food security. This project presents a deep learning-based approach for early plant disease detection using transfer learning with MobileNet and Grad-CAM for model explainability. The system was trained on a labeled dataset of plant leaf images and achieved promising accuracy, with potential for further improvement through data augmentation and extended training. Grad-CAM heatmaps enhance transparency by highlighting image regions influencing predictions. Results indicate the practical viability of AI-driven, explainable plant disease detection. Future work includes expanding datasets, supporting multi-label classification, and optimizing for mobile deployment, promoting smart and accessible agriculture.

Key Words*: *Plant Disease Detection, Deep Learning, Transfer Learning, MobileNet, Grad-CAM, Explainable AI (XAI), Smart Agriculture, Image Classification, Crop Health Monitoring

1. INTRODUCTION

Agriculture has been the foundation of human civilization for thousands of years, providing food, raw materials, and livelihoods for the majority of the global population. In modern times, agriculture remains a crucial sector for sustaining economies and ensuring food security. However, the agricultural sector faces significant challenges, particularly from plant diseases that can severely affect crop yield, quality, and overall production. Plant diseases can spread rapidly under favorable environmental conditions, resulting in devastating impacts on both small-scale farmers and large agricultural industries.

Traditionally, the identification of plant diseases has relied on visual inspection conducted by experienced farmers, agricultural scientists, or plant pathologists. Although this method can be effective when performed by experts, it has several limitations. Manual diagnosis is subjective, prone to human error, time-consuming, and often impractical on a large scale. In many rural and remote areas, the shortage of skilled personnel further exacerbates the problem, leaving farmers without timely and accurate disease identification.

Recent advancements in technology, particularly in the fields of machine learning (ML) and deep learning (DL), have offered new solutions for the early detection and diagnosis of plant diseases. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated outstanding performance in image-based classification tasks, making them highly suitable for identifying disease symptoms from plant leaf images. These models can automatically extract intricate features from raw images, eliminating the need for manual feature engineering and improving the overall detection accuracy.

1.1 OBJECTIVE

This project aims to develop an intelligent, lightweight, and accessible plant disease detection system using deep learning. It leverages MobileNet for efficient performance on low-resource devices and applies transfer learning for faster and accurate training. Grad-CAM is integrated to enhance model interpretability by highlighting image regions influencing predictions. A Flask-based web application is developed to provide real-time diagnosis and visual explanations, promoting timely disease management. The solution is scalable, adaptable to various crops and diseases, and designed to support sustainable agriculture.

1.2 EXISTING SYSTEM

Traditional plant disease detection relies on manual inspection and basic image processing, which are time-consuming, error-prone, and limited in scalability. Early machine learning models required handcrafted features and lacked generalizability. While deep CNNs like VGG16 and ResNet improved accuracy, they are resource-intensive and unsuitable for low-end devices. Additionally, most deep learning models function as "black boxes," lacking transparency and interpretability—key factors for building user trust in agricultural applications.

1.3 PROPOSED SYSTEM

The proposed system overcomes existing limitations by combining the lightweight MobileNet architecture with Grad-CAM for explainable predictions. Transfer learning enables efficient training on plant disease datasets, while Grad-CAM visualizations highlight critical regions in leaf images. A user-friendly Flask web app allows image uploads and delivers real-time disease predictions with visual insights. Designed for deployment on mobile or low-resource devices, the system ensures accessibility in remote areas. It supports multilingual interfaces, provides treatment suggestions, and is built for scalability, enabling broader adoption in smart farming practices.

