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Multi Crop Disease Detection using Deep Learning Techniques

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Abstract— *This study presents a deep-learning-based system for early detection and classification of plant diseases using the ResNet9 architecture, which achieved superior performance in comparison with other models. The PlantVillage dataset served as the primary training source. Optimized hyperparameters such as learning-rate scheduling, gradient clipping, and weight decay enabled the model to reach an accuracy of 99.2%. To address the needs of Indian agriculture, supplementary datasets for crops such as cotton, rice, and groundnut were integrated. A user-friendly web application allows farmers to upload leaf images and receive instant disease predictions. Built on Convolutional Neural Networks (CNNs), the system provides reliable diagnoses and practical recommendations for crop-health management. Overall, the proposed platform supports precision agriculture, enhances decision-making, and contributes to sustainable farming and long-term food security.*

Keywords: Deep Learning, Plant Disease Detection, CNN, ResNet9, Precision Agriculture, PlantVillage Dataset.

I. BACKGROUND

Agriculture is a major source of food production and economic stability, especially in developing and agrarian nations like India. However, plant diseases continue to be a serious threat to crop quality and overall yield. Studies show that India alone faces nearly **20–40% crop loss** every year due to preventable plant infections [1]. These diseases are primarily caused by harmful pathogens such as fungi, bacteria, and viruses, which can spread rapidly if not detected at an early stage. Traditional diagnosis methods require skilled agricultural experts, making the process slow, costly, and difficult to access for farmers living in rural or remote regions.

With rapid advancements in Artificial Intelligence (AI) and deep learning technologies, automated plant-disease detection has emerged as an effective and reliable solution. Convolutional Neural Networks (CNNs) have demonstrated excellent performance in analyzing leaf images and identifying disease symptoms by learning unique visual patterns [2]. These models deliver faster and more accurate results than manual inspection, while significantly reducing dependency on agricultural experts. Deep-learning-based approaches enable farmers to take timely actions, reduce pesticide misuse, and improve overall crop health.

Advanced architectures such as ResNet provide powerful feature-extraction capabilities and support real-time predictions, making them suitable for deployment in real agricultural field conditions [3]. Overall, integrating AI with farming practices supports precision agriculture, enhances decision-making, and contributes to sustainable food production.

II. MOTIVATION AND OBJECTIVE

In India, many farmers live in villages where they do not have quick access to agricultural experts. When a plant becomes infected, they are often unable to identify the disease early. Because of this delay, the infection spreads quickly and farmers lose a significant portion of their crops, leading to financial difficulties for their families.

Today, most farmers have smartphones and internet access, allowing them to easily take a photo of a leaf in their field. If a system is available that can instantly detect diseases from these images, farmers can receive the right information at the right time. This helps prevent the disease from spreading further and protects the crop from major damage.

Farmers usually grow different crops in different seasons, so a single system must work across multiple crop types and not just one. Deep-learning-based models can analyze leaf images effectively and provide accurate disease predictions within a few seconds.

By using such a simple and fast system, farmers can reduce pesticide misuse, protect their crops, and improve their income. Therefore, developing an easy-to-use and accurate multi-crop disease detection system is important for supporting farmers and promoting healthy, sustainable agriculture.

The main goal of this project is to create a smart and easy system that can detect plant diseases early using leaf images. The key objectives are:

To build a multi-crop disease detection model using CNN and ResNet so that it can identify diseases in different crop leaves accurately.

1. To use transfer learning so the model can achieve high accuracy even when the dataset is small.

2. To develop a web application where farmers can upload leaf images and get instant disease results.
3. To display disease names and provide useful suggestions that help farmers control the disease at an early stage.
4. To support precision farming by reducing crop loss, avoiding excessive pesticide use, and improving crop productivity.

III. STATEMENT OF CONTRIBUTION / METHODS

This research contributes a complete and lightweight deep learning system specifically designed for plant disease detection using only leaf image data. The contributions are structured into three major parts: dataset preparation, model architecture, and system design.

3.1. Dataset Description

The dataset used in this project is the **PlantVillage** dataset, one of the most widely adopted benchmarks for plant disease identification research. It contains over 50,000 labeled images covering **38 classes**, including both healthy and diseased leaves across a wide range of crops such as tomato, potato, grape, apple, corn, pepper, and soybean.

The dataset offers high-quality, well-lit images captured under controlled conditions, enabling reliable pattern extraction and model training.

