COMP9444 Project Summary

Leaf Disease Classification

z5401098 Xiaoyu Su z5437995 Sizhuo Long z5442066 Xuan Wang

z5500861 Yuxuan Dou z5499025 Ziwen Zheng

I. Introduction

Early detection and accurate classification of leaf diseases are crucial for crop health and yield optimization. Traditional manual inspection is labor-intensive, time-consuming, and prone to human error, especially in large-scale farming. Advanced AI techniques offer a promising solution for enhancing disease management. This research aims to develop an automated leaf disease classification system using state-of-the-art AI methods. The system will rapidly process images, provide consistent and accurate results, and operate in real-time, enabling timely interventions. By addressing the limitations of manual inspection, this AI-based solution will improve disease management practices, reduce crop losses, and enhance agricultural productivity and sustainability.

II. Related Work

Current research in crop disease detection using deep learning and machine learning has made significant progress but still faces some limitations.

The study of Paymode, A.S. and Malode, V.B. [1] leverages transfer learning and data augmentation for improved accuracy. This method requires large, diverse datasets. Future work should focus on broader datasets and better performance in uncontrolled environments.

Seyed Mohamad Javidan, Banakar, A., Keyvan Asefpour Vakilian and Yiannis Ampatzidis [2] combines multiple classifiers for higher accuracy but requires significant computational power and depends on dataset quality.

Lu, J., Tan, L. and Jiang, H.[3] uses CNNs for high-accuracy classification but relies heavily on large, labeled datasets. Developing data augmentation and transfer learning methods can reduce this dependency.

The research of Ma, L., Hu, Y., Meng, Y., Li, Z. and Chen, G. [4] employs ResNet18 for efficient disease classification but struggles with complex backgrounds and low-quality images. Enhancing robustness and improving data processing methods are needed.

III. Methods

We employed model CNN, YOLOv10, Resnet18, Resnet18 (non-transfer), VGG, and VGG (non-transfer) to classify leaf diseases.

Rationale for Method Choice

- CNN: As a fundamental architecture in deep learning, CNNs are well-suited for image classification tasks due to their ability to capture spatial hierarchies in images.
- ResNet18: ResNet18 allows for training deeper networks without vanishing gradient issues, making it effective for detailed image classification.
- ResNet18 (non-transfer): Trained from scratch to compare against the pre-trained version, assessing the benefits of transfer learning.

- VGG16: Chosen for its simplicity and proven effectiveness, VGG16's deep convolutional layers allow for powerful feature extraction, ideal for distinguishing leaf diseases.
- VGG16 (non-transfer): Trained from scratch to evaluate performance differences with and without pre-trained weights.
- YOLOv10: Utilized for its real-time object detection and classification capabilities, using the YOLOv10n pre-trained model.
- Majority Voting: Combined predictions from above models to enhance robustness and accuracy.

Pre-trained Models and Fine-tuning

- ResNet18: Pre-trained and fine-tuned by modifying the last fully connected layer to match our 39 classes.
- VGG16: Similarly pre-trained and fine-tuned, adapting the last layer for our specific task.
- YOLOv10: We used the pre-trained YOLOv10n model, which was fine-tuned on our leaf disease dataset. This involved training the model for 15 epochs with a batch size of 64 and an image size of 256x256, using our custom data configuration.

IV. Experimental Setup

In this research project, we utilize a comprehensive dataset aimed at the classification of plant leaf diseases. Link of dataset: https://data.mendeley.com/datasets/tywbtsjrjv/1

CNN: We used a Simple CNN model with two convolutional layers (3x32 and 32x64), a max pooling layer, and two fully connected layers (645656 to 128, and 128 to 39 classes). The model employs a dropout layer with a 0.5 probability, Adam optimizer with a learning rate of 0.001, and cross-entropy loss.

Resnet18(non-transfer) and Resnet18: We used the ResNet18 architecture without pre-trained weights and the ResNet18 architecture with pre-trained weights. The final fully connected layer was modified to output 39 classes. The model was trained with SGD optimizer (learning rate of 0.01) and cross-entropy loss.

Vgg16(non-transfer) and Vgg16: We used the Vgg16 architecture without pre-trained weights and the Vgg16 architecture with pre-trained weights. The final fully connected layer was modified to output 39 classes. The model was trained with the SGD optimizer (learning rate of 0.01) and cross-entropy loss.

Yolov10: We used the YOLOv10 model with pre-trained weights (jameslahm/yolov10n). The model was trained for 15 epochs with a batch size of 64 and an image size of 256x256 pixels. The data configuration was specified in leaf_disease.yaml.

For above models, the evaluation metrics included accuracy, precision, recall, F1 score, and the confusion matrix. The dataset was split into training, validation, and testing sets. The model was trained for 15 epochs, with performance metrics calculated and recorded for both the training and validation sets after each epoch. Finally, the model was evaluated on the test set to determine its final performance, and the best model was saved.

Majority voting: We implemented a majority voting ensemble method using above models. Each model was trained independently and their predictions were combined to make final classification decisions. The evaluation metrics of majority voting are the same as other models. The final predictions were made by aggregating the outputs of the individual models using majority voting. The performance of the ensemble model was then assessed on the test set, with results visualized through performance metrics and confusion matrices.

