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| Plant Disease Prediction Using Deep-Learning |

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I. Abstract

***Plant diseases contribute meaningfully to global agricultural production. Early detection and accurate diagnosis are critical in boosting crop yields and global food security. In this paper, we present a lightweight yet efficient deep model that is specifically designed for the classification of plant diseases using the "PlantVillage" dataset. We adopt MobileNetV2, a pre-trained CNN designed for optimized mobile and embedded vision applications. The model uses more than 54,305 images spread across 38 classes and achieves a validation accuracy of 94.32%. MobileNetV2 is enhanced with accelerated training, reduced computational costs, and increased accuracy, making it ideal for utilization in mobile and real-time field applications.***

**Keywords**: *Plant Disease Detection, MobileNetV2, Deep Learning, Convolutional Neural Networks, Image Classification*

# **II. Introduction**

Agriculture is one of the most important contributors to food security worldwide, and reliable crop yields are critical for both economic growth and environmental sustainability. One of the main barriers to agriculture and the creation of sustainable crop yields is the prevalence of plant diseases, which can dramatically decrease both quality and quantity of crops. Disease identification has traditionally relied on human visual inspection by farmers or agricultural professionals, and while these methods are commonly utilized and somewhat effective, they are often labor-intensive, time-consuming, and prone to user error, which can affect applicability to large scale agricultural systems [1, 4].

Recent developments in artificial intelligence (AI) and deep learning have revolutionized plant disease detection and diagnosis with advanced image processing methods. Convolutional Neural Networks (CNNs) have been effective in this type of research for their ability to automatically extract and learn complex hierarchical image features [2, 3, 5, 6]. These deep learning models add a scalable, efficient, and very accurate alternative for manual

inspection, and increase the rate and reliability of disease detection [7, 8].

# This research puts forth a customized lightweight CNN architecture for plant disease classification. The model trained on the PlantVillage dataset consisting of a training set of greater than 43,000 images and a validation set of greater than 10,000 images, across 38 plant-disease categories [9]. This study investigated how well it could perform in real-world scenarios, while demonstrating high accuracy and limited computational cost - both of which are critical when implementing solutions on mobile and web-based agricultural applications [10, 11]. The implications of deep learning to advance innovative technologies in the agriculture domain are discussed and future opportunities in building AI-powered plant health monitoring systems are proposed [12, 13].

# **III. Problem Definition**

Plant diseases are a critical challenge in agriculture, directly impacting crop productivity and quality. The timely identification and treatment of these diseases are crucial to prevent the spread and minimize losses. Traditional detection methods rely heavily on the expertise of farmers and agricultural experts, which can be subjective, error-prone, and inefficient, especially in large-scale farming. Farmers often face difficulties in diagnosing diseases accurately, leading to unnecessary pesticide use, increased costs, and environmental harm.

Existing diagnostic approaches such as microscopic examination and chemical tests are expensive, labor-intensive, and not feasible for widespread application. Moreover, traditional machine learning techniques require manually crafted features, which may not capture the complexity of plant diseases in varying environmental conditions. These limitations highlight the need for more efficient, scalable, and intelligent systems capable of providing precise disease predictions instantly.

Deep learning approaches using Convolutional Neural Networks (CNNs) represent a viable way forward because of their ability to automate the steps of feature extraction and classification of plant images. This would result in no human involvement in the process, a reduction in human error, and increased diagnostic accuracy. The system proposed in this research tackles this by using a custom lightweight CNN model with the potential to classify plant diseases using leaf images at scale for agricultural applications.

**IV. Related Work**

**4.1 ResNet-50 in Plant Disease Detection**

MobileNetV2 has been widely recognized for its efficient performance in various computer vision tasks, including plant disease detection, due to its lightweight architecture and efficient use of resources [8, 10]. Recent studies have highlighted the success of MobileNetV2 in classifying plant diseases, particularly in the context of its application to real-world scenarios where computational resources are constrained, such as mobile devices or edge computing platforms [6, 8].

For instance, “Zhou et al. (2020)” showcased the application of MobileNetV2 in detecting various plant diseases. The model achieved high accuracy, showing that MobileNetV2 is capable of identifying disease patterns in plant leaf images effectively, even with limited computational power [8]. The effectiveness of the model was evaluated based on par with more complex models, but with a significant reduction in size and inference time, making it ideal for mobile applications.

Additionally, Sari et al. (2020) employed MobileNetV2 in a hybrid model combined with transfer learning, achieving remarkable accuracy in detecting plant diseases across different species. This hybrid approach further boosted the model’s accuracy and robustness by leveraging weights that have been previously trained on the ImageNet dataset. The use of MobileNetV2's architecture not only improved classification performance but also minimized the computational burden, providing a scalable solution for large-scale agricultural applications [8, 11].

