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Plant Disease Detection Using SqueezeNet and MobileNetV3

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Abstract—The identification of plant diseases is essential for reducing crop loss and promoting sustainable agriculture. This study centers on the categorization of plant diseases with deep learning, namely the lightweight SqueezeNet model, selected for its efficiency and appropriateness for implementation on resource-limited platforms. A bespoke dataset consisting of leaf pictures from five plant species—Tomato, Potato, Pepper, Rice, and Millet—encompassing 19 disease categories was assembled and subjected to preprocessing via image scaling and normalization. The SqueezeNet model was trained and evaluated against other CNN architectures such as MobileNetV3 and ResNet50. Among them, SqueezeNet achieved competitive accuracy while keeping a substantially reduced parameter count, making it appropriate for realworld applications. This project's ultimate objective is to create a web application that enables to use real-time diagnosis of plant diseases using leaf photos. In order to facilitate prompt and well-informed crop management decisions, this solution seeks to provide farmers and agricultural professionals with an easily accessible, precise, and quick diagnostic tool.

Keywords—Deep learning, SqueezeNet, MobileNetV3, ResNet50, Plant Disease Detection.

I. INTRODUCTION

Agriculture forms the backbone of many economies, making crop health vital for ensuring sustainability, food security, and economic growth. However, plant diseases pose a serious threat to agricultural productivity, often resulting in significant reductions in both yield and quality. Detecting these diseases accurately and promptly is crucial to implementing preventive actions and minimizing losses. Traditionally, disease identification has relied on visual examination by farmers or agricultural experts. While common, this approach is often slow, subjective, and difficult to scale across large farming areas, leading to inconsistencies and potential misdiagnosis.

With rapid advancements in artificial intelligence and computer vision, deep learning—particularly Convolutional Neural Networks (CNNs)—has emerged as a powerful approach for image-based classification tasks. This research explores the application of CNNs for the automated detection of plant diseases using leaf images. The primary objective is to recognize various plant diseases that are widespread and have notable economic consequences. To achieve this, the study utilizes SqueezeNet, a lightweight CNN model known for its low memory usage and strong performance. Its compact design makes it well-suited for use on mobile devices, embedded systems, and other low-resource platforms commonly used in agricultural environments, enabling accurate and real-time disease diagnosis. Alongside SqueezeNet, this study also evaluates the performance of MobileNetV3 and ResNet50 models. These architectures are assessed based on several criteria, including computational efficiency, inference speed, and accuracy during both training and testing phases. The research uses a diverse dataset comprising leaf images from five plant types—rice, millet, pepper, tomato, and potato—covering a total of 19 distinct disease categories. After evaluation, SqueezeNet is identified as the best-performing model and is integrated into a Streamlit-based web application. This tool allows users to upload leaf images and receive real-time disease predictions, demonstrating the practical value of the proposed approach. The system is designed to be lightweight and accessible, making it suitable for daily use by farmers, even in areas with limited digital infrastructure. It offers a scalable, efficient, and user-friendly solution to support modern precision agriculture.

II .RELATED WORK

Patil et al. [1] combined GAN-based augmentation with MobileNet to classify Septoria leaf spot disease severity in tomato crops. Their approach leveraged a GAN to synthetically expand the dataset, improving MobileNet's ability to learn severity levels. The model achieved high classification accuracy across multiple severity categories. Results highlight the synergy between data augmentation and lightweight CNNs for crop disease severity estimation in real-world field scenarios. These findings underscore the potential for effective, low-resource deployment in agricultural settings.

Indira & Mallika [2] implemented deep learning models to classify various plant leaf diseases using a tailored CNN framework. They conducted experiments on a publicly available leaf-disease dataset, reporting strong classification performance. The study focused on optimizing the network architecture and preprocessing pipelines to enhance accuracy. Results validated deep learning's applicability in automated plant disease detection with reliable accuracy. The work lays groundwork for further model enhancements toward robust real-time disease identification.

Tarek et al. [3] proposed optimized deep learning algorithms for tomato leaf disease detection with emphasis on deploying the models on hardware platforms. Their study compared model performance across different architectures and deployment frameworks. They achieved fast inference and high detection accuracy while running on edge devices such as NVIDIA Jetson. The findings bridge the gap between lab-scale models and practical field deployment. This research highlights the importance of optimizing models for efficient hardware integration in agro-technology applications.

