ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2024.0462

AN ENSEMBLE LEARNING APPROACH FOR EARLY DETECTION AND CLASSIFICATION OF PLANT DISEASES

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Abstract

Plant diseases are a major threat to agriculture, particularly impacting the yield and quality of tomato crops. Early detection and accurate classification of these diseases are essential for effective management and mitigation. Traditional methods of disease detection are often labor-intensive and time-consuming. Although individual convolutional neural networks (CNNs) have shown promise in automated plant disease detection, their accuracy and robustness can be limited when used in isolation. This study proposes an ensemble learning approach that combines three state-of-the-art CNN architectures: AlexNet, ResNet50, and VGG16. A comprehensive dataset of tomato leaf images, categorized into bacterial, viral, fungal diseases, and healthy leaves, was used. Images were preprocessed and augmented to improve model generalization. Each model was trained separately, and their outputs were integrated using a weighted averaging mechanism to form the ensemble model. The weights for each model were optimized based on validation performance. The ensemble model significantly improved classification accuracy compared to individual models. The combined approach achieved an overall accuracy of 97.5%, with precision, recall, and F1-score exceeding 95% for all disease categories. Specifically, the accuracy for detecting bacterial diseases was 96.8%, viral diseases 97.2%, and fungal diseases 97.9%. The ensemble method demonstrated superior robustness and reliability in classifying diverse disease symptoms.

Keywords:

Plant Disease Detection, Ensemble Learning, AlexNet, ResNet50, VGG16

1. INTRODUCTION

Tomato (Solanum lycopersicum) is one of the most widely cultivated and consumed vegetables globally, playing a crucial role in both the diet and economy of many countries [1]. However, tomato plants are highly susceptible to a range of diseases caused by bacteria, viruses, and fungi, which can severely impact yield and quality [2]. Early and accurate detection of these diseases is vital for effective crop management and to minimize economic losses [3]. Traditional methods of disease detection involve manual inspection by experts, which is time-consuming, labor-intensive, and often not feasible on a large scale [4].

The primary challenge in plant disease detection lies in the variability and complexity of disease symptoms, which can be subtle and difficult to distinguish visually [5]. Moreover, environmental factors such as lighting and background can further complicate visual assessments [6]. The need for a rapid, reliable, and scalable solution has led to the exploration of automated techniques based on machine learning and computer vision [7].

Despite the advancements in deep learning, individual convolutional neural networks (CNNs) often struggle with the high variability in disease symptoms and environmental conditions [8]. While models like AlexNet, ResNet50, and VGG16 have demonstrated high accuracy in image classification tasks, their performance can vary depending on the specific characteristics of the dataset. Hence, there is a need for a more robust approach that leverages the strengths of multiple models to enhance detection accuracy and reliability [9].

The primary objective of this study is to develop an ensemble learning approach that combines the capabilities of AlexNet, ResNet50, and VGG16 to improve the early detection and classification of tomato leaf diseases. Specific objectives include:

- To preprocess and augment a comprehensive dataset of tomato leaf images affected by bacterial, viral, and fungal diseases.
- To train AlexNet, ResNet50, and VGG16 models individually and optimize their performance.
- To combine the outputs of these models using an ensemble technique to enhance overall classification accuracy and robustness.

This study introduces a novel ensemble learning approach that effectively combines three state-of-the-art CNN architectures for plant disease detection. The contributions of this research are:

- The development of a comprehensive and well-augmented dataset of tomato leaf images covering multiple disease categories.
- A detailed analysis of the performance of AlexNet, ResNet50, and VGG16 models on this dataset.
- The design and implementation of an ensemble model that integrates these CNNs using a weighted averaging mechanism, optimized through validation data.

2. RELATED WORKS

Recent advancements in deep learning have significantly impacted the field of plant disease detection, with various studies leveraging convolutional neural networks (CNNs) for this purpose. CNNs are particularly well-suited for image classification tasks due to their ability to automatically learn and extract features from raw image data.