The adaptability of MobileNetV2 to various datasets and its ability to achieve high accuracy with lower computational demands have made it a promising choice for real-time disease detection systems in agriculture [5]

**4.2 Advancements in Hybrid Models**

Recent research has also focused on hybrid models that combine MobileNetV2 with other architectures or techniques to improve plant disease detection:

**MobileNetV2 + SVM (Support Vector Machine):** A study combined MobileNetV2 with SVM for classifying plant diseases in tomato crops, where the feature vectors extracted from MobileNetV2 were passed to an SVM classifier. This hybrid model achieved an accuracy of 97.8%, outperforming standard CNN models by improving the decision boundaries between different classes of diseases [7].

**MobileNetV2 + Attention Mechanisms:** In a different approach, MobileNetV2 was combined with attention mechanisms to concentrate more on important regions of the plant leaf, such as spots or lesions. This hybrid model performance was superior in precision and recall metrics when detecting their disease symptoms in crops like tomato or maize. The attention mechanism helped the model "disregard" the in-consequential background 'noise' and essentially only focused on the relevant features of importance [12].

**4.3 Application Across Different Crops**

MobileNetV2 has been applied across various crops, demonstrating its versatility in handling different disease detection tasks:

**Tomato**: MobileNetV2 has been used to accurately identify diseases including late blight, early blight, and bacterial spot, with high accuracy rates. It is an excellent choice for disease detection for large-scale tomato farms [5, 8].

**Potato**: Studies have shown that MobileNetV2 effectively detects diseases like “late blight” and “early blight” in potatoes. Its capability to perform well across various potato varieties and environmental conditions has made it a widely used model for potato disease classification [6].

**Rice**: MobileNetV2 has been used in rice farming to detect bacterial leaf blight, brown spot, and rice blast. Its ability to efficiently process images of rice leaves and classify diseases in real-time has led to its deployment in field-level applications [8, 13].

**Apple and Grapes**: MobileNetV2 has been successfully used in the fruit industry for identifying diseases in apples and grapes, particularly for diseases like apple scab and grape downy mildew. These models have been integrated for management in orchards [10].

**5.1 System Architecture**

**A. Dataset Collection**

This model uses the PlantVillage dataset obtained from Kaggle. The PlantVillage dataset has categorized images of healthy and diseased plant leaves for many plant species. The dataset consists of extensive collections of images for training and validation across 38 categories. Image preprocessing techniques, such as resizing, normalization and augmentation, are applied to the images to improve the generalization and robustness of the model. Preprocessing techniques help the model recognize variations in lighting, environments, and leaf appearances.

**B. Feature Extraction withResNet-50**

MobileNetV2, a compact deep learning model tailored for mobile and embedded vision tasks, is employed for feature extraction. MobileNetV2 was chosen because of its efficiency with deep architectures with low computational costs, which is a requirement for a real-time application. Transfer learning was performed using ImageNet pre-trained weights to improve both efficiency and accuracy of the model due to the large amount of data.

**C. Classification & Prediction**

A fully connected layer is incorporated into the MobileNetV2 architecture for classification, the model is trained to predict whether a leaf is healthy or diseased. We use categorical cross-entropy loss function since we have to determine between multiple classes. We also apply the Adam optimizer to speed up convergence and learning

**D. Evaluation & Performance Metrics**

A diagram of a variety of rectangular objects

AI-generated content may be incorrect.

The model is calculated using metrics such as recall and F1-score. These metrics help us make sure the model is not only accurate overall but also in identifying diseased plants. A confusion matrix is used to visualize classification errors, and accuracy/loss curves are plotted to assess performance trends over the epochs. The validation dataset is utilized to check the model's generalization ability.

**E. Deployment & Real-World Application**

Once trained, the model is designed for deployment as either a mobile or web-based application. This allows farmers and agricultural experts to use a simple camera-based system to detect plant diseases in real time. By taking a photo of a plant's leaves, the application processes the image through the trained model and provides an immediate diagnosis, allowing for faster decision-making in managing plant health.

The application can be easily integrated into existing mobile or web platforms, Making it usable for a broad audience, including individuals with limited technical skills. Additionally, the system can be scaled to handle large volumes of images, enabling broader adoption in agricultural fields.

**5.2 Advantages of proposed system**

The system which is proposed offers several advantages that make plant disease detection more efficient and accessible. One of the primary benefits is **automation and speed**, which eliminates the need for manual inspection, providing a faster and scalable solution for detecting plant diseases. Additionally, the system ensures **high accuracy** due to the deep feature extraction capabilities of the custom CNN model, enhancing classification performance and reliability.

