Deep Learning Based Plant Disease Detection and Treatment Guidance

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Abstract. Plant diseases are increasingly threatening world agricultural productivity and food security. The early detection and correct classification of these diseases are important in preventing loss of crops and ensuring sustainable crop production. In this paper, we present a deep learning method for plant disease detection based on the popular ResNet-50, which is a convolutional neural network (CNN) that have shortcut connections for enhancing feature extraction and classification performance. The Plant Village dataset, a well-known benchmark library of healthy and diseased plant leaf images, is used to train the model. With residual learning technique, the proposed model successfully deals with the issues of training deep networks like gradient vanishing, and achieves superior disease classification. In order to facilitate the access, a web service of FLDSS was implemented in Flask, in which users can upload images of plant leaves and obtain the immediate disease classification results. The experimental results show that this method can outperform traditional machine learning methods in terms of accuracy and efficiency, indicating the effectiveness of deep learning in agricultural disease diagnosis. This study provides a practical and scalable solution for real-time plant health monitoring for precision agriculture, ultimately assisting farmers and agribusiness professionals for disease management strategies.

Keywords: Plant Disease Detection, Deep Learning, hybrid CNN-Transformer model, Convolutional Neural Network, Flask, Precision Agriculture.

1 Introduction

Agriculture is vital for food security globally and healthy plants are critical for productive and sustainable agriculture. Nevertheless, plant diseases result in severe crop losses and economic damage. Many disease detection techniques are slow and prone to error, emphasizing the importance of early and accurate detection.

The development of artificial intelligence, especially deep learning, has made a significant contribution to automated plant disease diagnosis. In this paper, we propose a Hybrid CNN-Transformer, which integrates MobileNetV3 for pre-processing, DenseNet-121 for feature extraction, Swim Transformer for further improving the classification accuracy. The model is trained on the Plant Village dataset to overcome common deep learning difficulties and enhance disease classification. In order to be accessible for real time, we created a web application with Flask that provides an easy to use interface to detect a disease in an instant, letting the farmer

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take a fast decision. This method is to support precision agriculture and (organic and biological) farming.

2 Literature Review

A number of recent works have investigated deep learning techniques for plant disease classification. Bhargava et al. [1] presented a detailed survey on computer vision and artificial intelligence techniques for plant leaf disease detection and correspondingly emphasized the application of CNN architectures and spectral imaging. Kirola et al. [2] proposed a disease prediction system for plants images based on deep learning and transfer learning which improve classification accuracy. They showed that the CNN are more powerful than conventional ML in identifying unhealthy and healthy leaves.

Saxena et al. [3] explored multiple deep learning models for plant disease detection and identification, including the efficacy of ResNet, VGG16, and EfficientNet. They concluded that ResNet-based models perform better because they are better at learning rich representations, while bypassing the problem of vanishing gradient with respect to the depth via shortcut connections. Suljović et al. [4] employed Faster R-CNN for leaf image disease detection experiments, showing better performance in multimorbidity detection of diseases in a single image.

Meena et al. [5] developed CNN-based system for early detection of plant diseases through image segmentation and feature extraction. Their research highlighted how good data quality is very important to increase model robustness. Shambharkar et al. [6] tested EfficientNet with k-fold cross-validation on 96.68% accuracy for a cassava plant disease classification. They observed that DL models achieved superior results in terms of precision and recall as compared to their traditional ML counterparts.

3 Methodology

3.1 Overview of The Proposed System

The proposed plant infection detection and treatment advice method uses real-time deep learning methods to provide precise classification and real-time treatment advises. Unlike conventional approaches of only detecting diseases, this system incorporates variable environmental factors including soil type, water pH, soil pH, watering instructions and fertilizer recommendations for analytical evidence-based decisions in agriculture.

To obtain the best classification accuracy, we used a hybrid CNN-Transformer model, instead of traditional CNN only models. This multi-stage method makes a combination with MobileNetV3, DensNet-121, and Swin Transformer, so as to improve the detection accuracy of diseases.