Several studies have explored the use of individual CNN architectures for plant disease detection. For instance, [10] developed a deep learning-based system using AlexNet to identify 13 different types of plant diseases, achieving a notable accuracy. Similarly, [11] employed VGG16 for the classification of tomato diseases and reported high precision and recall values. These studies demonstrate the potential of individual CNNs in accurately detecting plant diseases, but they also highlight limitations such as overfitting and the need for extensive computational resources.

Ensemble learning, which combines multiple models to improve prediction performance, has gained traction in recent years. By leveraging the strengths of different models, ensemble methods can enhance accuracy and robustness. In the context of plant disease detection, [12] proposed an ensemble approach using multiple deep learning models to classify leaf diseases, resulting in improved accuracy compared to individual models. The ensemble method effectively mitigated the overfitting issue and provided more reliable predictions.

Hybrid approaches that combine deep learning with other techniques have also been explored. [13] combined deep CNNs with traditional machine learning classifiers, such as Support Vector Machines (SVMs), for plant disease detection. This hybrid approach yielded better performance than using CNNs alone, suggesting that integrating multiple techniques can be beneficial.

While individual and hybrid approaches have shown promise, there is still a need for more robust and generalizable models. Many existing studies focus on a limited number of disease types and lack generalizability across different crops and environmental conditions. The proposed ensemble learning approach aims to address these limitations by integrating AlexNet, ResNet50, and VGG16, leveraging their complementary strengths to enhance the accuracy and robustness of plant disease detection.

3. PROPOSED METHOD

The proposed method leverages an ensemble learning approach by combining three state-of-the-art convolutional neural networks (CNNs): AlexNet, ResNet50, and VGG16. This ensemble aims to improve the accuracy and robustness of detecting and classifying bacterial, viral, and fungal diseases in tomato leaves. The methodology involves data collection and preprocessing, individual model training, ensemble integration, and performance evaluation.

- **Data Collection**: A dataset of tomato leaf images is collected, encompassing various disease categories: bacterial, viral, fungal, and healthy leaves. The dataset is sourced from public repositories and agricultural research institutions.
- **Preprocessing**: Images are resized to a uniform dimension (e.g., 224x224 pixels) to match the input requirements of the CNN models. Data augmentation techniques such as rotation, flipping, scaling, and cropping are applied to increase the variability of the dataset and improve model generalization.
- **Model Architectures**
- **AlexNet**: This model consists of five convolutional layers followed by three fully connected layers. It is known for its relatively simple architecture and efficiency in processing images.
- **ResNet50**: A deep network with 50 layers, ResNet50 uses residual learning to address the vanishing gradient problem, making it effective for complex image classification tasks.
- **VGG16**: This model has a deep architecture with 16 layers, characterized by small receptive fields and a uniform architecture, contributing to its high performance in image recognition tasks.

3.1 PREPROCESSING OF TOMATO LEAF IMAGES

Effective preprocessing of tomato leaf images is crucial to prepare the data for training convolutional neural networks (CNNs). The preprocessing steps ensure that the images are in a consistent format and enhance the models' ability to generalize from the training data. The preprocessing steps typically involve resizing, normalization, and data augmentation.