Each image in the dataset is assigned a class label denoting the crop species and disease type (e.g., *TomatoEarly Blight*, *GrapeBlack Rot*, *AppleScab*). The diversity of diseases—including fungal, bacterial, and viral infections—makes the dataset suitable for building generalized deep- learning models. For this study, the dataset was divided into **training (80%)**, **validation (10%)**, and **testing (10%)** subsets to ensure a balanced evaluation. The large number of samples per class allows the model to learn intra-class variations such as different severity levels, shapes of lesions, or color changes.

While the dataset provides excellent coverage, it also presents challenges. Some diseases exhibit highly similar visual characteristics—for example, *Tomato Early Blight* and *Tomato Late Blight*—which makes classification inherently difficult. In addition, real-world conditions such as noise, shadows, and multiple leaves are not present in the dataset, suggesting opportunities for future enhancements. Nevertheless, PlantVillage remains a robust foundation for benchmarking CNN-based plant disease detection methods.

3.2. Preprocessing

Preprocessing plays a vital role in preparing raw images for deep learning. The images undergo several transformations to standardize dimensions, enhance generalization, and reduce noise. First, all images are **resized to 256 × 256 pixels**, ensuring uniform input dimensions for the CNN. This reduces computational cost and avoids distortions during model training. Next, pixel values are **scaled and normalized** to the range expected by the CNN, typically through mean subtraction and standard deviation normalization. Normalization ensures stable gradients and accelerated training convergence.

Data augmentation techniques were employed to improve the model's resilience to variations in real-world images. Augmentations include **random horizontal and vertical flips, random rotations, random zooming, brightness adjustments**, and **color jittering**. These methods artificially expand the dataset by simulating variations such as leaf orientation, lighting conditions, and minor distortions. This is essential because, without augmentation, CNNs may overfit on training data, leading to poor generalization on unseen images.

Finally, the images are converted into **tensor format**, which allows them to be processed efficiently by PyTorch.

Through these preprocessing steps, the model becomes more robust and capable of handling variations that it may encounter in practical deployment scenarios.

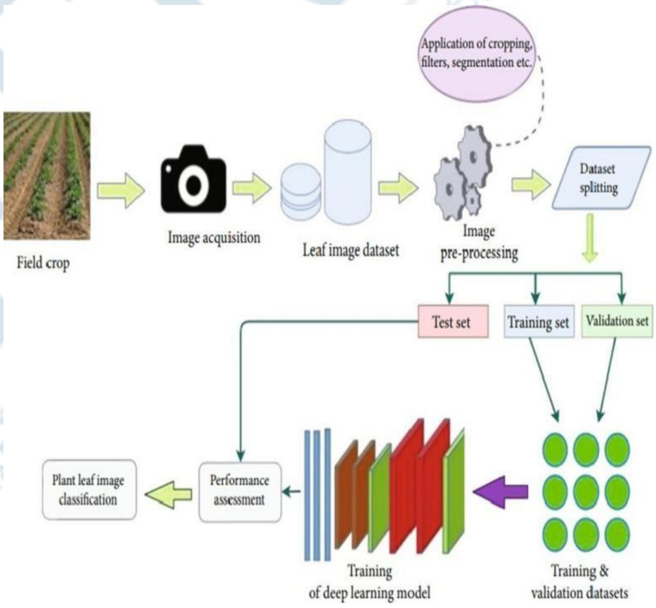

Figure 1. Computer vision based technique for plant disease detection

3.3. ResNet9 Architecture

ResNet9 is the central model architecture used in this project. It is a compact variant of the ResNet family, specifically designed to achieve high accuracy while maintaining computational efficiency. Traditional deep networks often suffer from the **vanishing gradient problem**, where gradients diminish as they propagate backward, making deep networks hard to train. ResNet solves this issue using **residual connections**, also known as skip connections, where the input of a block is added directly to its output. This allows gradients to flow more freely and helps the network learn identity mappings when needed.