Gerdan Koc et al. [4] explored the diagnosis of tomato plant diseases using a combination of pre-trained CNNs and a novel custom architecture. They fine-tuned models such as VGG, ResNet, and Inception, and compared them with their proposed compact CNN model. Evaluation on tomato-leaf datasets showed competitive accuracy, with their proposed architecture offering a good trade-off between complexity and performance. The research reinforces the value of designing tailored lightweight models for specific crop disease detection tasks. It provides insight into model architecture selection for agricultural diagnostics.

Vengaiah & Konda [5] reviewed recent deep learning approaches for tomato leaf disease detection, covering around 30 works from 2015–2023. They categorized methods based on CNN architectures, data augmentation techniques, and dataset benchmarks. The review analyzed performance trends, identifying challenges such as class imbalance and limited field data. They suggested future directions including explainable AI, transfer learning, and mobile deployment. Their comprehensive overview offers a roadmap for researchers aiming to develop robust and practical plant disease detection systems.

III. CROP AND DATASET

A. Crop:

This study focuses on five essential agricultural crops: Tomato, Potato, Millet, Rice, and Pepper, each exhibiting various diseases alongside healthy samples. For Tomato, the dataset includes diverse classes such as Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, Early Blight, Late Blight, Septoria Leaf Spot, Leaf Mold, Target Spot, Two-Spotted Spider Mite, Bacterial Spot, and healthy leaves. The Potato class comprises images of leaves affected by Early Blight, Late Blight, as well as healthy conditions. Similarly, the Millet crop includes categories like Leaf Blast, Brown Spot, Rust, and healthy leaves, while Rice covers Bacterial Leaf Blight and healthy samples. The Pepper (Bell Pepper) category consists of Bacterial Spot and healthy leaf images. The inclusion of such a wide range of disease types across multiple crops ensures that the model is trained to identify various plant diseases efficiently and accurately.

B. **Dataset:**

The dataset utilized in this project consists of over 24,000 leaf images, encompassing both healthy and diseased samples from the aforementioned crops. These images are organized into 19 distinct classes, representing different disease and health conditions. To maintain a balanced learning process, the dataset is divided into training (70%), validation (15%), and testing (15%) sets, ensuring proper representation of all classes in each subset. The images were sourced from reputed public repositories, including the PlantVillage dataset, Rice Leaf Disease Dataset, and Millet Crop Health Classification Dataset. This comprehensive and well- annotated dataset allows the CNN models to generalize effectively, enabling robust plant disease detection across a variety of crop types and disease severities.

Figure 1: shows sample images of healthy and diseased leaves from different crops used in this study. Images (a) and (b) represent Pepper leaves affected by bacterial spot and healthy condition. Images (c) to (e) display Potato leaves with early blight, late blight, and healthy samples. The range from (f) to (o) includes various diseases of the **Tomato** plant such as bacterial spot, early blight, late blight, leaf mould, septoria leaf spot, two-spotted spider mite, target spot, yellow leaf curl virus, mosaic virus, along with healthy leaves. Images (p) and (q) belong to **Millet**, showing healthy and blast-affected leaves. Finally, images (r) and (s) depict **Rice** leaves with bacterial leaf blight and healthy conditions.

IV. METHODOLOGY

The proposed methodology for plant leaf disease detection involves a systematic approach that includes dataset preparation, preprocessing, model selection, training, and evaluation. A custom dataset was created by combining three publicly available datasets containing images of healthy and diseased leaves from various crops. The images underwent preprocessing to ensure consistency in size and pixel values before being used to train the SqueezeNet model. Transfer learning techniques were applied to fine-tune the model, and its performance was evaluated using standard classification metrics to ensure reliability and accuracy in disease detection.