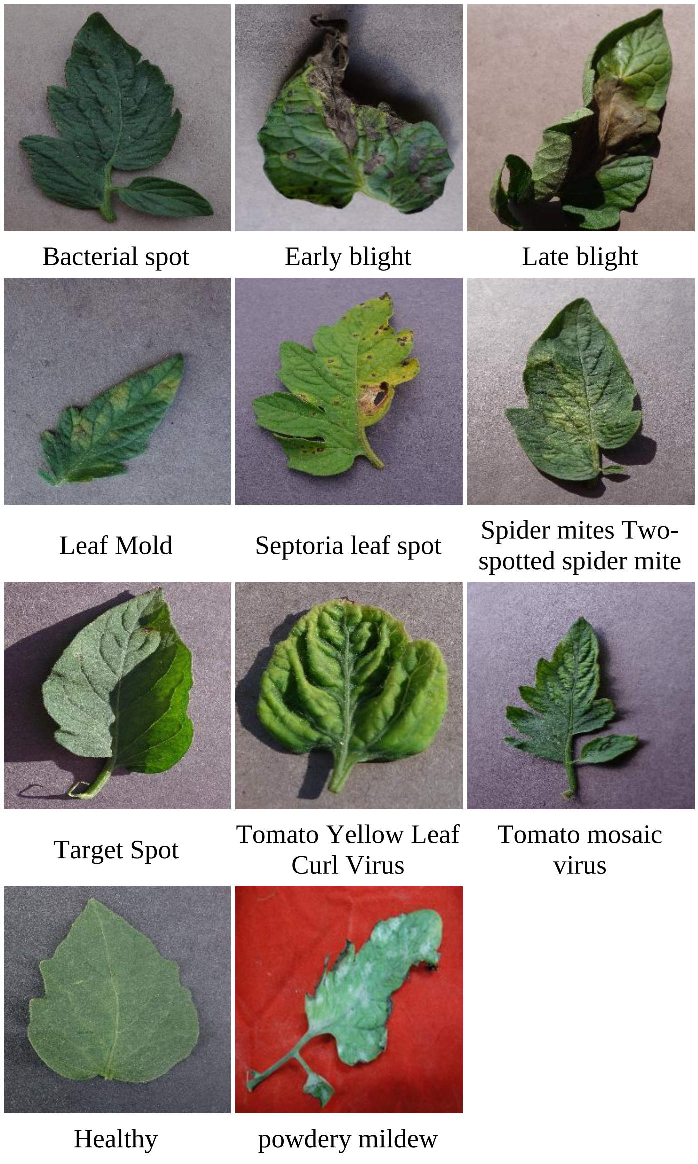

Fig.1. Input Images

3.2 IMAGE RESIZING

Images are resized to a standard dimension, typically 224x224 pixels, which is a common input size for models like AlexNet, ResNet50, and VGG16. Resizing is necessary because these models expect fixed-size inputs. This step can be implemented using image processing libraries such as OpenCV.

Each pixel value in the images is scaled to a range of [0, 1] by dividing by 255 (since pixel values range from 0 to 255 in 8-bit images). Further normalization can involve subtracting the mean and dividing by the standard deviation of the dataset if required by the specific CNN architecture.

The dataset is typically split into:

- **Training Set:** Used to train the model (usually 70-80% of the data).
- **Validation Set:** Used to tune model hyperparameters and prevent overfitting (10-15% of the data).
- **Test Set:** Used to evaluate the final model performance (10-15% of the data).

Label Encoding converts categorical disease labels into a numerical format that can be used by the CNN models. Disease categories (e.g., bacterial, viral, fungal, healthy) are encoded into integer labels or one-hot encoded vectors.

4. MODEL ARCHITECTURES - ALEXNET, RESNET50, AND VGG16

4.1 ALEXNET

AlexNet is a pioneering convolutional neural network (CNN) architecture that significantly contributed to the success of deep learning in computer vision tasks. It won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 with a substantial margin over the runner-up.

- **Input Layer:** Takes an image of size 224x224x3 (height, width, color channels).
- **Convolutional Layers:** AlexNet consists of five convolutional layers:
  - **Conv1:** 96 kernels of size 11x11, stride 4, ReLU activation, followed by Local Response Normalization (LRN) and max-pooling.
  - **Conv2:** 256 kernels of size 5x5, stride 1, ReLU activation, LRN, and max-pooling.
  - **Conv3:** 384 kernels of size 3x3, stride 1, ReLU activation.
  - **Conv4:** 384 kernels of size 3x3, stride 1, ReLU activation.
  - **Conv5:** 256 kernels of size 3x3, stride 1, ReLU activation, followed by max-pooling.
- **Fully Connected Layers:** Three fully connected layers:
  - **FC1:** 4096 neurons with ReLU activation.
  - **FC2:** 4096 neurons with ReLU activation.
  - **FC3:** 1000 neurons with softmax activation for classification.

