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Peach Leaf Disease Identification Using Image Processing Techniques

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***Abstract*— To preserve orchard health and maximize yield, peach leaf diseases must be accurately and promptly detected. Manual inspection is frequently used in traditional disease diagnosis techniques. In this study, we propose a comparative analysis of three state-of-the-art deep learning models—VGG16, MobileNetV2, and ResNet—for classifying peach leaves as either healthy or infected with bacterial disease. These models were trained and assessed using an entire dataset of peach leaf photos. The models were fine-tuned and optimized to enhance their performance in accurately identifying diseased leaves. Experimental results demonstrate that the ResNet model achieved the highest accuracy of 99.02%, 95.41% by VGG16 and MobileNetV2 at 95.65%. The proposed deep learning approach offers a highly accurate and efficient solution for automated peach leaf disease detection, enabling early intervention and effective disease management strategies.**

***Index Terms*— Peach leaf disease detection, Deep learning, VGG16, MobileNetV2, ResNet, Image classification.**

I. INTRODUCTION

Peach cultivation, a significant economic activity, faces the persistent threat of diseases like bacterial spot, brown rot, and leaf curl [1], [2]. These diseases can severely compromise peach tree health, leading to reduced yield, diminished fruit quality, and ultimately, significant financial losses for farmers [3]. Traditional disease detection methods, often manual and reliant on expert knowledge, are time-consuming, prone to human error, and hindered by the subtle visual distinctions between diseases [4], [5]. This difficulty calls for a more effective and precise method of early illness identification [6].

The aim of this project is to build a strong machine learning model that can precisely detect peach leaf diseases in order to address this urgent problem [2], [7]. By leveraging advanced image processing and deep learning techniques, the model will analyse digital images of peach leaves to distinguish between healthy and diseased specimens, as well as classify specific diseases [8]. This automated solution will empower farmers and agricultural experts to make timely and informed decisions regarding disease management strategies [9].

The proposed model will be trained on a diverse dataset comprising images of healthy peach leaves and leaves infected with bacterial spot, brown rot, and leaf curl [3], [10]. By learning to recognize the unique visual patterns associated with each disease, the model will be capable of accurately classifying new, unseen images [11]. This early detection capability will enable farmers to implement preventive measures, such as targeted pesticide applications or cultural practices, to minimize disease spread and maximize crop yield [12].

The successful development and implementation of this machine learning model will have a profound impact on peach cultivation. By providing a reliable and efficient tool for disease diagnosis, the model will contribute to sustainable peach production, reduce economic losses, and enhance the overall quality and quantity of peach harvests [13], [14].

II. LITERATURE REVIEW

A. Traditional Disease Detection Methods

Traditional methods for detecting peach leaf diseases predominantly rely on visual inspection by human experts [4], [5]. This approach involves carefully examining peach leaves for any signs of disease, such as discoloration, spots, lesions, or distorted growth [3]. While experienced horticulturists can often identify common diseases with reasonable accuracy, this method is inherently subjective and can be influenced by factors like lighting conditions, leaf maturity, and the expertise of the inspector [13].

In addition to visual inspection, more advanced techniques like microscopic examination and laboratory tests can be employed [9], [15]. Microscopic examination allows for a closer look at fungal spores, bacterial colonies, or viral particles on the leaf surface [16]. However, this method requires specialized equipment and technical expertise [17]. Although they can yield conclusive results, which are most frequently costly and time-consuming [5].

B. Deep Learning for Disease Detection

When dealing with subtle symptoms or early-stage

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infections, traditional methods for peach leaf disease detection frequently rely on expert manual inspection, which can be laborious, intuitive, and prone to human error [4], [6]. This limitation can lead to delayed diagnosis and ineffective disease management strategies [2].

A potential remedy for these issues is deep learning, especially convolutional neural networks (CNNs) [7], [18]. CNNs are properly designed for image classification tasks and can be trained on large datasets of healthy and diseased leaf images to learn to recognize patterns and features associated with specific diseases [19]. By analysing the pixel-level information in images, CNNs can accurately identify subtle visual cues that may be difficult for human experts to detect [20].

When compared to conventional methods, this automated approach has a number of advantages. It can be used for extensive disease screening and is quicker and more objective [1], [3]. Early detection enabled by deep learning models can lead to timely intervention, reducing disease spread and minimizing crop losses [8]. Additionally, these models can be easily deployed on mobile devices, empowering farmers to make informed decisions in the field [10].

