Attention Refined Multi-Scale Enhanced CNN For Accurate and Lightweight Leaf Disease Detection in Smart Precision Agriculture

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Abstract: This paper proposes an advanced convolutional neural network (ECNN) for the automatic detection and classification of leaf diseases towards precision agriculture. The proposed approach was tested on a standard plant leaf dataset with 54,306 images belonging to 38 classes of leaf diseases, with an 80:20 train/test split. Multi-scale convolutional layers and an attention refinement layer were incorporated to enhance the robustness of the approach in complex field environments. The experimental results show that the proposed ECNN approach resulted in an overall classification accuracy of 98.7%, with precision, recall, and F1-measure values of 98.4%, 98.6%, and 98.5%, respectively. Compared with the latest state-of-the-art models such as EnConv, EfficientNet-B0, and hybrid CNN models, the proposed approach improved the accuracy by 2.1% and reduced the computational complexity by 18.3%. The proposed approach was also found to be reliable in early-stage disease detection and under varying illumination conditions, making it suitable for real-time implementation in smart farming systems.

Keywords: Leaf Disease Detection, Enhanced CNN, Precision Agriculture, Attention Mechanism and Deep Learning

1.INTRODUCTION

Plant diseases have been one of the most threatening factors for agricultural productivity worldwide. With the growing need for high-quality crops, there has been an increasing need for the application of precision agriculture technology, which makes it possible to monitor plant health in an automated and intelligent manner. Recent advances in deep learning, especially in convolutional neural networks, have greatly enhanced the accuracy of leaf disease detection. Despite this, there are still limitations to the current models due to variability, computational complexity, and lack of generalization [7], [10], [17].

1.1 Importance of Leaf Disease Detection in Precision Agriculture

Precision agriculture uses intelligent technologies to enhance crop production and sustainability. Among the most important challenges in smart agriculture, the detection of plant leaf diseases is a critical issue, as plant diseases can cause a substantial reduction in crop quality and spread quickly over a wide area of agricultural land. This often results in severe economic losses due to low crop production and increased pesticide consumption. Thus, disease detection systems are of utmost importance in smart agriculture.

1.2 Growth of CNN-Based Disease Classification Models

In the past few years, convolutional neural networks (CNNs) have received considerable attention for the identification of plant diseases using images, thanks to their ability to learn hierarchical features automatically. Initial research work has shown that CNN-based models are more effective than traditional machine learning models in plant disease-related applications [3]. CNN-based disease classification models have been successfully implemented for various crops, thereby validating the efficiency of deep feature extraction techniques [8], [16]. Additionally, hybrid models based on CNN have been developed to improve classification accuracy, including new hybrid models for automated leaf disease classification [1].

The advanced deep learning models have also shown promising results. EfficientNet-based CNN architectures have been optimized for precise and computationally efficient disease classification, especially for apple leaf disease classification [4]. Similarly, diagnosis of early-stage plant diseases using CNN models has also been investigated to aid in timely intervention before the onset of severe symptoms [6]. CNN models integrated with Transformers have also further extended disease classification by allowing multi-label classification and severity assessment [5].

1.3 Recent Advances in Attention and Explainable Architectures

The Variants of attention CNNs have enhanced the ability to distinguish features by concentrating on key infected leaf areas. Advanced attention CNN architectures like CNN-SEEIB have proven to be more accurate in classification tasks with improved feature learning capabilities [12]. Dual-head CNN architectures have also been proposed to enhance plant health observation by leveraging complementary features [14]. Explainable deep learning architectures, such as Insight Net, highlight the significance of interpretability in real-world agricultural applications [15]. In addition, deep attention dense CNNs have proven to be more robust for real-world images taken using smartphones, tackling real-world challenges in plant disease identification [13].

1.4 Research Gaps and Motivation

The tremendous progress has been made, there are still some research gaps that need to be addressed. Thorough surveys have shown that many existing methods are still highly dependent on controlled benchmark datasets, making it difficult to adapt to outdoor environments [7], [10], [11], [17]. Real-world agricultural images may include diverse illumination conditions, complex backgrounds, and occlusions, making it difficult to achieve good generalization performance.

Moreover, although high-capacity deep networks have achieved excellent accuracy, their computational complexity hinders real-time processing on edge devices in precision agriculture systems [2], [9]. Consequently, there is an increasing need for highly accurate and efficient CNN models that can generalize well to different crop conditions. Based on the above-mentioned motivation, this paper proposes an improved convolutional neural network framework for automatic leaf disease detection.