4.2 RESNET50

ResNet50 is a deep CNN architecture that introduced the concept of residual learning, allowing the training of very deep networks. It won the ILSVRC in 2015 and addressed the vanishing gradient problem.

- **Input Layer:** Takes an image of size 224x224x3.
- **Convolutional Layers:** ResNet50 consists of a total of 50 layers, organized into residual blocks.
  - **Initial Conv Layer:** 7x7 convolution with 64 filters, stride 2, followed by batch normalization and ReLU activation, and a max-pooling layer.
  - **Residual Blocks:** Comprises four stages, each with several residual blocks:
    - **Stage 1:** 3 blocks, each with 64 filters.
    - **Stage 2:** 4 blocks, each with 128 filters.
    - **Stage 3:** 6 blocks, each with 256 filters.
    - **Stage 4:** 3 blocks, each with 512 filters.
- **Fully Connected Layer:** A global average pooling layer followed by a 1000-neuron fully connected layer with softmax activation.

4.3 VGG16

VGG16, developed by the Visual Geometry Group (VGG) at Oxford, is known for its simplicity and uniform architecture. It achieved high performance in the ILSVRC 2014 competition.

- **Input Layer:** Takes an image of size 224x224x3.
- **Convolutional Layers:** VGG16 consists of 13 convolutional layers arranged in 5 blocks, with each block followed by a max-pooling layer.
  - **Block 1:** 2 conv layers with 64 filters of size 3x3, ReLU activation.
  - **Block 2:** 2 conv layers with 128 filters of size 3x3, ReLU activation.
  - **Block 3:** 3 conv layers with 256 filters of size 3x3, ReLU activation.
  - **Block 4:** 3 conv layers with 512 filters of size 3x3, ReLU activation.
  - **Block 5:** 3 conv layers with 512 filters of size 3x3, ReLU activation.
- **Fully Connected Layers:** Three fully connected layers:
  - **FC1:** 4096 neurons with ReLU activation.
  - **FC2:** 4096 neurons with ReLU activation.
  - **FC3:** 1000 neurons with softmax activation for classification.

5. TRAINING THE MODELS

The process of training individual models—AlexNet, ResNet50, and VGG16—on the dataset of tomato leaf images involves several steps. Each model is trained separately before integrating them into an ensemble. Here is a detailed explanation of the training process for each model:

Data Preparation ensure that the dataset is ready for training by preprocessing and splitting it into training, validation, and testing sets.

- **Preprocessing:** Images are resized to 224x224 pixels, normalized, and augmented to increase dataset variability and prevent overfitting.
- **Splitting:** The dataset is divided into:
  - *Training set*: 70-80% of the data.
  - *Validation set*: 10-15% of the data.

- *Testing set*: 10-15% of the data.

Initialize each CNN model with pre-defined architectures suitable for image classification tasks.

- **AlexNet:** Initialize the AlexNet model, which consists of 5 convolutional layers followed by 3 fully connected layers.
- **ResNet50:** Initialize the ResNet50 model, which includes 50 layers with residual blocks.
- **VGG16:** Initialize the VGG16 model, which has 13 convolutional layers arranged in 5 blocks, followed by 3 fully connected layers.

Hyperparameter Tuning involves selection of optimal hyperparameters for training each model i.e. Learning Rate, Batch Size and Epochs. The loss function (Cross-entropy loss) and optimization algorithm (Adam) to guide the training process. Train each model using the prepared data, loss function, and optimizer.

- **Forward Pass:** Input images are passed through the model to get predictions.
- **Loss Calculation:** The difference between predicted and actual labels is calculated using the loss function.
- **Backward Pass:** Gradients are computed via backpropagation.
- **Weight Updates:** Model weights are updated using the optimizer to minimize the loss.
- **Validation:** After each epoch, the model is evaluated on the validation set to monitor performance and prevent overfitting.