C. Related Work

Many studies have traversed the benefits of deep learning techniques, especially convolutional neural networks (CNNs), for detecting plant diseases [1], [7], [20]. These studies have consistently demonstrated the effectiveness of CNNs in accurately identifying a wide range of plant diseases, including those that affect peach trees [2], [19].

Utilizing transfer learning to improve CNN models' performance for plant disease detection has been the subject of a substantial amount of research [3], [6], [18]. By utilizing pre-trained models, such as VGG16 and ResNet, which have been trained on massive image datasets, researchers can fine-tune these models on smaller, disease-specific datasets to achieve high accuracy [7], [9]. This method speeds up the creation of precise disease detection models and drastically lowers the quantity of training data needed [8].

Furthermore, recent research has explored the potential of real-time disease detection using mobile devices [10], [17], [21]. By deploying deep learning models on mobile devices, farmers can capture images of their crops and receive immediate disease diagnoses [16]. This technology has the capacity to extravagent agricultural practices by enabling early intervention and preventive measures [13].

Another research to improve aspect-based sentiment analysis (ABSA), this work suggests a cross approach that combines systematic techniques and a graph-theoretic model to handle polarity shifts with **"Latent Dirichlet Allocation (LDA) and Probabilistic Latent Semantic Analysis (PLSA)"** for aspect extraction. On SemEval 2014 datasets, experimental results demonstrate notable performance gains, outperforming baseline methods with high accuracy and F1 scores [24]. Another study introduces the Simplex Method-based Social Spider Optimization (SMSSO) technique, which outperforms other approaches in terms of prediction accuracy on medical datasets when paired with neural networks [25]. Another study for pattern categorization, this study investigates rule taken out from Radial Basis Functional Neural Networks (RBFNN) trained with Particle Swarm Optimization (PSO). PSO-trained RBFNN achieves effective generalization with less training time, according to simulation results on the PAT, WBC, and IRIS datasets [26].

III. METHODOLOGY

A. Dataset

A robust dataset comprising 4025 peach leaf images was meticulously curated from the PlantVillage dataset on Kaggle. This dataset is a valuable resource for developing and evaluating computer vision models for peach leaf disease detection.

The dataset encompasses two primary classes:

1. **Healthy leaves:** 1728 images representing healthy peach leaves.
2. **Diseased leaves:** 2297 images showcasing peach leaves infected with bacterial disease.

This diverse dataset offers a wide range of leaf variations, disease severities, and imaging conditions, making it acceptable for training and testing machine learning models. The availability of such a comprehensive dataset is crucial for advancing research in plant disease diagnosis and enabling early intervention strategies.

B. Preprocessing

The dataset was preprocessed in a number of ways to guarantee the best possible performance from the deep learning models. The 224x224 pixel standard was applied to all images in order to comply with the input specifications of the selected architectures. Several data augmentation methods, such as noise addition, flipping, and random rotation, were used to enhance the dataset and enhance model generalization. In order to improve model training efficiency and enable consistent input processing, pixel values were also normalized to a predetermined range, usually 0-1. These preprocessing procedures were essential for getting the dataset ready for efficient model training and precise disease detection that followed.

C. Model Selection

A careful choice of deep learning architectures is essential to solving the peach leaf disease detection task. Three cutting-edge models were selected for this investigation: VGG16, MobileNetV2, and ResNet.

1) VGG16:

A well-known convolutional neural network (CNN) for its simplicity and depth is VGG16. It uses a max-pooling layer

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after each layer in a stack to gradually withdraw more complex structures from the input images. Because of its depth, the architecture can accurately classify diseases by capturing subtleties and complex patterns in the leaf images. Its depth does, however, also contribute to a large number of parameters, which may result in longer training times and increased computational costs.

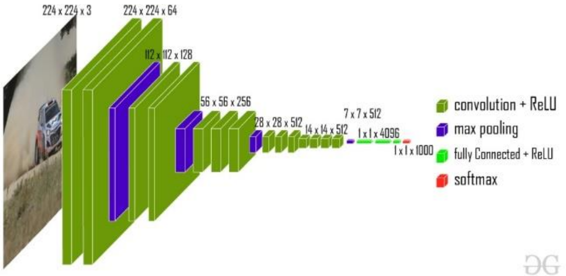

Fig. 1. VGG16 Model Architecture

2) MobileNetV2

A lightweight CNN architecture called MobileNetV2 was created especially for embedded and mobile devices. It makes use of depth wise separable convolutions, a method that splits conventional convolutions into pointwise and depth wise convolutions. Without sacrificing performance, this method drastically lowers the number of parameters and computational expense.

Because of its effectiveness, MobileNetV2 is a great option for real-time applications like on-device disease detection.