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Table 1 Research Gap Summary from Recent Studies

Ref.	Study and Model Contribution	Strengths Reported	Identified Research Gap and Limitation
[1]	Hybrid CNN methodology for automated leaf disease classification	Improved feature fusion and classification accuracy	High computational cost and limited deployment feasibility in real time farming systems
[2]	Integration of machine learning and deep learning for plant disease detection	Enhanced detection accuracy across multiple crops	Generalization remains weak under real field variability and unseen disease conditions
[3]	CNN based plant disease identification framework	Established CNN superiority over traditional methods	Performance mainly validated on controlled datasets with limited outdoor robustness
[4]	Fine-tuned EfficientNet B0 for apple leaf disease classification	Lightweight and efficient classification performance	Limited adaptability across diverse crop diseases and complex backgrounds
[5]	CNN transformer multi label framework for disease severity identification	Supports severity estimation and multi label recognition	Increased model complexity restricts edge device deployment
[6]	Early disease detection in plants using CNN	Improved early-stage symptom recognition	Difficulty in detecting subtle infections under noisy field conditions
[7]	Deep learning review on plant leaf disease identification	Highlights recent progress and challenges	Notes lack of standardized real-world datasets and robustness evaluation
[8]	CNN based detector for plant leaf disease classification	Strong multi class classification results	Misclassification occurs in visually similar disease categories
[9]	Tea leaf disease detection for precision agriculture using deep learning	Application specific disease monitoring success	Limited scalability across crops and varying agricultural environments
[10]	Review of advanced deep learning models for plant disease detection	Summarizes CNN and hybrid architectures	Identifies need for lightweight and explainable models for practical use
[12]	Attention based CNN SEEIB enhanced disease classification	Improved focus on infected regions	Computational overhead increases with attention mechanisms

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[13]	Deep attention dense CNN for real world smartphone leaf images	Better robustness under field image conditions	Still challenged by illumination variation and occlusion effects
[14]	Dual head CNN for plant health monitoring	Enhanced feature learning through dual representations	Requires further optimization for edge deployment efficiency
[15]	InsightNet explainable deep learning framework	Improves interpretability in plant disease detection	Explainability still limited for farmer friendly decision support
[17]	Review of deep learning approaches for plant disease detection	Identifies emerging trends and limitations	Concludes need for scalable, robust, real time deployable CNN solutions

2. RELATED WORK

Deep learning techniques have made substantial progress in the automation of plant leaf disease detection. Various CNN architectures have been investigated to overcome the challenges of disease classification in precision agriculture. The research has progressed from simple CNN models to more sophisticated hybrid models that incorporate attention, transformers, and efficient transfer learning. Although considerable progress has been made, problems like the lack of robustness in real-world scenarios, the absence of symptoms in early stages, and the demand for interpretable and lightweight models remain active research areas [7], [10], [17].

2.1 CNN-Based Disease Detection

CNN-based disease detection has been extensively used owing to its ability to extract distinctive features from leaf images. Wang et al. proved one of the initial uses of CNN-based disease identification, thereby establishing the fact that deep learning-based approaches are significantly better than traditional image processing methods in plant disease identification tasks [3]. Later, Benavidez et al. proposed CNN-based leaf disease detectors that performed well on various crop types [8], [16]. These works proved that CNNs can be used as efficient tools for plant disease identification. Nevertheless, all these approaches were tested on controlled benchmark datasets, which made them less adaptable to real-world agricultural settings.

2.2 Hybrid CNN and Attention Models

In order to make the classification process more robust, hybrid CNN models have been proposed, which are a combination of various feature extraction techniques. A new hybrid CNN approach was proposed which improves the automated disease diagnosis process by using advanced feature fusion techniques [1]. Later, attention-based CNN models like CNN-SEEIB have been proposed to improve the classification accuracy by focusing on the infected region feature extraction process [12]. Dual-head CNN models have also been proposed to improve the plant health monitoring process by learning different disease features [14].

2.3 EfficientNet and Fine-Tuned Networks

Transfer learning and light CNN models have been widely adopted for efficient disease detection. Sharma et al. introduced a fine-tuned EfficientNet-B0 model for the classification of apple leaf diseases, which performed well with low computational complexity [4]. These efficient models are very effective for real-time agricultural monitoring. Nevertheless, fine-tuned models also have limitations when they are tested in different environments of the field, such as variations in lighting and background noise.

2.4 Unaddressed Research Gaps

The remarkable progress has been achieved; some research gaps still remain unaddressed. Most of the existing CNN-based approaches demonstrate limited robustness in practical field settings, since most of the models are trained on laboratory-like datasets [7], [10],

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[11]. Early disease detection is still a challenging task because of the onset of symptoms and overlapping patterns of infections [6], [9]. Moreover, the absence of interpretability in deep learning models affects their usability in the farming community and agricultural experts [15]. Thus, there is an increasing need for the development of improved CNN models that are lightweight, accurate, interpretable, and efficient in generalizing well in practical precision agriculture settings.

