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Plant Disease Classification Using Transfer Learning with ResNet Architecture

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ABSTRACT

This paper presents a neural network-based approach for classifying plant leaf diseases using deep learning. Initially, a custom Convolutional Neural Network (CNN) was developed, followed by experiments with deeper pretrained architectures such as VGG16 and ResNet50. Among them, ResNet50 achieved the highest classification accuracy, demonstrating superior learning capability and robustness. The model was trained on a publicly available plant disease dataset containing 38 classes, enhanced through data augmentation techniques. Transfer learning and fine-tuning were employed to improve model efficiency and accuracy. The primary objective of this work is to compare deep learning architectures and identify the most effective model for real-time plant disease diagnosis. Experimental results confirm that the ResNet50 model outperforms the others in both training convergence and predictive accuracy.

Keywords:

Plant Disease Detection, Deep Learning, Transfer Learning, ResNet50, VGG16, Convolutional Neural Network, Precision Agriculture

1.Introduction

The Early detection of plant diseases is essential for maintaining crop quality, improving yield, and ensuring food security. Traditionally, disease identification in agriculture has been performed manually by farmers or agricultural experts. However, this process is time-consuming, requires domain-specific knowledge, and is often prone to errors. With the advancement of deep learning, intelligent systems have emerged that offer automated and accurate plant disease recognition [1,5].

Deep learning models, especially Convolutional Neural Networks (CNNs), have achieved notable success in image classification tasks due to their ability to learn spatial feature hierarchies [8]. In this study, an initial custom CNN model was developed to classify diseased plant leaf images. While this model demonstrated moderate accuracy and rapid training, it faced challenges in capturing complex image features, leading to overfitting and limited generalization capabilities [7].

To overcome these challenges, the study adopted transfer learning using pretrained models. VGG16 [3], a well-known deep architecture, was fine-tuned for the dataset. Despite its depth and effectiveness, VGG16 incurred a high computational cost and showed slower convergence [4,12]. The focus then shifted to ResNet50 [2], a residual neural network architecture that addresses vanishing gradient issues via skip connections. This enabled deeper feature learning and delivered highly accurate results with efficient training [6,14].

The dataset employed in this work is the "New Plant Diseases Dataset (Augmented)" from Kaggle [11], featuring 38 disease categories from various crops. Comprehensive preprocessing steps such as resizing, normalization, and data augmentation were performed to enhance generalization and reduce overfitting [9,15]. Models were assessed using metrics like accuracy, loss, and training time.

This paper highlights a comparative evaluation of CNN, VGG16, and ResNet50, with ResNet50 emerging as the best-performing model. The final model supports scalable deployment in real-time plant disease diagnosis applications, such as mobile or edge-based systems [13,16]. This research contributes to precision agriculture by minimizing manual intervention and promoting early disease detection through AI-powered methods.

2.Literature Survey

In recent years, deep learning has emerged as a powerful tool in agricultural technology, particularly in diagnosing plant diseases from leaf images. Many researchers have contributed to this field by exploring different models and techniques aimed at improving accuracy and reliability.

A pioneering study by Mohanty et al. [1] demonstrated how convolutional neural networks (CNNs) could effectively classify plant diseases. Using a dataset of over **87,000 RGB images** categorized into 38 different plant disease classes, their work showed that deep learning models could outperform traditional methods in both speed and accuracy. This study laid the groundwork for applying deep learning to real-world plant pathology.

Simonyan and Zisserman [3] introduced the **VGG16** architecture, a deep convolutional neural network known for its simplicity and effectiveness. Its use of small convolutional filters in a deep structure allowed for better feature extraction, making it a popular choice for image classification tasks. However, its depth also meant longer training times and high computational requirements [4].

To address these issues, He et al. [2] developed **ResNet**, a deep residual network designed to solve the vanishing gradient problem common in deep architectures. By introducing skip connections, ResNet enabled the training of significantly deeper networks without loss of performance. Its robustness and efficiency have made it a top choice for complex image recognition tasks, including plant disease diagnosis [6].