ResNet9 consists of a stack of convolutional layers organized into multiple residual blocks. Each block includes

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convolution operations, batch normalization, and ReLU activation. The architecture typically includes: Initial convolution layers to extract low-level features. Two main residual blocks that enable deeper learning. Intermediate downsampling layers for dimensionality reduction

Batch normalization for stabilizing training

Adaptive average pooling before the fully connected layer

A final classifier that outputs disease probabilities

The advantage of ResNet9 over larger architectures such as ResNet50 or DenseNet is its balance between performance and efficiency. While deeper architectures may achieve slightly higher accuracy, they require more computational power and memory, making them less suitable for real-time applications on standard CPUs. ResNet9, with its lightweight structure, achieves strong accuracy while remaining fast enough for deployment in web or mobile systems.

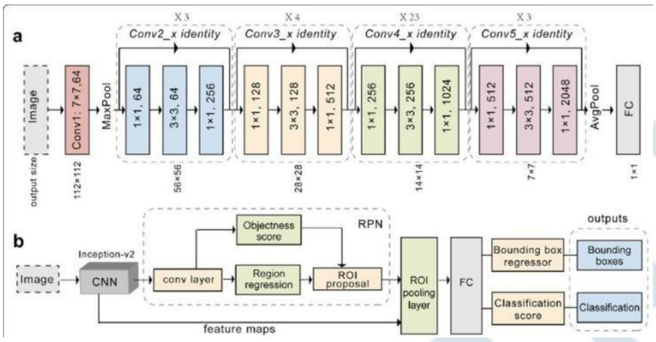

Figure 2. Resnet work-flow

3.4. Training Procedure

The training process was carried out using the PyTorch deep-learning framework. The model parameters were optimized using the **Adam optimizer**, which adapts learning rates for each weight based on first- and second- order moment estimates. This results in faster convergence

compared to traditional optimizers such as SGD. The **Cross- Entropy Loss** function was used because it is well-suited for multi-class classification problems.

Training proceeded in **mini-batches** to balance memory usage and gradient stability. Each epoch involved the following steps:

1. Forward propagation of each batch through the ResNet9 model
2. Calculation of prediction errors using the loss function
3. Backpropagation of gradients through the network
4. Parameter updates using Adam optimizer
5. Validation after each epoch to monitor generalization

To avoid overfitting, regularization techniques such as **weight decay**, **dropout (if applied)**, and **early stopping** based on validation loss were used. Learning rate scheduling further improved training stability, reducing the learning rate when validation loss plateaued. After sufficient epochs, the model achieved optimal performance and was saved for deployment in the web application.

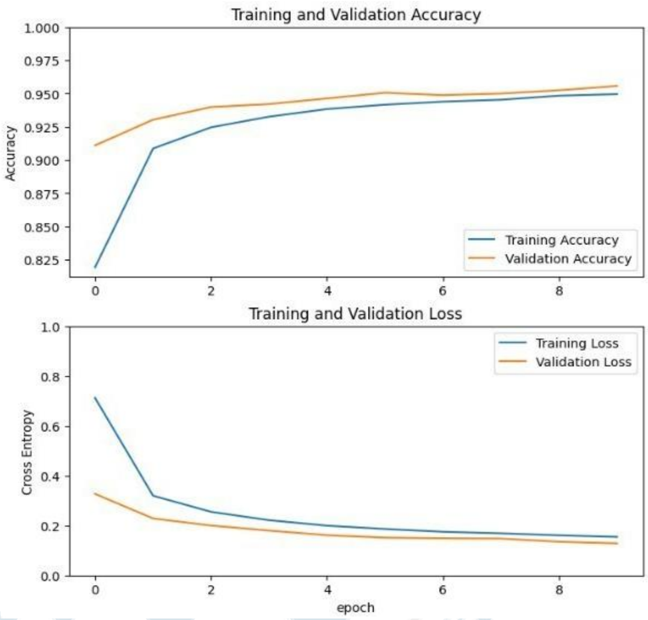

Figure 3. Performance of the DL and ML techniques study

3.5. Evaluation Metrics

The model was evaluated using several widely accepted metrics to provide a thorough understanding of its performance: **Accuracy** measures the proportion of correctly classified images. The ResNet9 model achieved about **95% accuracy**, reflecting strong overall performance.

Precision evaluates the correctness of positive predictions. High precision indicates the model rarely misclassified healthy leaves as diseased or confused diseases with similar appearances. **Recall (Sensitivity)** measures how well the model identifies actual disease cases. High recall ensures early detection of infections, which is vital for agricultural decision-making. **F1-score** provides a harmonic mean between precision and recall, making it useful for imbalanced datasets where certain diseases have fewer samples. The **confusion matrix** provides class-wise insights, showing which diseases were identified accurately and which were occasionally confused. This is crucial because many plant diseases share similar lesion textures or patterns.