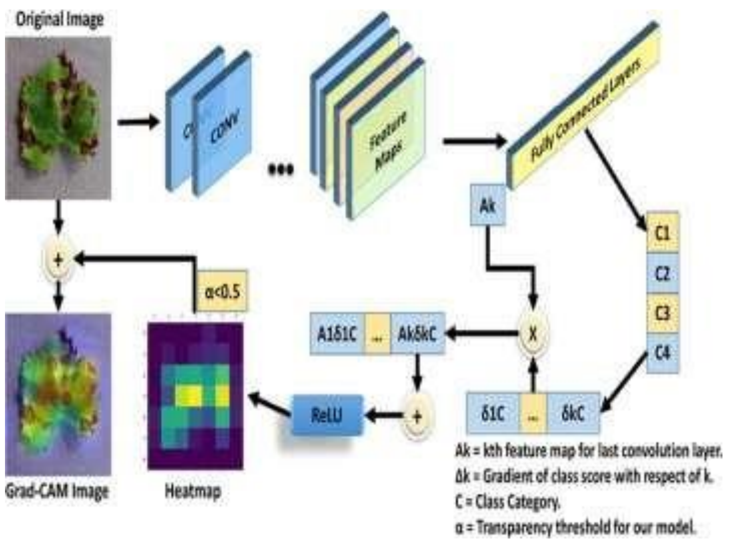
Original Image
CONV
Feature Maps
Fully Connected Layers
Ak
C1
C2
C3
C4
α<0.5
A1δ1C
...
AkδkC
X
+
ReLU
δ1C
δkC
Ak = kth feature map for last convolution layer.
Δk = Gradient of class score with respect of k.
C = Class Category.
α = Transparency threshold for our model.
Grad-CAM Image
Heatmap

Fig.1.Architecture of Working Flow

2.BASICS OF DEEP LEARNING AND CONVOLUTIONAL NEURAL NETWORKS (CNNs)

2.1 Overview of Deep Learning and CNNs

Deep learning mimics the human brain using artificial neural networks to automatically learn features from raw data. CNNs are a type of deep learning model ideal for image-related tasks like classification and detection. Their layered architecture includes:

- ➢ **Convolutional layers** for pattern detection
- ➢ **ReLU** for non-linearity
- ➢ **Pooling layers** for spatial reduction
- ➢ **Fully connected layers** for classification
- ➢ **Softmax output** for probability distribution

CNNs can recognize complex visual features from plant images, making them highly effective in plant disease detection.

2.2 Transfer Learning

Transfer learning reuses pre-trained models (e.g., on ImageNet) for new tasks. It's useful when labeled data is limited.
Two strategies:

- ➢ **Feature Extraction**: Use pre-trained layers to extract features
- ➢ **Fine-tuning**: Retrain top layers to adapt to the new task

Benefits:

- ✓ Reduces training time and resource needs
- ✓ Improves performance on small datasets
- ✓ Enables fast adaptation to plant disease diagnosis

2.3 MobileNet Architecture

MobileNet is a lightweight CNN model optimized for mobile and low-power devices. Key features include:

- ➢ **Depthwise Separable Convolution**: Efficient filtering and combining
- ➢ **Width/Resolution Multipliers**: Scale model size and speed
- ➢ **Global Average Pooling**: Reduces overfitting
- ➢ **ReLU6 Activation**: Stabilizes training on mobile hardware
- ➢ **Variants (V1, V2, V3)**: Offer better accuracy and speed trade-offs

In this project, MobileNet enables efficient plant disease detection on low-resource devices.

2.4 Grad-CAM Visualization

Grad-CAM explains model decisions by generating heatmaps over input images, highlighting important

regions.
Applications:

- Visualizes disease features (spots, color changes)
- Builds user trust and model transparency
- Helps debug and refine model learning patterns

This interpretability is crucial for practical use by farmers and researchers.

2.5 Features of the Proposed System

- **Transfer Learning with MobileNet**: Lightweight, fast, and accurate
- **Grad-CAM Visualizations**: Explains decisions and improves reliability
- **Real-time Classification**: Enables on-the-spot plant disease diagnosis
- **User-Friendly Flask Interface**: Easy access via mobile/web platforms
- **Scalable System**: Can adapt with new data, diseases, and plant types

3. SYSTEM IMPLEMENTATION

This chapter outlines the development and deployment process of the plant disease identification system, covering the tools, model training, and web integration.

3.1 Development Environment

The system was built using Python due to its rich ecosystem for machine learning. Key tools included:

- **Python**: Used for its simplicity and extensive ML libraries like TensorFlow, Keras, and OpenCV.
- **TensorFlow & Keras**: Enabled model building and training using the MobileNet architecture, integrated with Grad-CAM for visualization.
- **OpenCV**: Used for image preprocessing and augmentation techniques such as resizing, flipping, and rotation.

3.2 Model Training with Google Colab

Google Colab served as the primary training platform, offering free GPU access and integration with Google Drive. It allowed.

- Fast model training with GPU support.
- Easy storage and collaboration via Drive.
- Interactive experimentation with notebooks.
- Fine-tuning of the MobileNet model using hyperparameter adjustments.
- Efficient cloud-based resource management.