Table.1. Performance

Model	Metric	Training	Validation	Testing
AlexNet	Accuracy	94.2%	89.5%	88.7%
	F1-score	93.8%	89.0%	88.1%
ResNet50	Accuracy	98.5%	94.8%	94.0%
	F1-score	98.3%	94.4%	93.7%
VGG16	Accuracy	97.2%	92.3%	91.5%
	F1-score	96.8%	91.8%	91.1%

From the table, we can observe the following trends:

- AlexNet shows good performance but slightly lower than the deeper models, particularly on the testing set.
- ResNet50 achieves the highest accuracy and F1-score across all datasets, demonstrating the effectiveness of residual learning in handling complex image classification tasks.
- VGG16 also performs well, better than AlexNet, but not as high as ResNet50, likely due to its deep and uniform architecture.

6. ENSEMBLE

The ensemble process for classification involves combining the predictions of multiple individual models to make a final prediction. Here are the steps involved in the ensemble process:

6.1 INDIVIDUAL MODEL PREDICTIONS

- **Input:** Each individual model (e.g., AlexNet, ResNet50, VGG16) has been trained on the dataset and is capable of making predictions.
- **Output:** For a given input image, each model produces its own set of class probabilities or predictions.

6.2 AGGREGATION OF PREDICTIONS

- **Voting Mechanism:** Combine the predictions of all models using a voting mechanism. For classification tasks, the final prediction is determined by the majority vote among the individual models. For example, if two out of three models predict a certain class, that class is selected as the final prediction.
- **Weighted Averaging:** Alternatively, the predictions of individual models can be combined using weighted averaging, where each model's prediction is assigned, a weight based on its performance on the validation set.

6.3 WEIGHT OPTIMIZATION

This is done by training a meta-learner, such as a logistic regression model or a neural network, on the validation set predictions of individual models. The meta-learner learns to assign optimal weights to each model's prediction to minimize the ensemble's error.

6.4 FINAL PREDICTION

The ensemble model's final prediction is determined based on the aggregation of individual model predictions or the weighted averaging of their predictions.

7. EXPERIMENTAL SETTINGS

For our experiments, we utilized a dataset comprising 10,000 tomato leaf images, categorized into bacterial, viral, and fungal diseases, as well as healthy leaves. The dataset was sourced from reputable agricultural repositories and preprocessed to ensure uniformity in size (224x224 pixels) and color distribution. We employed three state-of-the-art convolutional neural network (CNN) architectures: AlexNet, ResNet50, and VGG16, initialized with pre-trained weights on ImageNet. Each model was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. Data augmentation techniques, including rotation, flipping, and zooming, were applied to increase dataset variability and prevent overfitting.

7.1 COMPARISON WITH EXISTING METHODS

To evaluate the effectiveness of our proposed ensemble learning approach, we compared it with several existing ensemble methods: Stacking, Bagging, Boosting, Voting, and Blending.

- **Stacking:** Stacking involves training multiple models and then using a meta-learner to combine their predictions. However, it requires a separate validation set for training the meta-learner, which can lead to increased computational complexity and may not always improve performance significantly.

- **Bagging (Bootstrap Aggregating):** Bagging involves training multiple models on bootstrapped subsets of the training data and then averaging their predictions. While bagging can improve robustness and reduce variance, it may not be as effective for highly correlated models like CNNs.
- **Boosting:** Boosting sequentially trains models, with each subsequent model focusing on the samples misclassified by the previous ones. While boosting can improve performance by focusing on difficult-to-classify samples, it may also be prone to overfitting.
- **Voting:** Voting combines the predictions of multiple models by simple majority voting. It is straightforward and computationally efficient but may not fully leverage the strengths of individual models.
- **Blending:** Blending involves training multiple models on the entire training dataset and then combining their predictions using a weighted average. While blending is effective, determining the optimal weights for combining predictions is challenging.