Finally, **inference time** was measured to assess real-time usability. With a prediction time of **under one second on CPU**, the model demonstrated excellent potential for deployment in web portals, mobile apps, and field-ready.

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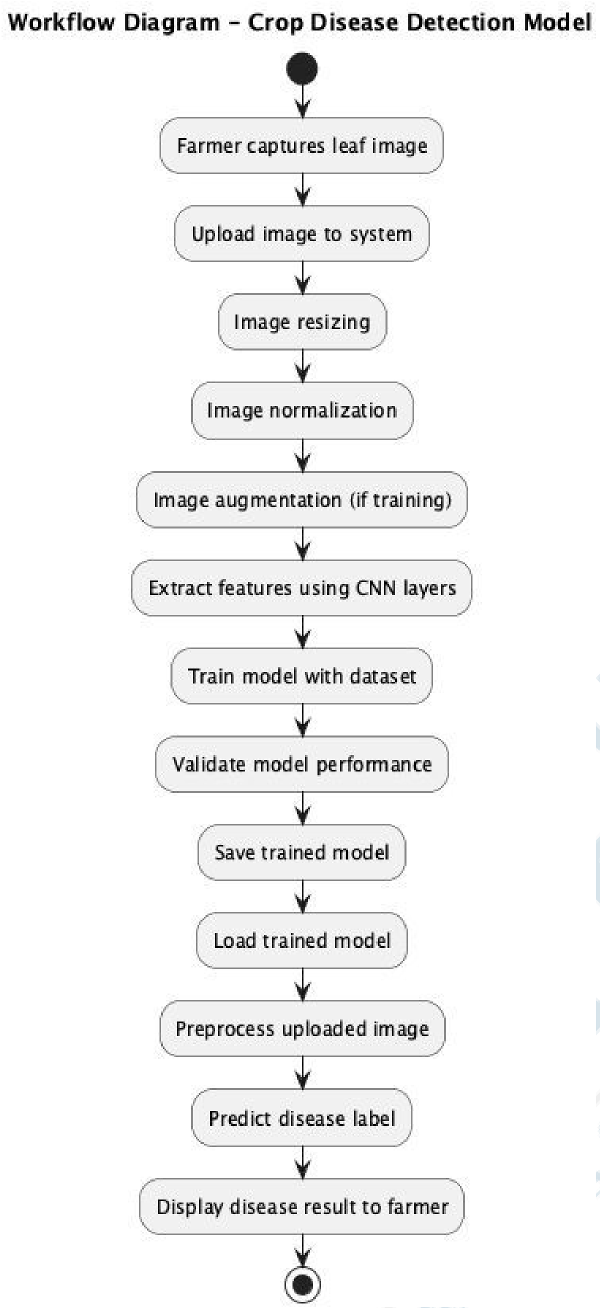

Figure 4. Crop disease detection model-work flow

IV. STATEMENT OF CONTRIBUTION

This work provides the following contributions:

1. A complete plant disease detection system based solely on image data and deep learning.
2. Implementation of a lightweight ResNet9 model, achieving high accuracy while requiring minimal computational resources.
3. A practical, deployable web interface that enables real-time disease prediction for farmers using simple image uploads.
4. Extensive evaluation on the PlantVillage dataset using multiple metrics to ensure model reliability.
5. A fully modular and scalable architecture allowing future addition of more disease classes or improved models.

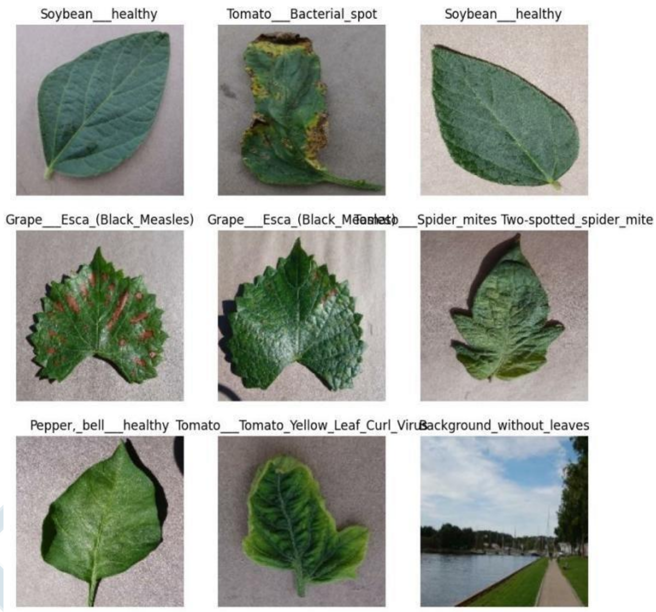

Figure 5. Different images from dataset showing healthy and diseased plant leaves