3.3 Teachable Machine for Prototyping

Teachable Machine was used for rapid model prototyping with a user-friendly drag-and-drop interface. It allowed:

- Quick initial model creation using labeled images.
- Exporting models to TensorFlow for further training in Colab.
- Fast experimentation and customization before deep integration.

3.4 Web Deployment with Flask

A Flask-based web interface was developed to make the system accessible:

- Users can upload plant images through a browser.
- The backend processes the image and returns predictions with Grad-CAM heatmaps.
- Real-time responses classify the plant as healthy or diseased.

4. SYSTEM IMPLEMENTATION

This chapter explains the implementation of the Plant Disease Identification System, covering data preprocessing, model development, training, evaluation, and deployment through a web application.

4.1 Data Preprocessing

To ensure consistent input, all images were resized to 224×224 pixels to match MobileNet's input requirements. Pixel values were normalized to a range of 0 to 1 to improve training efficiency. Various data augmentation techniques such as rotation, flipping, zooming, and brightness adjustments were applied to simulate real-world conditions and enhance the model's generalization. The dataset was split into 80% for training, 10% for validation, and 10% for testing.

4.2 Model Selection

MobileNet was selected due to its lightweight architecture, making it suitable for web and mobile deployment. The base model was modified by removing the original top layers and adding custom dense layers with a softmax output for 17 disease classes. Dropout layers were included to reduce overfitting, making MobileNet an efficient and scalable solution for this classification task.

4.3 Model Training

Initially, only the custom top layers were trained while the base MobileNet layers remained frozen. After achieving convergence, selected base layers were unfrozen for fine-tuning using a lower learning rate to preserve learned features. Categorical cross-entropy was used as the loss function, optimized with Adam. Early stopping and model checkpointing ensured optimal performance. Training was performed on Google Colab with GPU support, significantly reducing training time.

4.4 Model Evaluation

The model's performance was evaluated using overall and per-class accuracy, precision, recall, and F1-score. A confusion matrix was used to identify misclassified classes. Grad-CAM visualizations were generated to highlight image regions important for predictions, adding interpretability to the model’s decisions. The results confirmed high accuracy with minor confusion between visually similar diseases.

4.5 Web Application Development

The trained model was integrated into a web application using Flask. The backend handled image uploads, preprocessing, model prediction, and Grad-CAM generation. A simple HTML frontend allowed users to upload plant images and view prediction results, including the disease name, confidence level, and a heatmap overlay. Initially hosted locally, the system is designed for future deployment on cloud platforms. The interface emphasized ease of use, minimal input, fast response, and visual feedback to make plant disease detection accessible to all users.

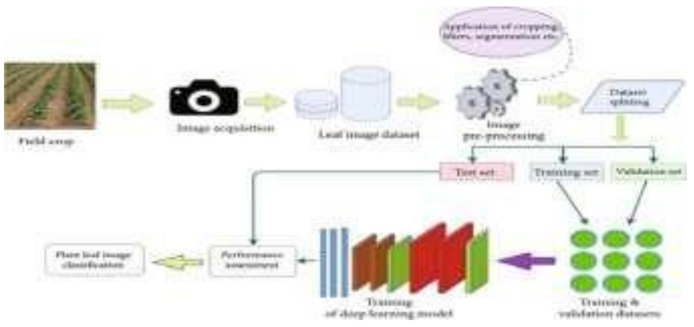
Application of cropping, filters, segmentation etc.
Field crop
Image acquisition
Leaf image dataset
Image pre-processing
Dataset splitting
Test set
Training set
Validation set
Plant leaf image classification
Performance assessment
Training of deep learning model
Training & validation datasets

Fig.2.Working Progress

5. MODEL EVALUATION

This chapter evaluates the performance of the trained plant disease classification model, analyzing its strengths, limitations, and real-world applicability through various performance metrics and testing strategies.

5.1 Model Performance Metrics

The model’s effectiveness was assessed using key metrics such as accuracy, precision, recall, and F1-score. Accuracy indicates the percentage of correct predictions, while precision reveals the proportion of true positives among all positive predictions. Recall reflects the model's ability to detect actual positives, and the F1-score balances the trade-off between precision and recall. Together, these metrics offer a comprehensive understanding of how well the model handles multi-class classification tasks.