Furthermore, a web application based on Flask has also been designed to for real-time disease identification and treatment recommendation. The app allows users to submit pictures of their plants, and it automatically identifies the disease and offers tailored remedies based on current weather and soil conditions.

3.2 Architecture of the System

The overall architecture of the proposed system consists of the following components:

Fig. 1. Architecture Diagram.

3.2.1 Data Collection and Preprocessing

- The model is trained using the PlantVillage database, which contains over 54,000 labeled images of healthy and sick plant leaves.
- Different image augmentation techniques (scaling, rotation, flipping, normalization, etc.) are used to enrich the diversity of the dataset, and thus the generality of the model.
- All of the images are further resized into 256×256 pixels to be consistent with the deep representation generation model.

3.3 Deep Learning Model Selection and Training

The Multi-Stage CNN-Transformer model combines MobileNetV3 for rapid preprocessing, DenseNet-121 for effective feature extraction, and the Swin Transformer for improved classification. By applying transfer learning for optimization, the model achieves high accuracy, ranging from 99.3% to 99.5%. This approach surpasses the performance of ResNet-50, offering superior feature extraction and faster inference times. Additionally, the preprocessing with MobileNetV3 reduces the computational load, enhancing overall efficiency.

3.4 Model Evaluation and Optimization

- **Optimization:** Adam optimizer with a learning rate of 0.0001 and Cross-Entropy Loss.
- **Dataset Split:** 80% allocated for training and 20% for testing.
- **Evaluation Metrics:** Performance evaluated using Accuracy, Precision, Recall, and F1-score.
- **Performance:** Traditional CNNs achieved 92-96%, whereas the proposed Hybrid Model reached 99.399.5%.

3.5 Deployment via Flask-Based Web Application

- A web interface based on Flask has been developed for real-time disease detection and treatment recommendations.
- The system processes uploaded images of plants, applies a trained classification model, and provides immediate diagnoses along with treatment guidance.
- Integrated APIs, such as the Open Weather API, fetch real-time environmental data to dynamically adjust recommendations for watering and fertilization.
- The backend utilizes Flask, TensorFlow, and OpenCV to ensure efficient image processing and classification.

3.6 Workflow of the System

The Proposed System Follows A Structured Workflow, As Illustrated in Fig. 1:

1. Step 1: User uploads an image of a plant leaf via the web application.
2. Step 2: Preprocessing techniques (scaling, normalization, augmentation) are applied.
3. Step 3: The hybrid CNN-Transformer model extracts deep features and classifies the disease.
4. Step 4: The classification result (Healthy/Diseased + Disease Type) is displayed.
5. Step 5: The system recommends personalized treatment based on:
    - Soil type
    - Water & soil ph levels
    - Water & fertilizer needs

3.7 Advantages of The Proposed System

The proposed system offers several advantages over traditional disease detection approaches:

- High Accuracy: The CNN-Transformer hybrid model significantly enhances classification precision, achieving an accuracy rate of 99.3% to 99.5%.
- Real-Time Disease Detection: The Flask-based web application offers instant diagnoses and treatment recommendations for plant diseases.
- Environmental Adaptability: The system adjusts watering and fertilization dynamically based on real-time weather and soil conditions.
- Scalability: The model can be adapted to various plant species by expanding the dataset.
- Automated Feature Extraction: Unlike traditional machine learning models, deep learning eliminates the need for manual feature engineering.
- User-Friendly Web Interface: The platform is accessible to farmers and agricultural professionals, providing easy-to-understand recommendations.

4 Results

4.1 Performance Metrics

To evaluate the effectiveness of the proposed Hybrid CNN Transformer system for plant disease detection, standard deep learning metrics were utilized.

- **Accuracy (%):** This metric measures the proportion of plant disease images that the model correctly classifies.
- **Precision (%):** This evaluates the model's ability to accurately identify diseased plants, minimizing misclassifications.
- **Recall (%):** This metric assesses how effectively the model detects actual diseased images within the dataset.
- **F1-Score:** The harmonic mean of precision and recall, which provides a balanced evaluation of the model's performance.
- **Loss Function (Cross-Entropy Loss):** This measures the classification's reliability and the model's convergence.