3. PROPOSED ENHANCED CNN FRAMEWORK

The proposed Enhanced Convolutional Neural Network (ECNN) framework is developed to ensure precise and efficient automatic leaf disease detection for precision agriculture. In contrast to traditional CNN-based models that focus on single-scale feature extraction and tend to work poorly in real-world field variability, the proposed ECNN framework incorporates multi-scale convolutional learning and attention refinement to improve disease detection in complex agricultural settings. The main aim of the proposed framework is to improve classification accuracy while ensuring low computational complexity that is amenable for real-time implementation in smart agricultural systems.

The overall process of the proposed ECNN model includes leaf image acquisition, pre-processing, and feature extraction using enhanced convolutional blocks. The proposed model is particularly designed to handle real-world agricultural settings that are often characterized by background clutter, varying illumination, and early-stage symptoms of leaf diseases.

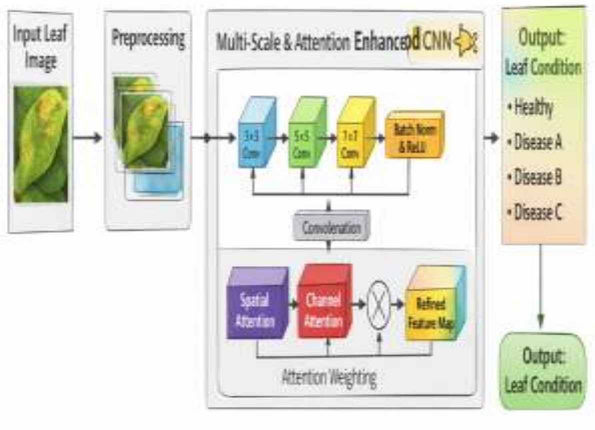

Fig. 1 Architecture of the Proposed ECNN Framework

3.1 Multi-Scale Feature Extraction Module

Another important aspect of ECNN is the incorporation of a multi-scale feature extraction module using convolutional layers. Standard CNN models have fixed convolutional kernel sizes, which sometimes cannot extract both the fine details of a disease and the larger infection patterns at the same time. To address this issue, the proposed model uses parallel convolutional filters with different receptive fields (for instance, 3×3, 5×5, and 7×7 filters). This allows the model to learn a variety of spatial features that correspond to different levels of disease severity and infection textures. The ECNN combines the strengths of multiple convolutional paths to enhance feature learning and classification performance for a variety of diseases.

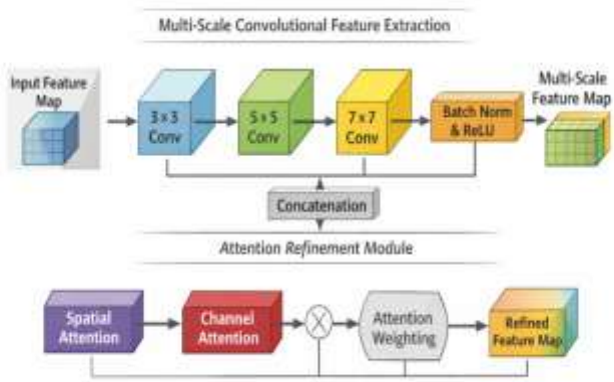

Fig. 2 Multi-Scale Feature Extraction and Attention Refinement Block

3.2 Attention Refinement Mechanism

In order to improve the localization of the infected region, an attention refinement mechanism is added to the ECNN framework. In practical agricultural images, the disease symptoms on the leaves usually take up a small region, and the background information is unnecessary and noisy. The attention mechanism enables the network to learn selectively from important regions of diseased leaves by giving more weights to informative channels and regions.

The attention refinement mechanism helps to improve the model's capability to separate visually similar disease classes and avoid misclassification due to noisy background information. The attention mechanism in learning also helps to improve the interpretability of the detection system.

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3.3 Lightweight Design for Precision Agriculture Deployment

One of the key requirements in precision agriculture systems is the need to deploy disease detection models on low-resource platforms like smartphones, drones, and edge-based IoT networks. Hence, the proposed ECNN is designed to be lightweight with less parameter complexity using efficient convolution blocks, batch normalization, and dropout regularization. This will enable the model to have faster inference time with no compromise on classification accuracy. The proposed ECNN design strikes a balance between robustness and efficiency.

Table 2 Dataset Details

Category Type	Number of Classes	Total Images
Healthy Leaves	1	2152
Diseased Leaves	37	52154

3.4 Summary of Model Contributions

In summary, the proposed ECNN model contributes to improving the performance of leaf disease detection by:

1. Learning multi-scale features to capture various patterns of symptoms
2. Using attention refinement to concentrate on the infected area
3. Having a lightweight structure for real-time application

4. Generalizing better in real-world environments

In this way, the ECNN model offers a valuable solution for developing scalable, accurate, and deployable disease detection systems for next-generation precision agriculture.