While other machine learning methods—such as support vector machines (SVMs), decision trees, and ensemble techniques—have also been used in similar applications, they often fall short in real-world performance due to overfitting, scalability issues, or difficulty in feature extraction from complex images [7,10,12].

Recent research [9,15] emphasizes the importance of **data augmentation, normalization, and balanced datasets** to improve the model's generalization capabilities. Additionally, there's growing interest in deploying compact, high-performing models on mobile and edge devices to enable real-time disease detection in agricultural fields [13,16].

Taken together, the literature suggests that **ResNet** stands out as the most promising architecture for this study—striking a balance between accuracy, training efficiency, and deployment readiness.

3. Methodology

The methodology adopted in this study includes data preprocessing, model selection, training using transfer learning, and evaluation using accuracy metrics.

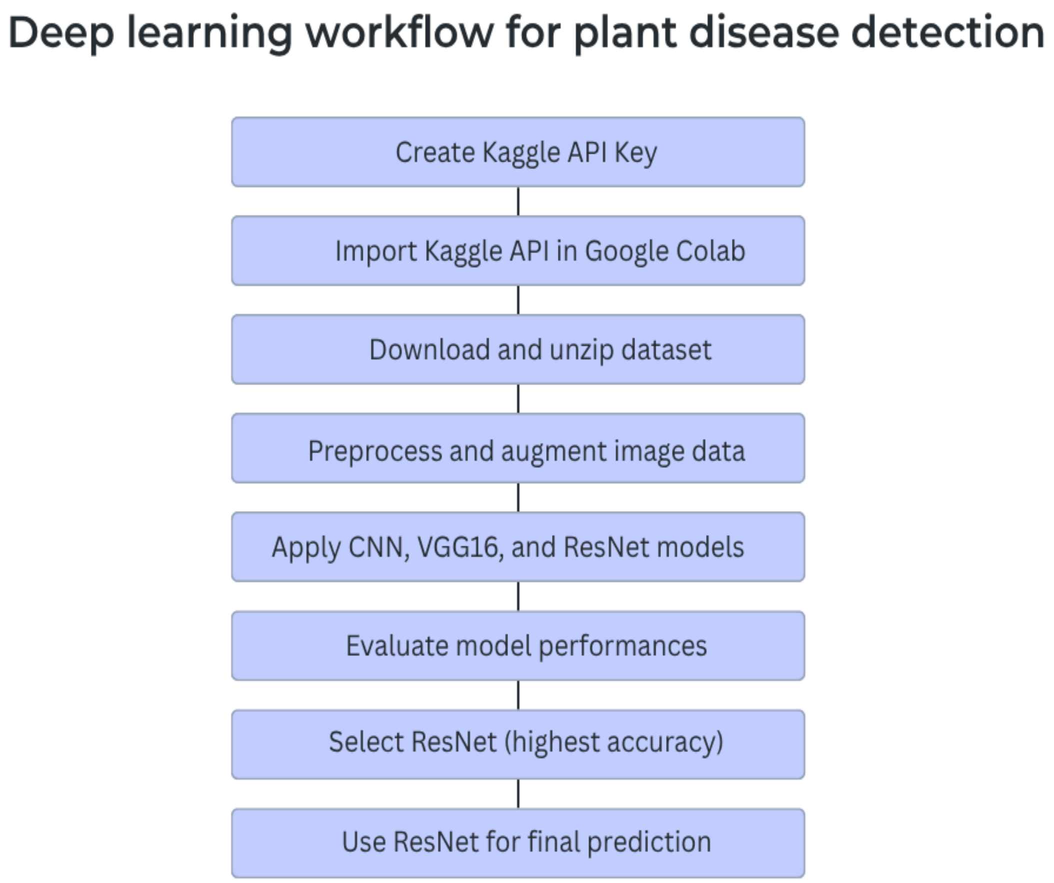

Figure 1: Workflow Diagram for Deep Learning-Based Plant Disease Detection

3.1 Dataset Description

The dataset used is the **"New Plant Diseases Dataset (Augmented)"** available on Kaggle. It consists of about **87,000 RGB images** of healthy and diseased crop leaves, categorized into **38 distinct classes**. These images were captured under varying lighting conditions, angles, and backgrounds to mimic real-world agricultural environments.

