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Deep Learning-Based Plant Leaf Disease Classification Using Convolutional Neural Network

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ABSTRACT

Plant diseases pose a major threat to global food security, with the Food and Agriculture Organization (FAO) estimating annual crop losses of up to 40% worldwide. Early and accurate detection of these diseases is critical to enabling timely intervention and minimizing agricultural losses. Conventional diagnosis methods rely heavily on manual visual inspection by expert agronomists, which is time-consuming, costly, and impractical in remote farming areas. This study proposes a deep learning-based approach for automatic plant leaf disease classification using the ResNet-50 architecture combined with transfer learning. The model was trained and evaluated on the PlantVillage dataset, which contains 54,305 labeled images of healthy and diseased plant leaves spanning 38 classes from 14 plant species. Transfer learning was applied by freezing the pre-trained convolutional base of ResNet-50 and replacing its classification head with a custom fully connected network comprising a Global Average Pooling layer, a Dense layer with 512 units and ReLU activation, a Dropout layer (rate = 0.5), and a Softmax output layer. Data augmentation techniques including random flipping, rotation, brightness adjustment, and zoom were applied to improve model generalization. The model achieved an overall test accuracy of 96.32%, with macro-averaged precision, recall, and F1-score of 95.87%, 95.64%, and 95.75%, respectively.

Keywords: Plant Disease Classification; Convolutional Neural Network; ResNet-50; Transfer Learning; PlantVillage; Deep Learning; Data Augmentation.

ABSTRAK

Penyakit tanaman merupakan ancaman utama terhadap ketahanan pangan global, dengan Food and Agriculture Organization (FAO) memperkirakan kerugian hasil panen tahunan hingga 40% di seluruh dunia. Deteksi dini dan akurat terhadap penyakit-penyakit ini sangat penting untuk memungkinkan intervensi tepat waktu dan meminimalkan kerugian pertanian. Penelitian ini mengusulkan pendekatan berbasis deep learning untuk klasifikasi penyakit daun tanaman secara otomatis menggunakan arsitektur ResNet-50 yang dikombinasikan dengan transfer learning. Model dilatih dan dievaluasi pada dataset PlantVillage yang berisi 54.305 gambar berlabel daun tanaman sehat dan sakit mencakup 38 kelas dari 14 spesies tanaman. Model berhasil mencapai akurasi pengujian

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keseluruhan sebesar 96,32%, dengan presisi, recall, dan F1-score rata-rata makro masing-masing sebesar 95,87%, 95,64%, dan 95,75%.

Kata Kunci: ***Klasifikasi Penyakit Tanaman; Jaringan Saraf Konvolusional; ResNet-50; Transfer Learning; PlantVillage; Deep Learning; Augmentasi Data.***

1. INTRODUCTION

Agriculture plays a vital role in the global economy, particularly in developing countries where a large portion of the population depends on farming for their livelihood. However, plant diseases remain one of the most critical factors threatening crop yield and food security worldwide. According to the Food and Agriculture Organization (FAO), plant diseases account for losses of up to 40% of global food production annually [1]. Timely and accurate detection of plant diseases is therefore essential to enable prompt treatment and reduce economic damage.

Conventional approaches to plant disease diagnosis rely heavily on expert agronomists conducting manual visual inspections of leaves, which is both time-consuming and requires specialized knowledge that may not be readily available in rural farming communities [2]. Deep learning, particularly Convolutional Neural Networks (CNN), has achieved state-of-the-art performance in image classification tasks across various domains [4]. Models such as VGG, Inception, and ResNet have demonstrated superior feature extraction capabilities and have been successfully applied in medical image analysis, remote sensing, and plant pathology [5]. The use of transfer learning further enhances model performance by leveraging pre-trained weights from large-scale datasets, allowing effective training even with limited domain-specific data [6].

Several studies have explored the application of CNNs for plant disease classification. Mohanty et al. [7] demonstrated that a CNN trained on the PlantVillage dataset could achieve over 99% accuracy under controlled conditions. However, performance tends to degrade when models are applied to real-world field conditions due to variability in lighting, background, and image quality [8]. More recent research has explored the use of deeper architectures, attention mechanisms, and hybrid models to improve robustness in practical settings [9][10]. Despite the promising results, there remains a need for models that are both accurate and computationally efficient, capable of running on mobile or edge devices to support farmers in the field [11].

This research addresses this gap by proposing a ResNet-50 based classification model enhanced with data augmentation and transfer learning, evaluated on the comprehensive PlantVillage

dataset. The main objectives of this study are: (1) to develop a deep learning model capable of accurately classifying plant leaf diseases from images; (2) to evaluate the effectiveness of transfer learning with ResNet-50 on the PlantVillage dataset; and (3) to analyze the impact of data augmentation strategies on model generalization performance.