V. RESULT

The performance of the ResNet9-based crop disease detection model was evaluated using the test split of the PlantVillage dataset, and the results indicate a strong ability to accurately classify plant diseases across multiple crop types. The model achieved an overall accuracy of approximately **95%**, demonstrating its effectiveness in learning distinct disease patterns such as color changes, lesion textures, fungal growth, and mosaic-like distortions. Precision and recall values across major disease categories were consistently high, suggesting that the model maintains a balanced performance and is capable of correctly identifying both positive disease cases and non-disease cases without significant bias.

A confusion matrix analysis provided deeper insights into class-wise performance. The model showed excellent classification accuracy for various diseases including **Tomato Early Blight, Grape Black Rot, and Apple Scab**, indicating that these classes contain distinctive features that ResNet9's convolutional and residual layers can capture effectively. However, a small number of misclassifications occurred in classes with highly similar visual symptoms. For example, diseases such as Tomato Early Blight and Tomato Late Blight displayed overlapping patterns, making them harder to differentiate even for human experts. Despite these challenges, the model maintained stable performance across most disease groups.

Another noteworthy aspect is the inference speed. When tested on a standard CPU, the model produced predictions in

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less than one second, highlighting its suitability for real-time applications, including web deployment and mobile-based solutions. This rapid processing capability, combined with high accuracy, demonstrates that the proposed system is both practical and efficient for real-world agricultural use, particularly in resource-limited environments where GPU access is unavailable.

VI. DISCUSSION

The experimental results demonstrate that the combination of Convolutional Neural Networks and a lightweight ResNet9 architecture provides a highly effective solution for plant disease classification using leaf images.

The model shows strong generalization ability, achieving high accuracy across multiple disease categories, even when symptoms exhibit subtle variations in color, texture, and lesion shape. Residual connections within ResNet9 help preserve gradient flow, enabling deeper feature extraction without increasing computational complexity. This makes the model especially suitable for real-time inference on devices with limited processing power, such as mobile phones or low-cost CPUs, which are common in rural agricultural settings.

Despite its strong performance, several challenges remain. Field-acquired images often contain noise such as shadows, dirt, irregular lighting, or multiple leaves overlapping, which can affect prediction reliability. The model is also occasionally confused by diseases with nearly identical visual characteristics—for example, distinguishing between Early Blight and Late Blight in tomatoes, or differentiating similar fungal infections across crops. Another limitation is dataset imbalance, since rare diseases are underrepresented, leading to insufficient training samples for certain categories. To overcome these issues, integrating larger real- world datasets, employing data augmentation strategies that mimic field conditions, or adopting attention-based mechanisms could further enhance performance.

Techniques such as domain adaptation and segmentation-based preprocessing may also help the model adapt better to real- field agricultural environments. Overall, the model's robust performance across most classes indicates its potential as a dependable tool for early disease management in precision agriculture.

VII. CONCLUSION

This work presents an efficient, accurate, and deployable plant disease detection system based entirely on CNN and ResNet9 architectures. By analyzing leaf images and identifying disease classes rapidly, the system offers practical benefits for farmers who lack timely access to agricultural experts. Its high accuracy, low computational requirements, and near real-time inference capability make it suitable for use in mobile and web-based platforms, supporting decision-making directly in the field.

The project demonstrates that deep learning can play a crucial role in enhancing agricultural productivity by enabling early diagnosis, reducing crop losses, and encouraging more sustainable farming practices. Moving forward, the system can be further improved through the integration of larger field-level datasets, mobile offline deployment for remote environments, real-time monitoring and alert systems, and advanced interpretability tools such as Grad-CAM to visualize model decision processes. These enhancements would increase the model's reliability, user trust, and overall applicability in diverse agricultural contexts. Ultimately, the research highlights the potential of AI-driven solutions to transform traditional farming practices and support global food security.

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