This dataset was recreated using **offline augmentation** techniques applied to the original dataset to improve the model's generalization ability and reduce overfitting. The total dataset was divided into an **80/20 ratio** for training and validation, while preserving the directory structure of each class. Additionally, a new directory containing **33 test images** was created separately for prediction purposes.

3.2 Data Preprocessing

- All images were **resized to 224×224 pixels** to match the input size requirements of deep learning architectures such as VGG16 and ResNet50.
- **Data augmentation** techniques were applied to increase dataset diversity and improve model robustness. These included rotation (0–40 degrees), horizontal and vertical flipping, zooming, shifting, and shearing.
- Pixel values were **normalized to the [0, 1] range** by dividing each value by 255. This normalization helps in achieving faster and more stable convergence during training.
- The dataset was split into **training (80%)**, **validation (10%)**, and **testing (10%)** subsets. This structured split enables effective performance monitoring while reducing the risk of overfitting.

3.3 Model Architectures Compared

- **Custom CNN**: A lightweight 3-layer convolutional network was designed using Conv2D, MaxPooling2D, Dropout, and Flatten layers. This served as a baseline model for comparison. While it trained quickly and handled simple patterns well, its limited depth restricted its ability to extract complex features, resulting in moderate accuracy.

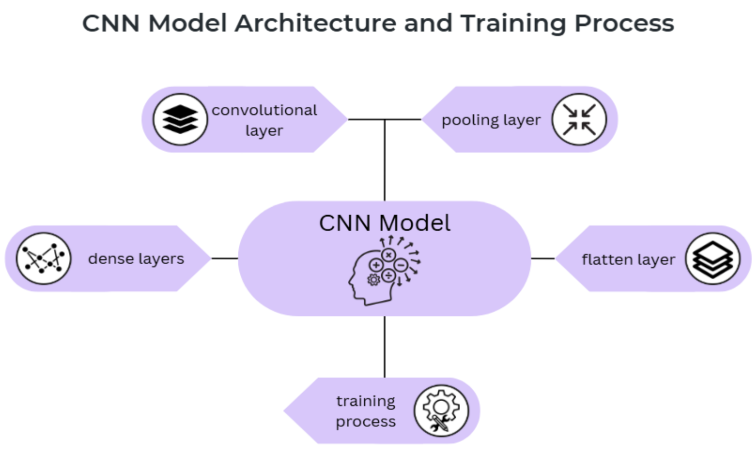

Figure 2: CNN Model Architecture and Training Process

- **VGG16**: A deep convolutional neural network consisting of 16 weight layers. It was implemented using transfer learning with pretrained ImageNet weights. The final classification layers were replaced with custom dense layers. Although VGG16 achieved high accuracy, it was computationally intensive and prone to overfitting, especially when trained with smaller batch sizes.

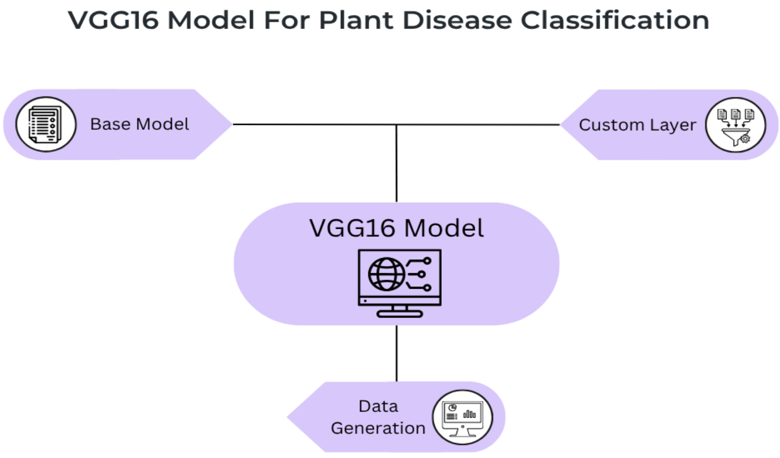

Figure 3: VGG16 Model for Plant Disease Classification

- **ResNet50**: This 50-layer residual network was leveraged through transfer learning using ImageNet weights. The model architecture included a GlobalAveragePooling2D layer, followed by dense and dropout layers for classification. ResNet50 effectively handled vanishing gradients using skip connections and demonstrated superior performance in accuracy, convergence speed, and generalization.