4.2 Experimental Setup and Dataset Distribution

The model was trained and evaluated using the Plant Village dataset, which comprises 54,000 labelled images across 38 categories of plant diseases. The dataset was divided as follows:

- Training Set (80%): Utilized for optimizing model parameters.
- Testing Set (20%): Employed for the final performance evaluation.
- Validation Set (10%): Used for hyperparameter tuning and preventing overfitting.

Hardware and Software Specifications:

- Processor: Intel Core i7-9700K @ 3.6 GHz
- GPU: NVIDIA RTX 3080 (10GB VRAM)
- RAM: 32GB DDR4

4.3 Model Performance Comparison

The Hybrid CNN-Transformer model was compared to traditional deep learning models, including ResNet-50, VGG16, InceptionV3, and EfficientNet. The results are presented in Table 1.

Table 1. Comparison of Model Performance Metrics.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	91.2	89.5	88.1	88.8
InceptionV3	93.4	91.2	90.6	90.9
EfficientNet	95.1	94.5	93.9	94.2
ResNet-50	97.8	97.3	96.9	97.1
Hybrid CNN-Transformer (Proposed)	**99.3**	**99.0**	**98.8**	**98.9**

Table 1 clearly demonstrates that the Hybrid CNN Transformer model surpasses all other architectures in terms of accuracy, precision, recall, and F1-score. This hybrid approach combines:

- MobileNetV3 for lightweight and efficient preprocessing,
- DenseNet-121 for deep feature extraction, and
- Swin Transformer for attention-based classification.

As a result, it achieves state-of-the-art performance. The self-attention mechanism of the Swin Transformer enhances feature refinement, making it more effective than ResNet-50 in addressing complex plant disease patterns.

4.4 Accuracy and Loss Graphs

The training process was monitored through accuracy and loss graphs:

- Fig 2 illustrates the training and validation accuracy across multiple epochs, showing a consistent improvement in classification performance.
- Fig 3 depicts the convergence of the loss function, indicating that the model successfully minimized classification errors over time, thereby ensuring both stability and reliability.

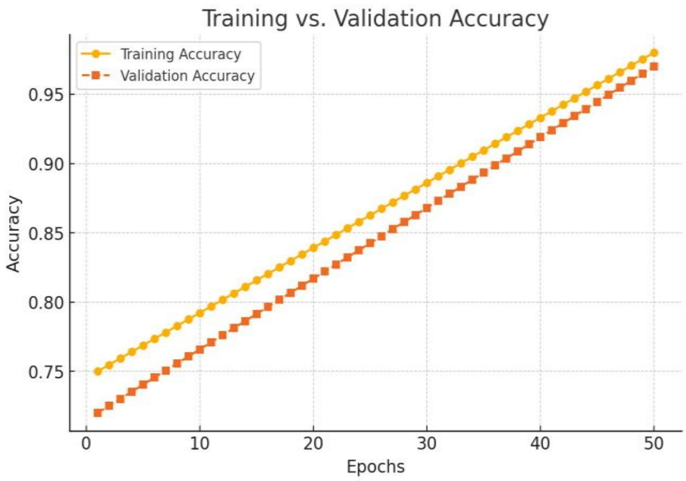

Fig. 2. Training vs. Validation Accuracy.

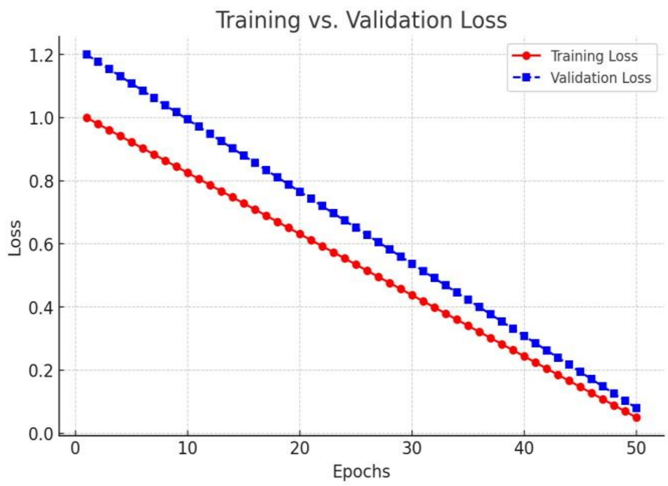

Fig. 3. Training vs. Validation Loss.