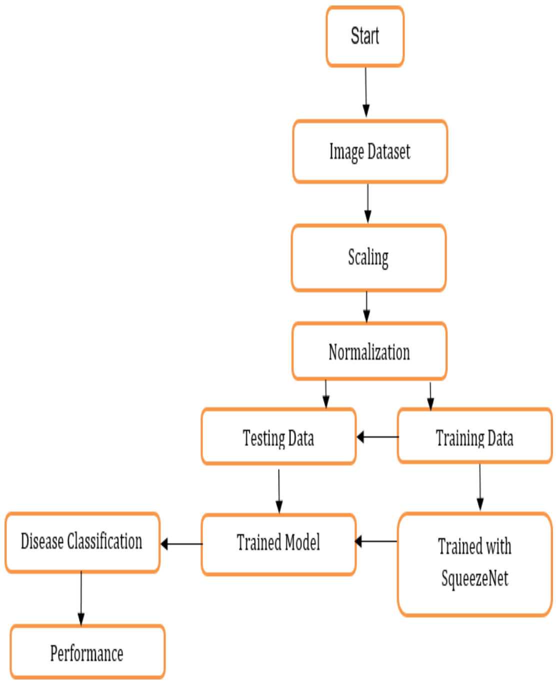

Figure 2: Methodology Block Diagram

A. Deep Learning Models

1. SqueezeNet:

SqueezeNet is a lightweight CNN designed for high accuracy with a minimal number of parameters, making it suitable for devices with limited resources. Its core component, the Fire module, consists of a squeeze layer with 1x1 convolutions and an expand layer with 1x1 and 3x3 convolutions, effectively reducing model size while retaining performance. Global average pooling and softmax layers are used for final classification.

2. MobileNetV3

MobileNetV3 is a highly efficient deep learning architecture designed specifically for mobile and edge devices.It incorporates depthwise separable convolutions, squeeze-and-excitation (SE) modules, and a streamlined design to balance accuracy with computational efficiency. This lightweight model enables fast inference and minimal memory usage, making it well-suited for real-time plant disease detection applications.

3. ResNet50

ResNet50 is a powerful deep learning model known for its deep architecture and residual learning framework. It utilizes skip connections to overcome the vanishing gradient problem, allowing for the effective training of very deep networks. With 50 layers, ResNet50 achieves high accuracy in image classification tasks while maintaining reasonable computational efficiency. Its robust feature extraction capabilities make it suitable for tasks such as plant disease detection, even in complex and high-resolution datasets

V. RESULTS AND DISCUSSION

A. Training Results (Summary)

In this study, SqueezeNet, MobileNetV3, and ResNet50 models were trained and evaluated for plant leaf disease classification using the prepared dataset. The training process was conducted in a CPU environment using Visual Studio Code. All models were trained over 30 epochs with a standard 70:15:15 data split for training, validation, and testing.

SqueezeNet Model:

SqueezeNet achieved a training accuracy of 99.48% by the 25th epoch with a total of 1906728 trainable parameters. The model showed quick convergence with a steady drop in loss and a consistent rise in accuracy, demonstrating efficient learning suitable for real-time applications.

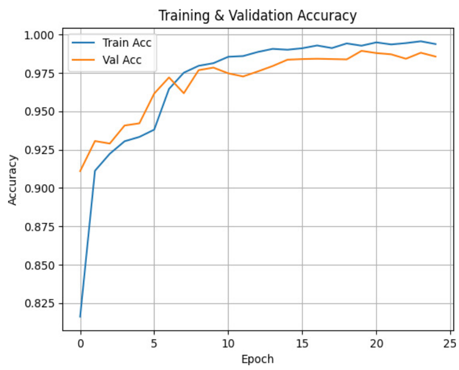

Figure 3: Accuracy Graphs for SqueezeNet model

The training curves of the SqueezeNet model show a rapid decrease in loss and a steady increase in accuracy across 25 epochs. This reflects effective learning and good convergence without overfitting.