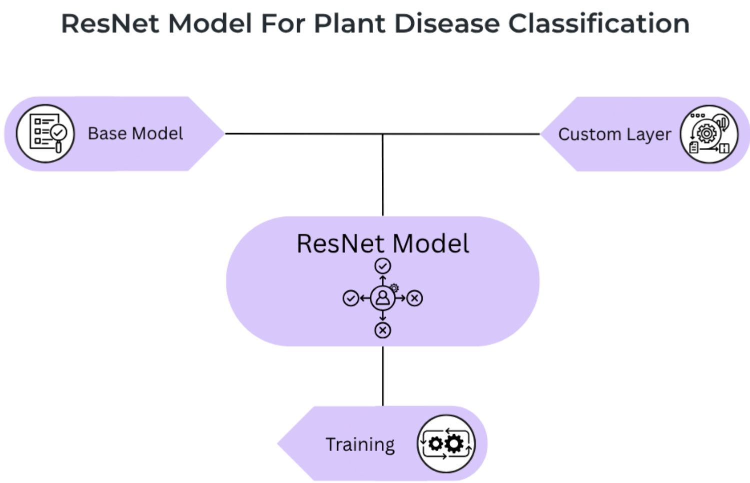

Figure 4: ResNet Model for Plant Disease Classification

4.Results and Analysis

The models were trained for 10 epochs with a batch size of 38. The performance of each model was evaluated using accuracy, loss curves, and confusion matrices. The detailed results are as follows:

4.1 Custom CNN

- **Training Accuracy**: ~90%
- **Validation Accuracy**: ~95%
- **Observation**: The model trained rapidly and learned simpler patterns well. However, it struggled with more complex features, leading to limited generalization and mild underfitting.