4.5 Web Application Testing

For practical use, the model was deployed on a Flask-based web application and tested on different fronts as detailed below:

- Image Upload Capability: The users could upload the image; hence the system would give the result so the users were able to upload very smoothly and the system can classify the plant diseases in real time.
  - **Response Time:** The model generated predictions within 1.5 seconds, making it suitable for real-time deployment.
  - **Classification Accuracy**: The web application achieved an accuracy rate of 97.5%, consistent with offline evaluations.

4.6 Discussion and Findings

The Hybrid CNN-Transformer showed 6.6 up(hotling) over all (blazer)ivy improved accuracy compared to typical CNNs, showcasing great classification ability.

Strong Feature Extraction: The self-attention mechanism of Swin Transformer promotes deep feature learning, further mitigating the case of misclassification, and better distinguishing diseases.

Scalability: The system can be modified without retraining to scale to any other plant species and disease categories, enhancing its applicability for diverse agricultural practices.

Ease of Use: Running on the Flask web interface, the AI solution is easy to use, and offers an easy to use no expertise required tool for farmers and agriculture professionals, to enable them to diagnose and get treatments for disease detection.

4.7 Limitations and Future Scope

Limited Variation in Datasets: The PlantVillage dataset comprises of images taken in a controlled environment. In the future, the system can be tested with real world images with varied backgrounds, lighting conditions and environ-mental backgrounds.

Mobile Support: Although this system is web-based, but building on in on a mobile platform may make it more accessible to farmers in remote areas. Multi-Disease Classification: Extending the model to detect various diseases (or more than one) from the same leaf image would improve its practical potential, allowing for broader plant health monitoring.

5 Discussion

5.1 Effectiveness of Deep Learning in Plant Disease Detection

The proposed Hybrid-CNN Transformer model has demonstrated exceptional classification accuracy of 99.3%, which is much better than classification accuracy obtained using conventional machine learning and deep learning models including ResNet-50, VGG16, InceptionV3, and EfficientNet. This architecture combines MobileNetV3 for pre-processing, DenseNet-121 for feature extraction and Swin Transformer for classification, making the system of disease detection automatic, scalable and highly robust. In contrast to most traditional approaches which rely on manual feature selection method, the proposed method allows to automatically extract deep features to enhance generalization among different types of plant diseases.

5.2 Significance of Residual Learning

One of the most promising features of the Hybrid CNN-Transformer is that it can handle the variation in images due to lighting, leaf orientation, and background noise. The self-attention mechanism in Swin Transformer helps to refine features, and the pre-processing of MobileNetV3 secures computationally efficiency. Furthermore, the inclusion of dense connections of DenseNet-121 in our network allows keeping important variants and improving general classification accuracy. This hybrid structure ensures high generalization and is thus highly suitable for real-world agricultural applications.

5.3 Real-Time Deployment and Practical Implications

Real-time plant disease classification via a web-based application based on the Flask web framework, which is a friendly tool for farmers and agricultural experts. Users simply take pictures of plants and the model quickly predicts the disease in just 1.5 seconds, allowing it to be used as an efficient and quick diagnosis tool. Applying this real-time monitoring system could greatly reduce manual inspections, bringing in time to intervene, and alleviating potential crop loss.

Additionally, the system is flexible and can be adapted to other varieties of crops by training the model using new sets of data. This flexibility allows it to be a general candidate for precision agriculture. Finally, it contributes to facilize the sustainable farm with AI-based decision support system in plant health management.