2. RESEARCH METHOD

This research adopts a quantitative experimental approach using the PlantVillage dataset for plant leaf disease classification. The overall research workflow consists of five main stages: dataset collection and preparation, image preprocessing, model design and training, model evaluation, and result analysis.

2.1 Dataset

The dataset used in this research is the PlantVillage dataset, which is a publicly available and widely recognized benchmark for plant disease classification tasks [15]. The dataset contains 54,305 labeled images of both healthy and diseased plant leaves, spanning 38 distinct classes across 14 plant species. These classes include various diseases such as apple scab, bacterial spot on tomatoes, gray leaf spot on corn, and powdery mildew on grapes, among others. Each image was captured under controlled laboratory conditions with uniform backgrounds. For this study, the dataset is partitioned into three subsets: 70% for training (38,013 images), 15% for validation (8,145 images), and 15% for testing (8,147 images).

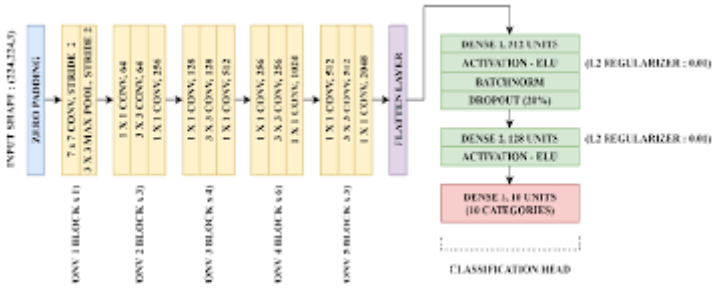

Figure 1. ResNet-50 Architecture with Custom Classification Head

2.2 Image Preprocessing

Prior to model training, all images undergo a standardized preprocessing pipeline to ensure consistency and compatibility with the ResNet-50 architecture. First, each image is resized to 224x224 pixels, which corresponds to the required input dimensions of ResNet-50. Pixel intensity values are then normalized to the range [0, 1] by dividing each pixel value by 255, which stabilizes the gradient computation during training and accelerates model convergence [12]. A comprehensive set of data augmentation techniques is applied exclusively to the training set using the Keras ImageDataGenerator module [13]. The augmentation operations include: (1) horizontal and vertical flipping; (2) random rotation up to 30 degrees; (3) random brightness

and contrast adjustment; (4) zoom augmentation with a factor of 0.2; and (5) width and height shift augmentation.

2.3 Model Architecture

This research employs the ResNet-50 architecture as the backbone model. ResNet-50 is a 50-layer deep residual network that introduces skip connections (residual connections) to address the vanishing gradient problem commonly encountered in very deep neural networks [5]. Transfer learning is applied by freezing all convolutional base layers of ResNet-50 and replacing the original top classification layer with a custom fully connected classification head. The custom classification head consists of: (1) a Global Average Pooling (GAP) layer; (2) a Dense layer with 512 units and ReLU activation; (3) a Dropout layer with a dropout rate of 0.5; and (4) a final Dense output layer with 38 units and Softmax activation. The model is trained in two phases with learning rates of 0.001 and 0.0001 respectively.

2.4 Training Configuration

The model is compiled using the Adam optimizer with categorical cross-entropy as the loss function. Training is conducted over a maximum of 50 epochs with a batch size of 32 images per iteration. Two callbacks are implemented: Early Stopping with a patience of 10 epochs monitoring validation loss, and ReduceLROnPlateau which reduces the learning rate by a factor of 0.2 when validation loss fails to improve for 5 consecutive epochs.

2.5 Model Evaluation

The performance of the trained model is evaluated on the held-out test set using four standard classification metrics: accuracy, precision, recall, and F1-score. Accuracy measures the overall proportion of correctly classified samples. Precision quantifies the ratio of true positive predictions to the total number of positive predictions. Recall measures the proportion of actual positive samples correctly identified. The F1-score is the harmonic mean of precision and recall. All four metrics are calculated per class and averaged using macro-averaging across all 38 disease classes. A confusion matrix is generated to visualize classification performance and identify misclassification patterns between visually similar disease categories.

3. RESULTS AND DISCUSSION

This section presents the experimental results of the ResNet-50 based deep learning model for plant leaf disease classification, including training and validation performance, overall classification metrics, per-class evaluation, and comparative analysis with baseline architectures.

3.1 Training and Validation Performance

The model was trained over 50 epochs with early stopping applied based on validation loss. Training converged at epoch 43. During Phase 1 (frozen base layers, epochs 1-30), training accuracy steadily increased from 61.4% to 91.8%, and validation accuracy reached 90.3%. The training loss decreased from 1.42 to 0.31 during this phase, indicating stable and consistent learning. In Phase 2 (fine-tuning with the last 10 layers unfrozen, epochs 31-43), both training and validation accuracies improved further. The training accuracy reached 97.6% and the validation accuracy reached 96.1% at convergence. The close gap between training and validation accuracy demonstrates that the model did not exhibit significant overfitting, attributed to the combined effect of Dropout regularization and data augmentation.