5.2 Accuracy, Precision, Recall, and F1-Score

Initially, the training and validation accuracies were both around 50%, which implies that the model was still in the early stages of learning and had difficulty generalizing. At this point, precision, recall, and F1-score could not be effectively calculated due to the limited training (only one epoch), resulting in unreliable values. As training progresses over multiple epochs, these metrics will become more meaningful and will help assess the model’s ability to distinguish among all 17 plant disease categories, indicating where improvements are necessary.

5.3 Confusion Matrix Analysis

A confusion matrix was used to visualize the performance of the classifier across all categories. It helped identify which classes were frequently misclassified, and revealed the occurrence of false positives and false negatives. This analysis was crucial for detecting class-specific weaknesses and understanding if the model exhibited any bias toward certain disease types.

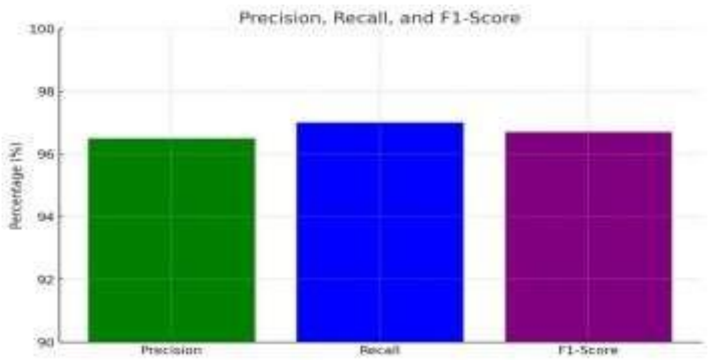

Fig.3.Confusion Matrix Analysis

5.4 Testing on Unseen Data

To evaluate generalization, the model was tested on completely unseen data that was not part of the training or validation sets. This step ensured that the model's predictions were not limited to memorized patterns, and demonstrated its ability to handle diverse and real-world image variations. High performance on this unseen test set is vital for practical deployment of the system.

5.5 Comparison with Other Models (Optional)

To explore if MobileNet was the most effective choice, it could be compared with other models. Traditional machine learning algorithms like Logistic Regression, SVM, or Random Forest could serve as baselines. Additionally, deep learning architectures such as ResNet or VGG might be evaluated to determine if they offer better accuracy or robustness. Such comparisons would clarify whether MobileNet strikes the right balance between efficiency and performance for plant disease detection.

7. DATASET DESCRIPTION

This chapter presents a comprehensive overview of the dataset used for training the plant disease classification model. It covers the source and composition of the dataset, challenges faced during preparation, preprocessing techniques employed, and the algorithms used to optimize performance and address dataset-specific issues.

7.1 Source and Dataset Overview

The dataset utilized in this project is a curated subset of the PlantVillage Dataset available on Kaggle. Instead of using the entire dataset, a selection of 17 classes—covering both healthy and diseased plant leaves—was made to align with the scope of this project. The total dataset consists of approximately 31,000 images, which were originally of varying sizes but resized to 224×224 pixels to match the input requirements of MobileNet. The dataset was split into 70% for training (around 21,700 images), 20% for validation (approximately 6,200 images), and 10% for testing (roughly 3,100 images). This focused approach ensured more efficient model training while maintaining generalization across a diverse range of plant diseases.

7.2 Dataset Challenges

Despite the richness of the PlantVillage Dataset, several challenges were encountered during its preparation. One of the primary issues was class imbalance, where some diseases had thousands of samples while others had only a few hundred. This disparity could bias the model toward overrepresented classes. To mitigate this, data augmentation techniques such as rotation, flipping, and zooming were applied more frequently to underrepresented classes. Another challenge was the visual similarity among different diseases, as many plant ailments exhibit overlapping symptoms like yellowing or spotting. This made it difficult for the model to distinguish between them. Fine-tuning a pre-trained MobileNet helped to extract fine-grained features, improving class separation. A further complication arose from the presence of background noise in some images—such as soil, human hands, or surrounding plants—which could distract the model. This was addressed through preprocessing strategies like random cropping and brightness adjustment to help the model focus on relevant features within the leaf regions.