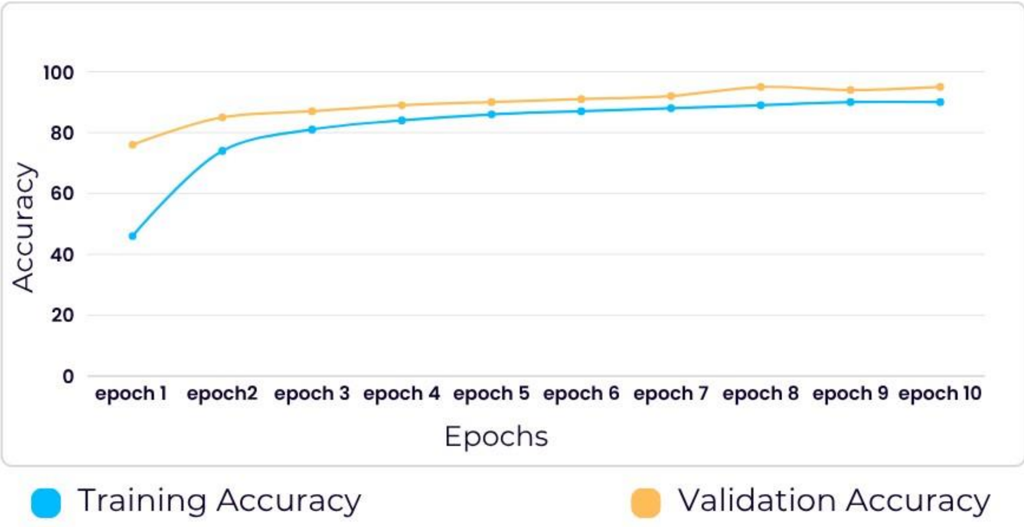

Figure 5: Training vs Validation Accuracy for CNN Model

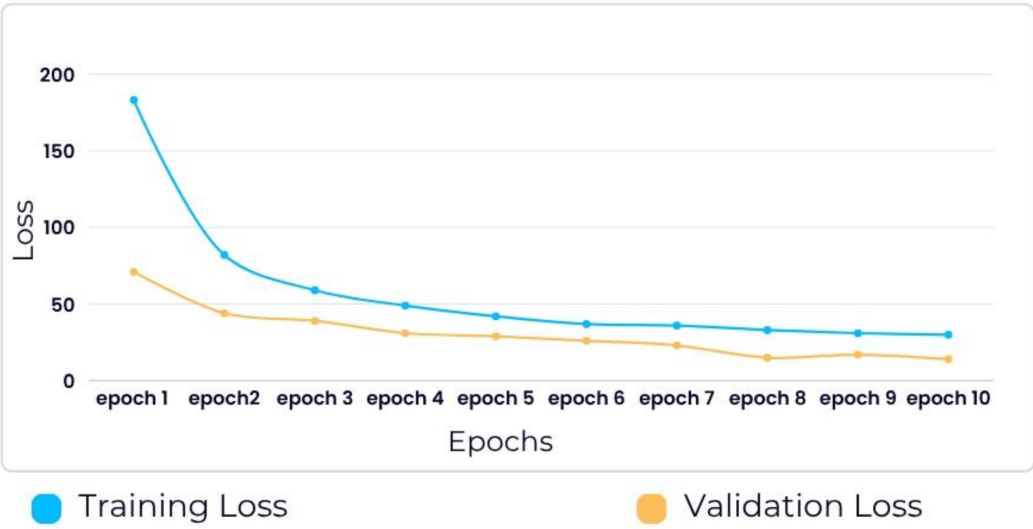

Figure 6: Training vs Validation Loss for CNN Model

4.2 VGG16 (Transfer Learning)

- **Training Accuracy**: ~82%
- **Validation Accuracy**: ~92%
- **Observation**: The model achieved reasonable validation accuracy but faced issues with slow

convergence and overfitting. It required high computational resources and longer training time.