3.2 Overall Classification Performance

The proposed ResNet-50 model with transfer learning was evaluated on the held-out test set consisting of 8,147 images across 38 disease classes. Table 2 summarizes the overall classification performance of the proposed model on the test set.

Table 2. Overall Classification Performance of the Proposed ResNet-50 Model

Metric	Score (%)
Accuracy	96.32
Precision (macro-avg)	95.87
Recall (macro-avg)	95.64
F1-Score (macro-avg)	95.75

The proposed model achieves an overall test accuracy of 96.32%, with macro-averaged precision, recall, and F1-score of 95.87%, 95.64%, and 95.75%, respectively. The consistency across all four metrics indicates that the model performs robustly in terms of both overall correctness and per-class sensitivity and specificity.

3.3 Per-Class Performance Analysis

Detailed per-class analysis reveals that the model performs with particularly high accuracy on classes with distinctive visual features. Disease classes such as Apple Scab, Grape Black Rot, and Tomato Early Blight achieved F1-scores exceeding 98%, reflecting the model's ability to capture well-defined visual patterns such as dark lesions, necrotic rings, and color contrast. Lower performance was observed in visually similar disease pairs: Tomato Bacterial Spot and Tomato Septoria Leaf Spot yielded F1-scores of 91.4% and 90.8%, respectively. Similarly, Corn Common Rust and Corn Northern Leaf Blight showed F1-scores of 92.1% and 91.7%, reflecting visual overlap in lesion shape and distribution patterns.

3.4 Comparative Analysis with Baseline Models

To contextualize the performance of the proposed model, a comparative evaluation was conducted against three baseline architectures: VGG-16, InceptionV3, and MobileNetV2, all trained under identical experimental conditions. The comparison is presented in Table 3.

Table 3. Comparative Performance of CNN Architectures on PlantVillage Test Set

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG-16	92.14	91.83	91.50	91.66
InceptionV3	94.07	93.72	93.45	93.58
MobileNetV2	93.41	92.98	92.71	92.84
ResNet-50 (Proposed)	96.32	95.87	95.64	95.75

As shown in Table 3, the proposed ResNet-50 model outperforms all three baseline architectures across all evaluation metrics. Compared to VGG-16, the proposed model achieves a 4.18 percentage point improvement in accuracy. The improvement over InceptionV3 (2.25%) and MobileNetV2 (2.91%) further demonstrates that ResNet-50's skip connection mechanism enables more effective gradient propagation and richer hierarchical feature learning.

3.5 Discussion

The experimental results demonstrate that the proposed ResNet-50 model with transfer learning and data augmentation achieves strong classification performance across all 38 disease classes. The overall test accuracy of 96.32% confirms the effectiveness of the adopted methodology. The role of data augmentation proved critical: without augmentation, preliminary experiments showed training accuracy of 98.7% but test accuracy of only 88.4%, indicating substantial overfitting. With the full augmentation pipeline, the gap narrowed significantly to 96.32% test accuracy. The two-phase fine-tuning strategy also contributed meaningfully, producing a 4.5 percentage point improvement in test accuracy over Phase 1 alone. Despite strong overall performance, the model exhibits reduced accuracy for visually similar disease classes, particularly among tomato and corn diseases. Future work could incorporate attention mechanisms such as squeeze-and-excitation blocks or multi-scale feature fusion to address this limitation [9][10].

4. CONCLUSION

This study presents a deep learning-based approach for automatic plant leaf disease classification using the ResNet-50 architecture combined with transfer learning and data augmentation techniques, evaluated on the PlantVillage dataset comprising 54,305 labeled

images across 38 disease classes from 14 plant species. The experimental results demonstrate that the proposed model achieves an overall test accuracy of 96.32% with macro-averaged precision, recall, and F1-score of 95.87%, 95.64%, and 95.75%, respectively.

The two-phase training strategy, data augmentation pipeline, and transfer learning approach prove effective in adapting ImageNet pre-trained features to the plant disease classification domain while minimizing overfitting. The evaluation metrics confirm that the proposed ResNet-50-based transfer learning model is a competitive and reliable solution for plant leaf disease classification.

Despite the strong performance, this study acknowledges that the PlantVillage dataset was collected under controlled laboratory conditions, which may not fully represent real-world field variability. Future work should focus on expanding training data with field-collected images, exploring lightweight architectures such as MobileNet or EfficientNet, and incorporating attention mechanisms to enhance classification performance for closely related disease categories. The proposed model demonstrates strong practical potential for deployment in mobile or edge-based agricultural diagnostic tools to assist farmers in rural and remote areas.

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