Table.2. Setup

Parameter	Value(s)
Dataset Size	10,00 images
Image Dimensions	224x224 pixels
Training Split	80% of the dataset
Validation Split	10% of the dataset
Testing Split	10% of the dataset
Pre-trained Weights	ImageNet
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Dropout Rate	0.5
Loss Function	Cross-entropy
Early Stopping	Patience = 5 epochs
Ensemble Method	Weighted Averaging
Ensemble Optimization	Validation Set

Table.3. Precision

Test Data	Stacking	Bagging	Boosting	Voting	Blending	Proposed Method
60	0.85	0.82	0.87	0.84	0.86	0.88
120	0.88	0.84	0.90	0.87	0.88	0.91
180	0.90	0.86	0.92	0.89	0.90	0.93
240	0.92	0.88	0.94	0.91	0.92	0.95
300	0.94	0.90	0.95	0.93	0.94	0.96

Table.4. Recall

Test Data	Stacking	Bagging	Boosting	Voting	Blending	Proposed Method
60	0.80	0.75	0.82	0.78	0.81	0.85
120	0.83	0.78	0.85	0.81	0.83	0.87
180	0.86	0.81	0.88	0.84	0.86	0.90
240	0.89	0.84	0.91	0.87	0.89	0.92
300	0.92	0.87	0.94	0.90	0.92	0.95

Table.5. Computational Efficiency (%)

Test Data	Stacking	Bagging	Boosting	Voting	Blending	Proposed Method
60	88.5%	90.2%	87.8%	91.0%	89.7%	93.2%
120	89.1%	91.5%	88.6%	91.8%	90.2%	93.8%
180	89.7%	92.0%	89.1%	92.3%	90.7%	94.5%
240	90.2%	92.5%	89.6%	92.6%	91.2%	95.0%
300	90.8%	93.0%	90.0%	93.2%	91.7%	95.5%

Table.6. Response time (ms)

Test Data	Stacking	Bagging	Boosting	Voting	Blending	Proposed Method
60	120.5	118.2	123.0	115.7	121.4	110.6
120	122.8	119.5	124.7	117.2	123.6	112.8
180	125.1	121.0	126.4	119.0	125.8	115.2
240	127.3	12	128.1	120.5	127.4	117.6
300	130.0	125.2	131.0	123.0	130.1	120.0

We observe variations in performance metrics such as precision, recall, computational efficiency, and response time among different ensemble methods.

- The proposed ensemble method consistently outperforms existing methods (Stacking, Bagging, Boosting, Voting, Blending) in terms of precision and recall across all test data points. On average, the proposed method achieves a 5% improvement in precision and recall compared to existing methods.
- Computational efficiency, represented as the percentage of successful classifications relative to total test data, is higher for the proposed ensemble method compared to existing methods. On average, the proposed method exhibits a % increase in computational efficiency compared to existing methods. This higher computational efficiency suggests that the proposed ensemble method can handle larger datasets and perform classifications more quickly.
- Response time, measured in milliseconds, reflects the time taken by each ensemble method to process and classify test data. The proposed ensemble method consistently demonstrates lower response times compared to existing methods. On average, the proposed method shows a 10% reduction in response time compared to existing methods. This reduction in response time indicates that the proposed ensemble method can deliver faster results, making it suitable for real-time applications.

8. CONCLUSION

Our study presents a exploration of ensemble learning methods for the early detection and classification of plant diseases, focusing specifically on tomato leaf diseases. Through experimental evaluation and comparison with existing ensemble methods (Stacking, Bagging, Boosting, Voting, Blending), we have demonstrated the effectiveness of our proposed ensemble approach. The results reveal that our ensemble method consistently outperforms existing methods in terms of precision, recall, computational efficiency, and response time. With an average improvement of 5% in precision and recall, a % increase in computational efficiency, and a 10% reduction in response time, the proposed ensemble method showcases its superiority in accurately and efficiently classifying tomato leaf diseases.

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