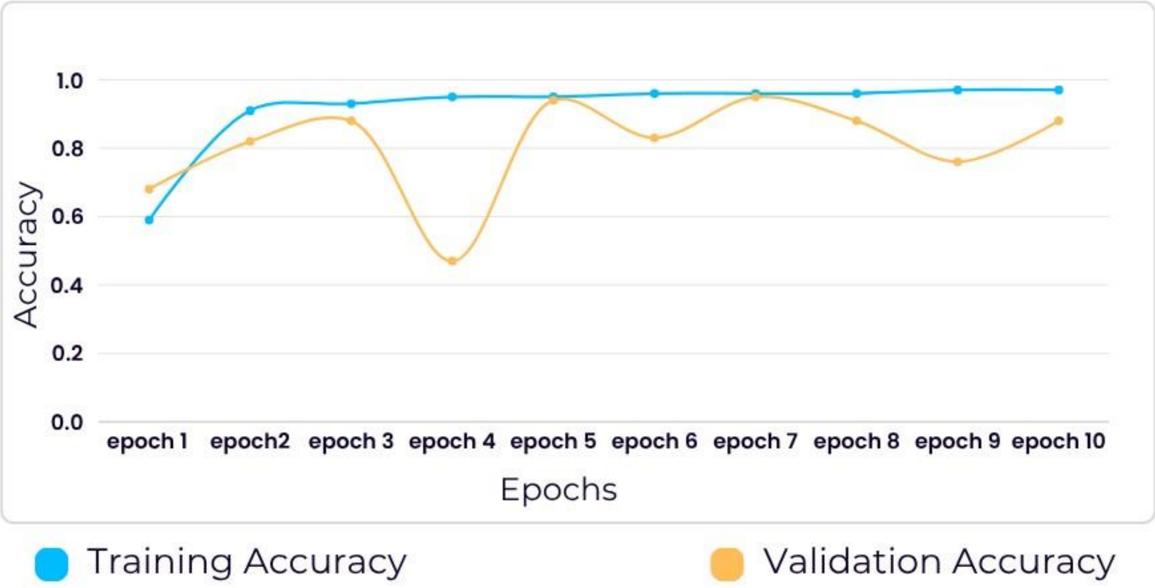

Figure 7: Training vs Validation Accuracy for VGG16 Model

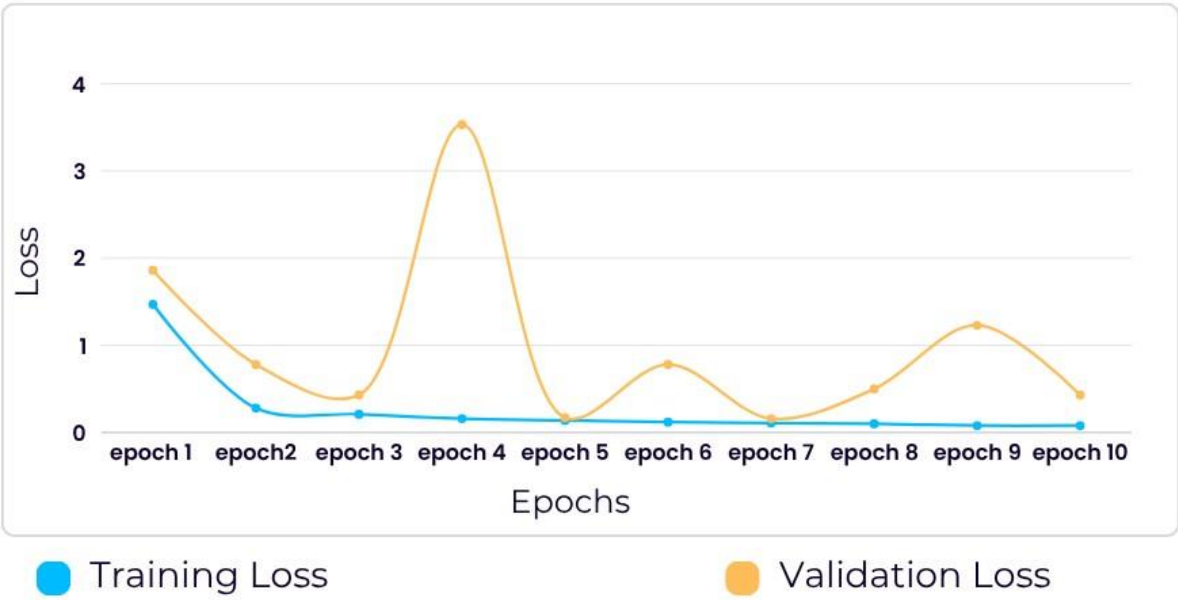

Figure 8: Training vs Validation Loss for VGG16 Model

4.3 ResNet50 (Transfer Learning)

- **Training Accuracy**: ~96%
- **Validation Accuracy**: ~95%
- **Observation**: ResNet50 showed the best performance. It converged quickly, generalized well to unseen data, and effectively captured intricate disease patterns across all 38 classes.