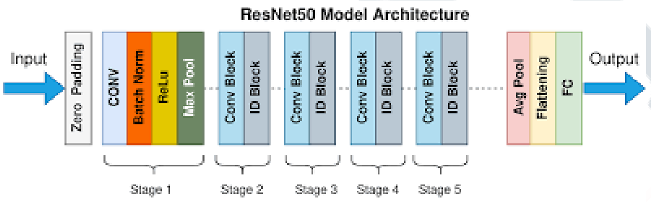

Fig. 2. MobileNetV2 Model Architecture

3) ResNet:

The vanishing gradient issue, which can make deep network training challenging, is addressed by the potent CNN architecture known as ResNet, or Residual Network.8. ResNet uses residual connections, which enable data to move straight from earlier layers to later layers, to address this problem. The network can efficiently train deeper architectures and learn more intricate representations thanks to these connections. ResNet is ideally suited for tasks like image classification, where it is crucial to capture subtle visual differences, due to its capacity to learn deep representations. Our goal is to determine the best architecture for precise and effective disease detection by assessing these models' performance on the peach leaf disease dataset.

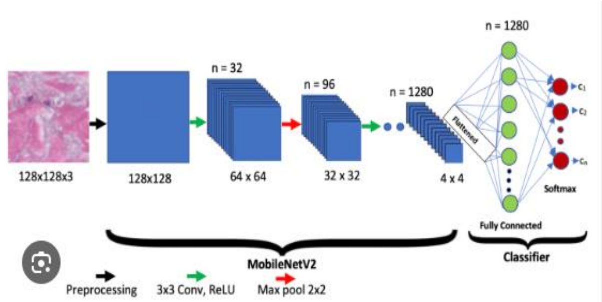

Fig. 3. ResNet Model Architecture

D. Training Process

Dataset loading: For effective training, the dataset was pre-processed and split into batches. To enable seamless input processing during training, each batch contained a collection of images along with the labels that went with them.

Data Augmentation: Rotation, zooming, width/height shifts, and flips were used to augment the training data in order to improve model generalization. Data used for testing and validation were normalized without any augmentation.

Model Building: A pre-trained deep learning model (MobileNetV2, VGG16, or ResNet) was used as the base, with the top layers removed. A custom classifier with a Global-Average-Pooling layer, dense layers, and SoftMax output added.

Compilation: The Adam optimizer was used to compile the model, with clear-cut logarithmic loss serving as the loss function and a learning rate of 0.001. The evaluation metric that was employed was accuracy.

Model Training: For a predetermined number of aeras, the model was skilled using the extended training set. In order to track performance and make sure the model generalizes well to new data, validation data was used during training.

Evaluation: Using confusion matrices and classification reports, the model was assessed on a test dataset following training in order to compute metrics like accuracy, loss, and class wise performance.

Training Insights: Over epochs, performance trends were tracked, including training and validation accuracy/loss. To enhance model performance, these insights directed changes to the architecture or hyperparameters.

The objective of this training process was to attain high accuracy in identifying peach leaf images as either healthy or diseased by iteratively fine-tuning the model's parameters.

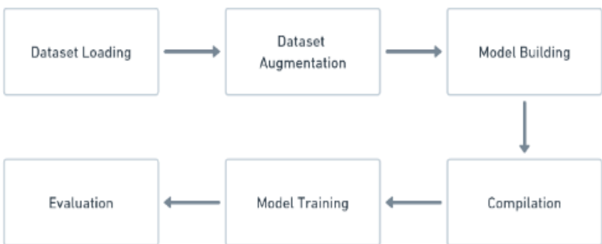

Fig. 4. Flow Chart of Training Procedure

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E. Evaluation Metrics

To evaluate the efficiency of the deep learning models in accurately classifying peach leaf diseases, a combination of evaluation metrics was employed.

1) **Accuracy:** Accuracy is the most important metric that defines the correctly classified occurrences i.e. both true positives and true negative among the total number of instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2) **Recall:** Recall measures the aptitude of the model to find actual positive cases from total cases. It is also called Sensitivity and it is formulated by.

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

3) **Precision:** The metric Precision is defined as the predicting actual positive cases from the cases which were already positive.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

4) **F1-Score:** F1 score is a corrective way to measure how good the model is by finding harmonic mean of Precision and Recall.

$$F1 = \frac{1}{\frac{1}{Recall}+\frac{1}{Precision}} \quad (4)$$

Confusion Matrix: This tabular representation offers a thorough analysis of both accurate and inaccurate classifications. It facilitates the visualization of the model's performance by grouping predictions into four groups:

a. Diseased leaf that is accurately identified as such is known as a True Positive (TP).
b. True Negative (TN): A leaf that is healthy is appropriately categorized as such.
c. A healthy leaf that is mistakenly identified as diseased is known as a false positive (FP).
d. False Negative (FN): A sick leaf that was mistakenly identified as healthy.