Another significant advantage is **cost-effectiveness**, as it reduces dependence on expensive chemical tests and expert consultations, making it a more affordable solution for farmers. The system supports **real-time application**, allowing farmers to detect plant diseases using a simple smartphone or camera-based system, enabling quick and effective disease management in agricultural fields.

**VI. Experiments**

The dataset employed in this experiment was obtained from the “PlantVillage” dataset available on Kaggle , which contains a total of 43,444 images were used for training, and 10,861 images were reserved for validation across 38 plant disease classes. The images were carefully preprocessed to improve model performance and generalization. The preprocessing involved resizing the images to a uniform size, normalization to scale pixel values between 0 and 1, and data augmentation methods including random rotations, flipping, and zooming. These augmentation techniques helped the model learn to handle variations in environmental conditions, camera angles, and lighting, making it more robust.

The custom CNN model underwent training for 20 epochs using a batch size of 32. The Adam optimizer was used for its efficiency in terms of both time and computation. The model’s performance was assessed on the validation set after each epoch.

The model successfully obtained a training accuracy of 90.18% and a validation accuracy of 94.32% after twenty epochs of training, suggesting that it learned and generalized well. This shows strong potential for accurately identifying plant diseases, even on unseen data.

**6.1 Dataset Images**

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**VII. Challenges in Plant Disease Detection**

Despite the high accuracy of DL models like MobileNetV2, “plant disease detection” still faces several challenges that can hinder its practical and scalable implementation. These challenges include data availability, image variability, computational complexity, and overfitting

**7.1 Data Availability and Imbalance**

Deep learning models typically need extensive and varied datasets to effectively generalize across multiple plant species and disease scenarios. While the **PlantVillage dataset** contains a substantial number of images, there still exists a need for more comprehensive data across various plant species, regions, and growing conditions to improve robustness.

**7.2 Image Noise and Variability**

Lighting Conditions: Variations in lighting affect image quality, making it difficult for the model to recognize disease patterns accurately. Occlusions and Leaf Overlapping: Overlapping leaves, background clutter, and external factors can introduce noise, reducing classification accuracy.

## **7.3 Computational Complexity**

## MobileNetV2 and other deep learning models require lots of computation for both training and inference. While training models like these on large data sets, it's likely that many researchers and farmers will leverage high-performance GPUs. Not everyone has access to that type of compute infrastructure. It is possible that limited computing resources can increase or even prevent the ability to train your model.

## Deployment on Edge Devices: Running large models on low-power edge devices (e.g., smartphones, IoT-based systems) remains a challenge due to high memory and processing requirements.

## **VIII. Future Directions**

**8.1 Larger and More Diverse Datasets**

It is important to expand the dataset to include additional species, diseases, and environmental variable levels in order to improve the generalization of the model. A larger dataset would provide more examples for the model to recognize the variability of disease patterns, and how different environments impact plant health.

**8.2 Hybrid and Attention-Based Models**

Combining CNNs with transformers to enhance disease classification accuracy. Utilizing attention mechanisms to highlight critical image regions for better disease identification.

**8.3Real-Time Deployment in Precision Agriculture**

Developing mobile and web applications powered by ResNet-50 for on-the-go plant disease detection. Integrating AI-based disease detection systems with smart farming tools like drones and IoT devices.

**8.4 Edge Computing and Lightweight Models**

Optimizing MobileNetV2 for deployment on low-power IoT devices can allow farmers to perform disease detection without the need for an internet connection. Edge computing enables local inference, making disease diagnosis accessible even in remote agricultural areas with limited connectivity.

**8.5 Explainability and Interpretability**

Enhancing model transparency by incorporating visualization techniques such as Grad-CAM to highlight affected leaf regions. Providing interpretable AI solutions to help farmers and agricultural experts trust deep learning predictions

**IX. Conclusion**

As discussed, using MobileNetV2 for plant disease detection has been a major step forward in automating precision agriculture. Using lightweight, yet powerful architecture, the model exhibited strong performance in classifying a wide variety of plant species and disease classes. Although there were instances where the model misclassified the leaf disease, to have a validation accuracy of 94% shows that the system may have strong potential for successfully identifying and classifying healthy and diseased leafs. Such a high accuracy level does suggest that these types of models may be used reliably in the real-world, particularly in mobile or resource-limited agricultural contexts. These factors alongside dataset availability, computational load associated with model training, and the difficulty in launching models in commercial-sized farming systems are all areas that merits more improvement and research.

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