V. Results

Model	Accuracy	Precission	Recall	F1-score
CNN	0.8749	0.8792	0.8749	0.8744
Resnet18(non-transfer)	0.8246	0.8481	0.8246	0.8254
Resnet18	0.9872	0.9876	0.9872	0.9871
VGG16(non-transfer)	0.7815	0.8100	0.7815	0.7733
VGG16	0.9892	0.9895	0.9892	0.9892
YOLOv10	0.97385	0.97343	0.95716	0.96987
Majority Vote	0.99197	0.99192	0.99197	0.99172

Table 1: summary of results

Analysis of Model Performance：

Table 1 summarizes all model performance. We can see that the worst performing model is VGG16 (non-transfer) and the best performing single model is VGG16. The majority voting combines the prediction results of multiple models, reducing the error of a single model, and thus obtaining the best results.Now we will discuss each model in more detail.

- CNN: Despite its simple structure, it performed well with 87% accuracy.
- Resnet18 is a deep residual network that can effectively alleviate the gradient vanishing problem. However, Resnet18 without pre-trained weights needs to learn all features from scratch, resulting in poor performance, but all results also reached about 82%.
- Resnet18 (pre-trained): Significantly improved with 98.8% accuracy. which is the single model second only to the VGG16 result.
- Although VGG16 is a deep convolutional neural network with a large number of layers and parameters, VGG16 (non-transfer) has poor results being only about 78% due to learning from scratch.
- VGG16 (pre-trained): Best single model with 98.9% accuracy.
- The YOLOv10 model is mainly used for object detection tasks. Using the yolo model is a novel attempt for this task. Although yolo does not perform as well as specialized classification models (such as ResNet18 and VGG16) in classification tasks, the model also achieves good results in leaf disease classification, with each result reaching about 96%.
- Majority Vote: The majority voting method combines the prediction results of multiple models and selects the final prediction category through a voting mechanism. This method can effectively reduce the error of a single model and improve the overall prediction accuracy and robustness. Therefore, the majority voting method finally obtained the best results, with each result reaching about 99%.

Comparison of Existing Methods in Literature

We refer to the paper by Barbedo[5], which uses a pre-trained CNN with a GoogLeNet architecture, and the accuracy of each crop ranges from 75% to 100%. This variation is caused by differences in the number of images, the number of diseases, the diversity of diseases, and the resulting difficulty level. The overall accuracy using a single lesion and spot is 94%. Our majority voting model has an accuracy of 99.197%, and the VGG16 model has an accuracy of 98.92%, both of which are better than previous references.

In the leaf disease classification task, one of the state-of-the-art models is EfficientNetV2. According to the research of Tan and Le[6], EfficientNetV2 has an accuracy of more than 98% on multiple datasets. In the specific leaf disease classification task, EfficientNetV2 has an accuracy of 99%. This model introduces more efficient training strategies such as progressive learning rate scheduling and data augmentation techniques. Compared with them, our VGG16 model has lower training efficiency and longer training time.

Practical application of the models
In summary, our model results are good enough to be deployed in practical applications. Both majority voting and VGG16 achieved good results. The majority voting results reached about 99%. After using the pre-trained weights, the VGG16 model also reached about 98.9%, which shows that it has high reliability and accuracy in practical applications.

VI. Conclusions

Contributions

1. We developed a robust ensemble model using majority voting, which achieved a high accuracy of 99.197% in leaf disease classification. It combines diverse models, leading to more robust and accurate predictions by leveraging different models' strengths in recognizing various aspects of leaf diseases.
2. We demonstrated the effectiveness of transfer learning by comparing pre-trained and non-pre-trained models. The pre-trained VGG16 model (98.92% accuracy) significantly outperformed its non-pre-trained counterpart (78% accuracy).
3. We successfully adapted a specialized object detection model (YOLO) for classification tasks, achieving 96% accuracy and adding diversity to our ensemble.

Key Strengths

1. High Accuracy: Our majority voting model and single models (e.g., VGG16) achieved very high accuracy rates.
2. Robustness: The ensemble approach improves overall prediction accuracy and robustness by combining multiple models' predictions.
3. Versatility: Our solution effectively utilizes both general classification models and specialized models like YOLO.

Limitations

1. Data Diversity: Our model struggles with diseases that have similar visual characteristics, especially in early stages. This indicates a need for more diverse and representative training data.
2. Misclassifications: Despite high overall accuracy, there are still some misclassifications, particularly between visually similar diseases (e.g., corn leaf spot vs. northern leaf blight, tomato early blight vs. target spot).
3. Model Complexity: While the majority voting mechanism improves accuracy, it also increases the system's complexity and computational cost.

Future Work for Improvement

1. Verify and improve image labels to ensure data quality.
2. Enhance image quality control, focusing on lighting and cropping to preserve critical lesion features.
3. Augment the training set with more examples of frequently misclassified diseases.
4. Develop specific image augmentation techniques tailored to leaf disease characteristics.
5. Implement advanced data augmentation to increase training set diversity.
6. Explore more efficient model architectures like EfficientNetV2.
7. Developing methods to provide better interpretability and explainability of the model's predictions.

References:

[1] Paymode, A.S. and Malode, V.B. (2022). Transfer learning for multi-crop leaf disease image classification using convolutional neural networks VGG. Artificial Intelligence in Agriculture. doi:https://doi.org/10.1016/j.aiia.2021.12.002.

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