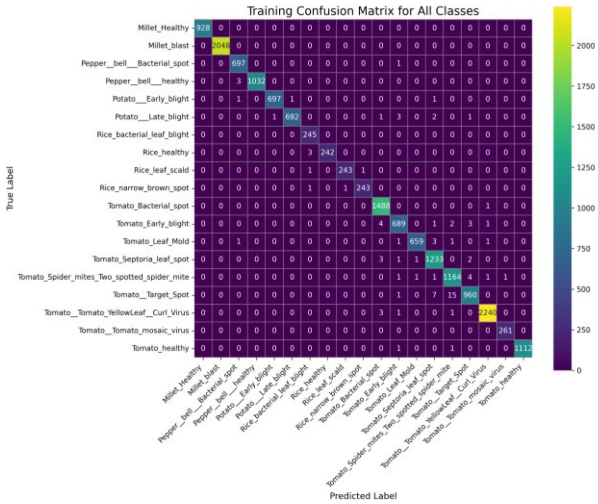

Figure 4: Confusion Matrix for SqueezeNet model

The model accurately classified 16,960 samples across all 19 classes, effectively distinguishing between both healthy and diseased leaves. It showed high precision in identifying multiple plant diseases and healthy conditions, demonstrating strong generalization and reliability in plant disease detection

MobileNetV3 Model:

MobileNet reached a maximum training accuracy of 99.67% at epoch 24 with 3873808 trainable parameters. The model exhibited rapid improvement in early epochs and maintained low loss values, indicating stable and efficient training performance.

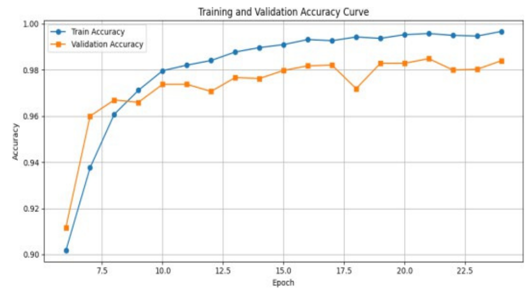

Figure 4: Accuracy For MobileNetV3 model

The MobileNetV3 model shows a rapid decline in training loss and a sharp rise in accuracy during the initial epochs. It achieves stable convergence with high accuracy, indicating effective learning without overfitting.

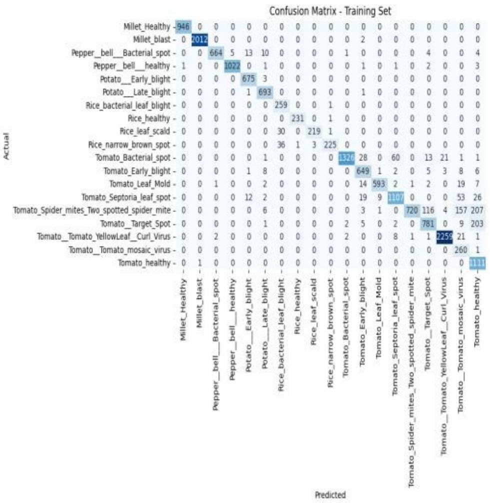

Figure 5: Confusion Matrix for MobileNetV3 model

The dataset contains 15752 images across 19 plant disease and healthy classes, with Tomato Yellow Leaf Curl Virus and Millet Blast having the most samples. Some rice-related classes have fewer images, causing minor imbalance, but overall, the dataset remains diverse enough to ensure effective model training and generalization.

ResNet50 Model:

ResNet50 recorded the highest training accuracy of 99.20% at epoch 14 with 48614376 trainable parameters. The model showed reliable learning behavior, though with a higher parameter count, making it more resource-intensive compared to SqueezeNet and MobileNet.

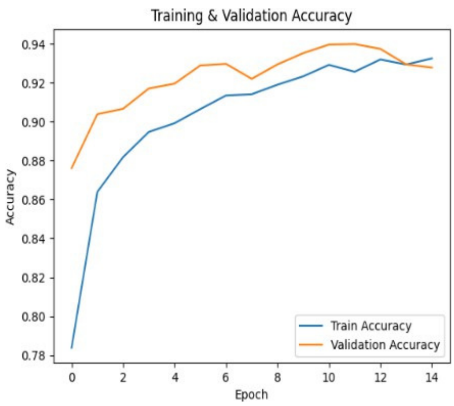

Figure 4.9: Accuracy for ResNet50 model

The ResNet50 model shows a steady decrease in training loss with a rapid rise in accuracy during early epochs. The model converges well, ensuring reliable and accurate predictions without overfitting