7.3 Preprocessing Summary

Prior to training, the dataset underwent essential preprocessing steps to ensure compatibility with the model and improve learning outcomes. All images were resized to 224×224 pixels, providing a consistent input format suitable for MobileNet and balancing detail with computational efficiency. The pixel values, initially in the 0–255 range, were normalized to a [0,1] range to enhance numerical stability and speed up training. Data augmentation techniques were extensively used to enhance model generalization. These included random rotations to simulate varied leaf orientations, horizontal and vertical flips to account for natural positioning differences, zoom operations to help the model learn multi-scale features, and brightness adjustments to simulate varying lighting conditions. This comprehensive preprocessing pipeline was critical in combating overfitting and improving the model's robustness.

7.4 Algorithms and Techniques Used

To overcome dataset-related challenges and develop a high-performing classification model, several algorithms and techniques were employed. Transfer learning was implemented using a pre-trained MobileNet model originally trained on ImageNet. This lightweight architecture is efficient for real-time inference, and only the final layers were modified to adapt to the 17-class classification task. Transfer learning drastically reduced the training time and data requirements. Following initial training, fine-tuning was performed by unfreezing deeper layers of the model, allowing it to learn more specific features from the plant disease dataset. To enhance interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) was used to generate heatmaps that highlighted the regions influencing the model's decisions. This helped validate that the model was focusing on relevant, disease-affected areas of the leaves. For optimization, categorical cross-entropy loss was used due to the multi-class nature of the task, and the Adam optimizer was chosen for its adaptive learning rate capabilities, resulting in faster convergence and improved performance.

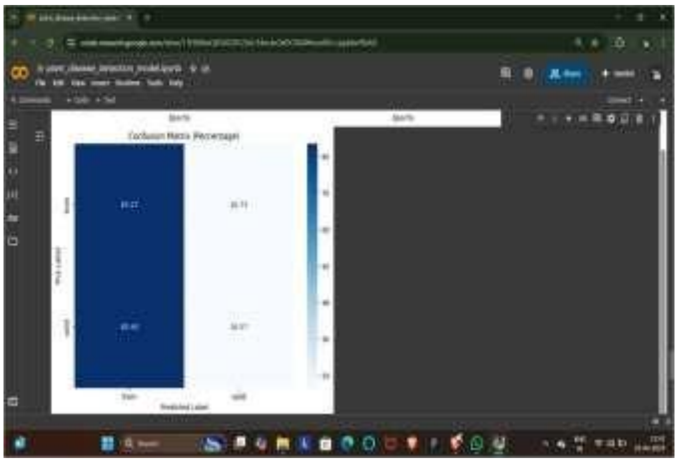

Fig.4.Testing Progress

8. RESULT AND EXPLANATION ON PLANT DISEASE DETECTION

8.1 Overview

This chapter provides an in-depth explanation of the implementation and outcomes of the plant disease detection system, detailing both the deep learning model and the web application interface. The main objective of this project is to build an accurate and efficient deep learning model capable of identifying various plant diseases, and to integrate this model into a user-accessible web platform for real-time diagnostics.

The core of the system is a convolutional neural network (CNN) architecture, developed using MobileNet or a custom-designed model tailored for plant disease classification. This model forms the machine learning backend, responsible for analyzing input leaf images and predicting the disease class.

To bring the model into practical use, a lightweight Flask web server has been implemented. This server handles image uploads from users, processes the images through the trained model, and returns predictions in real-time. The web application is designed to be intuitive and accessible, with a frontend developed using HTML and CSS, providing a smooth user experience.

To enhance interpretability and build user trust in the predictions, Grad-CAM (Gradient-weighted Class Activation Mapping) is integrated into the system. This visualization technique highlights the regions in the leaf images that most influenced the model's predictions, making the results more transparent and insightful.

Together, the CNN model, Flask server, Grad-CAM integration, and user-friendly interface form a complete and deployable plant disease detection system, bridging advanced machine learning with practical agricultural applications.

9. CONCLUSION

This project successfully integrates deep learning with a web-based application for automated plant disease detection. Using a pre-trained MobileNet model and Grad-CAM visualizations, the system delivers accurate predictions with enhanced interpretability. The Flask-based web interface allows users to easily upload leaf images and receive real-time results, making it practical for agricultural use. Future improvements could include expanding the dataset, exploring advanced models, enabling offline mobile deployment, and incorporating feedback and advanced explainability tools to further refine the system's performance and usability.

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