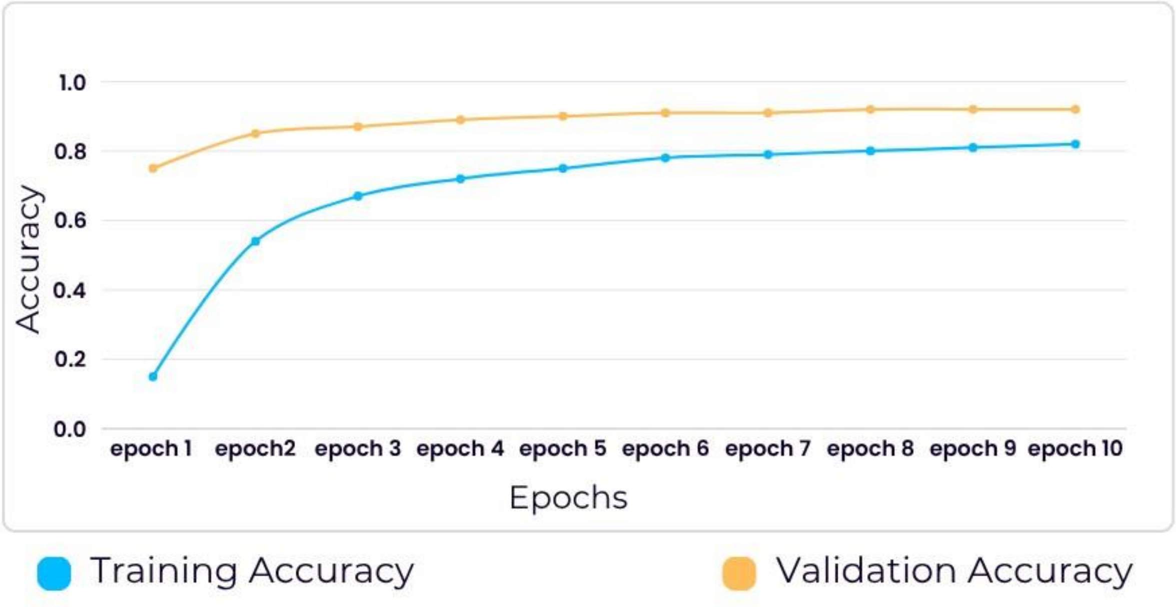

Figure 9: Training vs Validation Accuracy for ResNet Model

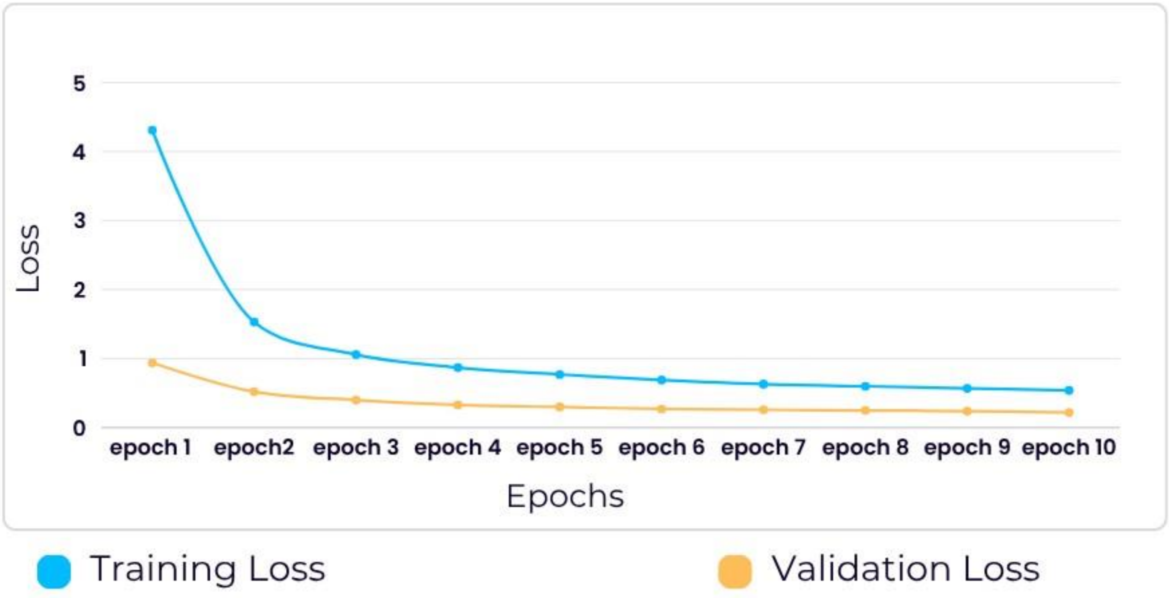

Figure 10: Training vs Validation Loss for ResNet Model

Confusion Matrix Analysis:

The confusion matrix for ResNet50 displayed strong diagonal dominance, indicating that the model made correct predictions across most classes. Misclassifications were minimal and generally occurred between classes with visually similar symptoms. Overall, precision, recall, and F1-scores remained consistently high across the board.