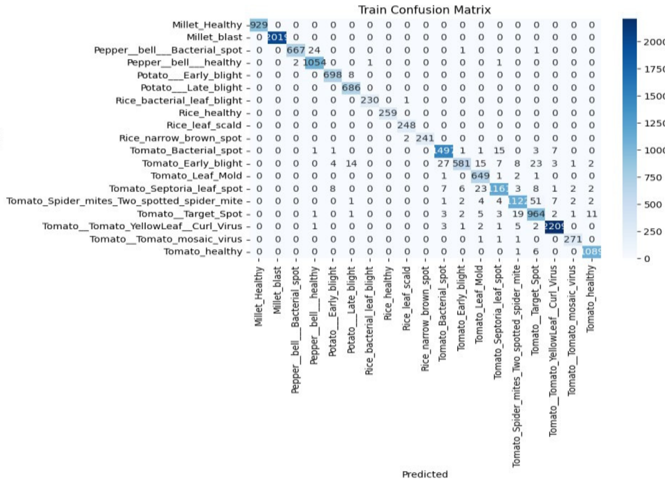

Figure 6: Confusion Matrix for ResNet50 model

The training dataset includes 15,432 images across 19 classes, with Tomato Yellow Leaf Curl Virus, Millet Blast, and Tomato Bacterial Spot being the most represented. Rice disease classes have fewer samples, but the dataset remains sufficiently diverse for effective model learning and classification.

Overall SqueezeNet and MobileNetV3 outperformed ResNet50 in terms of training efficiency and computational cost, confirming their suitability for deployment in resource-limited environments.

B. Comparison of Training Results:

comparative analysis of training results of three deep learning models considered as SqueezeNet, MobileNetV3 and ResNet50, each set with a maximum of 30 epochs along with early stopping. The evaluation is based on four primary metrics: training accuracy, training loss, the total number of trainable parameters. This comparison highlights the balance between model performance and computational efficiency, helping to illustrate the strengths and limitations of each architecture. Among the three, SqueezeNet emerged as the most efficient model, achieving the highest training accuracy of 99.48% with a minimal loss of 0.0167. It accomplished this using only 1956200 total parameters, significantly fewer than the other models. This lightweight structure directly contributes to its faster training time and low memory footprint, making it especially suitable for deployment in **real-** time agricultural applications such as mobile or edge-based plant disease detection systems

Table 1: Comparison of Training results of Deep learning models

Models	SqueezeNet	MobileNetV3	ResNet50
Total Epochs	25	24	14
Accuracy	99.48%	99.67%	99.20%
Loss	0.0167	0.0539	0.0770
No.of parameters	19,56200	38,73808	49,055528

C. Testing Results (Summary):

The **SqueezeNet model** demonstrated excellent classification accuracy, correctly predicting both healthy and diseased classes across 19 categories, achieving an overall accuracy of **98%**. It effectively distinguished between similar disease classes, as reflected in its strong confusion matrix and classification report.

The **MobileNet model** also performed exceptionally well with an accuracy of **99%**, maintaining high precision and recall across most classes. Slight misclassifications were observed in a few rice disease categories due to class similarities, but overall robustness remained high.

The **ResNet50 model** achieved a commendable accuracy of **97.72%**, showing reliable classification across most classes. However, minor misclassifications occurred in visually similar tomato disease categories. Despite this, the model maintained balanced performance, supported by a high F1-score and an informative confusion matrix.

Table 2: Comparison of Testing results of Deep learning Models

Models	SqueezeNet	MobileNetV3	ResNet50
Accuracy	98%	99%	97.72.%
Precision	0.99	0.92	0.93
Recall	0.99	0.92	0.93
F1-score	0.99	0.91	0.93

As shown in Table 2, SqueezeNet achieved an accuracy of 98%, which is slightly lower than MobileNetV3 (99%) but with a much lighter architecture, making it more suitable for deployment.. Although SqueezeNet exhibited slightly lower precision and recall, its lightweight architecture makes it highly suitable for deployment on resource-constrained devices. This demonstrates that SqueezeNet offers an excellent balance between performance and efficiency, making it a strong candidate for real-time plant disease detection.

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