We can pinpoint specific areas where the model might be having trouble, like incorrectly classifying particular disease types or finding it difficult to discern between minute variations in leaf appearance, by examining the confusion matrix.

ROC Curve: It plots the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings graphically.

a. **True Positive Rate (TPR):**

$$TPR = \frac{TP}{\mathrm{TP+FN}} \quad (5)$$

b. **False Positive Rate (FPR):**

$$FPR = \frac{FP}{\mathrm{FP+TN}} \quad (6)$$

The area under the ROC curve, offers a thorough assessment of the model's overall effectiveness. Better discriminatory power is indicated by a higher AUC-ROC value. We can evaluate the model's capacity to discriminate between diseased and healthy leaves at various sensitivity and specificity levels by looking at the ROC curve.

IV. RESULTS

The assessment also examined the efficacy and accuracy of deep learning models, namely ResNet and VGG16, in categorizing peach leaf illnesses. Through the use of transfer learning, the peach leaf dataset was used to optimize these models demonstrating their capacity to extract significant features for precise and identifiable classification. Their performance demonstrates the advanced convolutional neural networks' versatility and architectures for dealing with plant disease issues detection.

The effectiveness of the deep learning models ResNet, VGG16, and MobileNetV2 in categorizing peach leaf images into "Diseased" and "Healthy" categories is explained and elaborated in the performance evaluation. As demonstrated in Figures 5 and 7, the ResNet model produced a satisfactory accuracy of 99.02% with a precision of 0.99, and its robust and consistent performance was demonstrated by the F1 scores and recall values for both the "Diseased" and "Healthy" classes, which were 0.9900.

As seen in Figures 5 and 8 VGG16 performed well on all metrics, including accuracy, precision, recall, and F1 score of 0.95 for the "Diseased" and "Healthy" classes. This demonstrates its exceptional capacity to discriminate between the categories with flawless accuracy.

With a precision of 0.93 and recall of 1.0 for the "Bacterial" class, MobileNetV2 a model with less complexity, also demonstrated impressive performance, yielding outcomes such as an F1 score of 0.96 and a correctness of 0.96. As seen in Figures 5 and 6 the 'Healthy' class attained an accurateness of 95.65%, a precision of 1.0, a recall of 0.9, and an F1 score of 0.95. These findings demonstrate the versatility and promise of these cutting-edge deep learning architectural models in the identification of plant diseases, with each model exhibiting distinct visual strengths appropriate for various scenarios.

In agriculture, AI/ML plays a vital role in facilitating early disease detection and enhancing crop management, as this study affirms. According to the results, model selection may also be enhanced and better optimized depending on the degree of precision needed and the resources available.

Table 1: Tabular Representation of Outcomes from the Model

RESULTS	MODELS		
	ResNet	**VGG16**	**MobileNetV2**
F1 score	0.99	0.95	0.96
Accuracy	99.02%	95.41%	95.65%
Precision	0.99	0.96	0.93
Recall	0.99	0.95	0.90