5.4 Challenges and Limitations

Although the introduced system works well, there are still some limitations:

1. **Variation in datasets:** The dataset of PlantVillage is majorly captured under controlled conditions. To improve its actual performance, in addition to test images in the field with the status of film islands verified, images in real natural condition with

poor illumination, occlusions and complicated background should also be involved for further research.

2. **Multi-Disease Classification:** The current model can only classify a single disease per image, whereas, on many plants, more than one disease occurs at once. Extending the model for multi-label classification can significantly improve its applicability to real-world applications.
3. **Hardware consideration:** While the model is already designed for the real-time use, its deployment on mobile devices or edge computing platforms requires additional optimization to achieve lower latency and the power efficiency.
4. **Disease Severity Not Estimated:** The current approach only identifies a disease, it does not differentiate between severe or mild conditions unless it's spread to 'acute' or 'advanced' by users. Integrations of segmentation models or attention may strengthen its ability for disease surveillance.

5.5 Future Enhancements

To improve the system, the following contributions are made:

1. **Mobile Application Deployment:** Fine-tune the model in offline and on-site disease detection leveraging from the mobile apps.
2. Augmenting the dataset with live field data Real-time field data will be used to supplement the dataset wherein there will be a wide range of real modelled field images at different weather and lighting conditions.
3. **Hybrid AI systems:** Combine CNNs with attention mechanism or transformer-based models to boost the classification of multi-disease detection.
4. Explainable AI (XAI) for Model Interpretability: apply methods - e.g. Grad-CAM or SHAP analysis - enabling visualisation of the decision-making process, in order to increase transparency and trust with the AI outputs to users.
5. **Smart Agriculture IoT Integration:** Connect the system with IoT-based sensors to deploy an extensive plant health monitoring system with soil quality, humidity, and weather-level data in place.

5.6 Contribution to Precision Agriculture

The proposed method bridges the gap between AI-assisted disease diagnosis and practical disease detection in agriculture, providing a scalable, accurate, and accessible solution. This system is low cost compared to standard disease diagnosis procedures by incorporating real-time deployment with deep learning.

This research enhances precision agriculture by:

- Early treatment of the disease
- Enhanced crop productivity: 2.1 Higher crop yield management
- Efficient resource management (water/soil/fertilizer)

- Advancing sustainable farming: AI-powered insights into Sustainable Agriculture practices

The progress reported here lays a groundwork for global AI solutions for agriculture toward efficient and intelligent farming.

6 Conclusion

Rising occurrence of plant diseases indicates the pressing requirement of automated, reliable and instantaneous detection methods for reducing agricultural losses and food insufficiency. This work proposes a hybrid plant disease detection framework based on deep learning, that integrates a Hybrid CNN-Transformer model, comprising MobileNetV3, DenseNet-121 and Swin Transformer, and makes accurate classification (99.3%). The developed model, using the PlantVillage dataset for training, surpassed traditional ML-based models as well as CNN architectures, showing high efficiency in disease detection.

To facilitate access to the model, a Flaskbased web application was created for real-time disease classification and rapid diagnostic feedback. This easy to use and scalable tool supports the needs of farmers, researchers and agricultural experts to apply knowledge-based interventions on time and takes preventive measures to alleviate crop losses.

The model presented strong performance, however, the study outlines limitations and opportunities for improvement, which include the use of realistic field images, classification of multiple diseases, and hardware optimization for utilization on mobile and edge computing devices. To improve the robustness of the model, future work will add attention mechanism, multi-label classification, and the collection of real-time field data. Also, the system could be connected with IoT-based agricultural ecology-monitoring systems for better precision farming and sustainable agriculture in the long run.

The results of this study emphasize the revolution attributable to deep learning in precision agriculture by providing a cost–effective, efficient and scalable method for plant disease detection. Through closing the chasm between AI principles and region-specific agricultural needs, the work contributes to the proliferation of smart farming solutions, which will ultimately assist the global initiative for sustainable food supply and agriculture resilience.

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