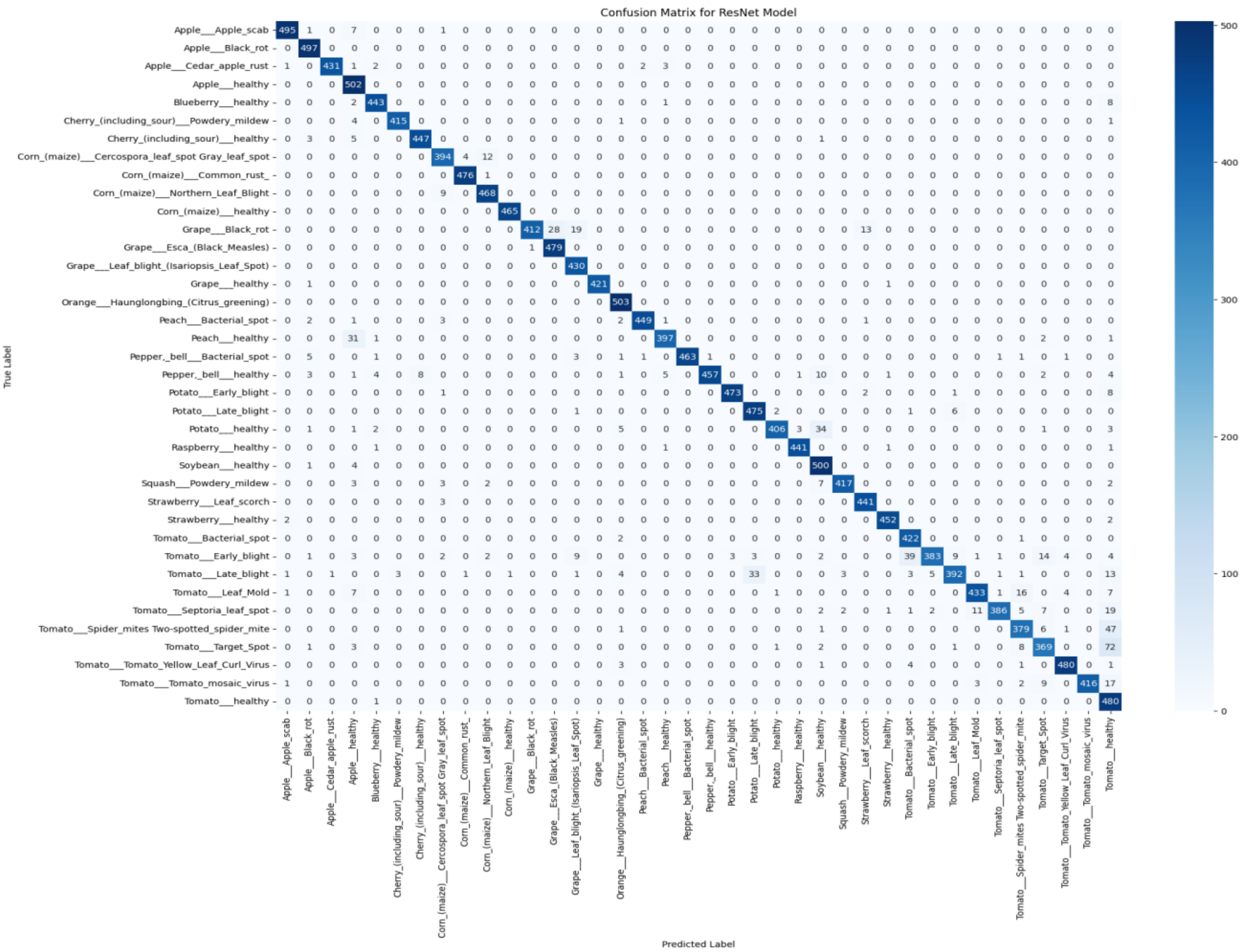

Figure 11: Confusion Matrix for ResNet Model

Confusion Matrix Analysis: Demonstrated strong diagonal dominance in the confusion matrix, indicating correct classification for most classes. Misclassifications were minimal and largely confined to diseases with visually overlapping symptoms. Precision, recall, and F1-scores were consistently high across the board.

5.Conclusion

This study explored the application of deep learning techniques for classifying plant leaf diseases. While a custom CNN provided a foundational model, VGG16 and ResNet50 significantly improved classification performance. Among them, ResNet50 delivered the best results due to its residual learning capabilities and robust feature extraction. The model demonstrated high accuracy and reliability, making it suitable for real-time agricultural diagnostics. Future work may focus on deploying the model in mobile applications and expanding it to cover more crop types and disease variants.

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