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A. Confusion Matrix

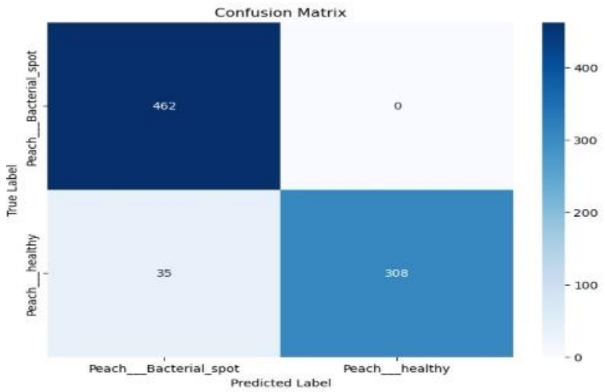

Fig. 5. Confusion Matrix of MobileNetV2 Model

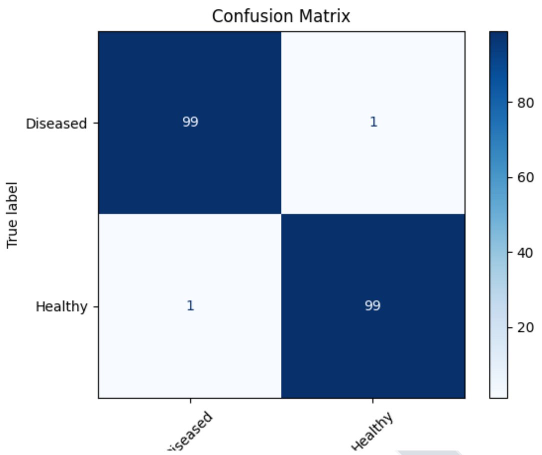

Fig. 6. Confusion Matrix of ResNet Model

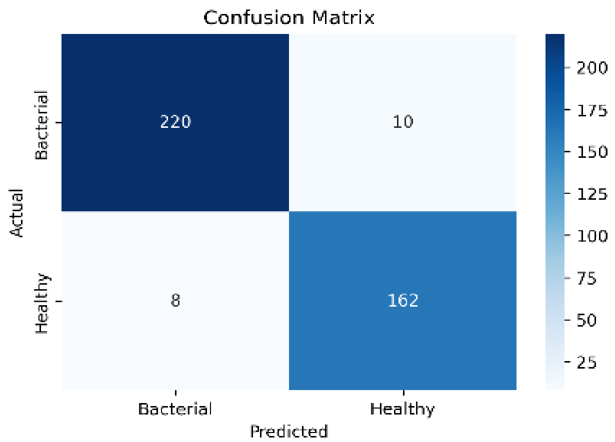

Fig. 7. Confusion Matrix of VGG16 Model

All the above Confusion Matrices are generated by splitting the data into training (64%), validation (16%), and testing (20%).

B. ROC(Receiver Operating Characteristic) Curve

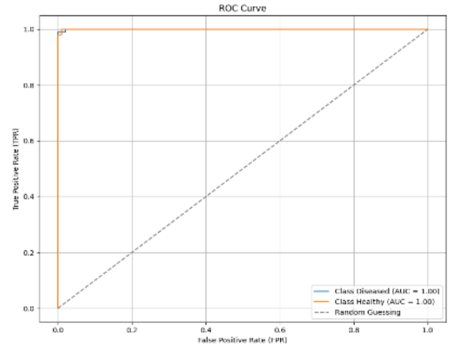

Fig. 8.ROC Curve of ResNet Model

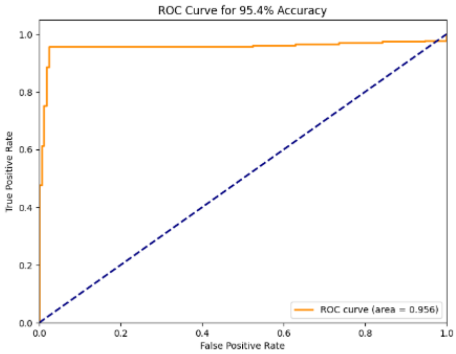

Fig. 9. ROC Curve of VGG16 Model

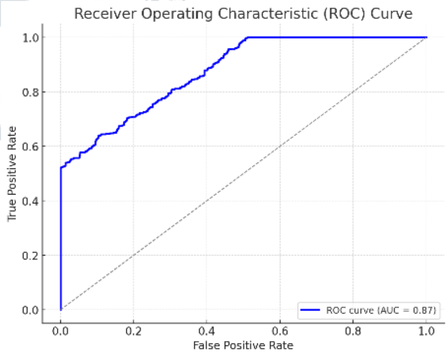

Fig. 10. ROC Curve of MobileNet Model

V. CONCLUSION AND FUTURE WORK

This study successfully implemented and compared trio up-to-the-minute deep learning models—VGG16, MobileNetV2, and ResNet—for the recognition of peach leaf diseases. The models were qualified and evaluated on a inclusive dataset of peach leaf pictures, showcasing high performance. ResNet attained the highest exactness of 99.02%, trailed by MobileNetV2 at 95.65%, and VGG16 at 95.41%.

This research contributes significantly to plant disease detection by proposing accurate deep learning models for early disease identification, enabling effective management strategies. The automated nature of this approach reduces manual labour, saves time, and enhances agricultural practices, expanding the application of deep learning in agriculture.

While the models show promising results, there are several avenues for future research. Model optimization techniques can be explored to further improve accuracy and efficiency. Real-time detection systems using mobile devices or edge computing can enable rapid on-site diagnosis. Expanding the dataset to include multiple diseases can allow for the development of models capable of detecting various diseases simultaneously. Additionally, integrating remote sensing techniques can facilitate large-scale disease monitoring and early warning systems.

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