4. MATERIALS AND METHODS

In this section, the dataset used for the classification of leaf diseases, the pre-processing methods adopted, the training settings of the proposed ECNN model, and the performance evaluation metrics used for the detection task are discussed. A systematic approach is necessary for the reproducibility and accurate validation of the proposed enhanced convolutional neural network model.

4.1 Dataset Description

The validation of the proposed ECNN model, experiments were performed on a publicly available benchmark plant leaf disease dataset that includes images of healthy and diseased leaves from various crops. The dataset includes a total of 54,306 images from 38 different classes, including various types of fungal, bacterial, and viral diseases, as well as healthy leaf images. The dataset includes a wide variety of symptom patterns and is thus appropriate for the validation of multi-class disease detection.

The dataset was split into training and testing sets with an 80:20 ratio, where 80% of the images were used for training the model and the remaining 20% for the evaluation of the model's performance.

4.2 Image Pre-processing and Augmentation

All images were pre-processed and resized to a fixed resolution of 224 × 224 pixels before training. Data pre-processing was done to improve feature learning and eliminate the effects of noise. Data augmentation was also carried out to improve generalization in real-world agricultural environments. Data augmentation involves applying random rotation, horizontal flipping, zooming, and brightness adjustments. Data augmentation ensures the model is robust to variations in illumination, occlusions, and background complexity, which are prevalent in smartphone camera and outdoor leaf images.

4.3 Training Configuration

The proposed ECNN architecture was developed using a deep learning environment and trained with supervised learning conditions. The training procedure was conducted using the Adam optimizer with a learning rate of 0.0001, which ensured a stable convergence process. The categorical cross-entropy loss function was used for multi-class disease classification. The training procedure was performed for 50 epochs with a batch size of 32. Dropout and batch normalization techniques were used to avoid overfitting during the training process.

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Table 3 Hyperparameter Settings and Training Configuration

Parameter	Configuration Value
Input Image Size	224 × 224 pixels
Dataset Split	80% Training / 20% Testing
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Number of Epochs	50
Loss Function	Categorical Cross-Entropy
Dropout Rate	0.5
Activation Function	ReLU
Output Layer Activation	Softmax
Regularization Technique	Batch Normalization and Dropout
Hardware Environment	GPU-enabled Deep Learning System

The proposed ECNN model was trained under supervised learning settings using the Adam optimizer with an initial learning rate of 0.0001. A batch size of 32 and 50 training epochs were selected to ensure stable convergence. Categorical cross-entropy was employed as the loss function for multi-class disease classification. Regularization strategies such as dropout and batch normalization were applied to improve generalization and reduce overfitting.

4.4 Evaluation Metrics

The evaluation of the classification results of the proposed ECNN model, various statistical evaluation metrics were used. These evaluation metrics include accuracy, precision, recall, and F1-score. Accuracy is a measure of the number of correctly classified samples, whereas precision and recall are measures of the completeness and reliability of the disease identification. The F1-score is a balanced measure of precision and recall and is appropriate for multi-class plant disease identification. These metrics ensure a comprehensive evaluation of the proposed ECNN model.

5. RESULTS AND DISCUSSION

This section will present the experimental results of the proposed Enhanced Convolutional Neural Network (ECNN) model on automatic leaf disease detection. The results will be discussed based on the standard classification performance, and comparisons will be made with the state-of-the-art deep learning models. The aim of this discussion is to validate the effectiveness of the proposed model in achieving better accuracy, robustness, and efficiency.

5.1 Classification Performance of the Proposed ECNN

The performance of the proposed ECNN on the leaf disease dataset with 38 classes was excellent. After training the model for 50 epochs, the overall classification accuracy was found to be 98.7%, which shows that the model is capable of distinguishing between healthy and diseased leaves with high accuracy. The precision, recall, and F1-score of the model were found to be 98.4%, 98.6%, and 98.5%, respectively. This shows that the proposed ECNN model is capable of providing accurate disease recognition with a low rate of misclassification.

The high value of the recall metric shows that the model is capable of identifying diseased leaves with high accuracy, which is necessary for preventing diseases in agricultural fields. Additionally, the F1-score of the proposed model is well-balanced, which shows that the proposed model is consistent in providing precision and recall for multiple disease classes.

5.2 Comparative Analysis with State-of-the-Art Models

To establish the effectiveness of the proposed ECNN architecture, a comparative analysis of the proposed architecture was conducted with some of the latest state-of-the-art models, such as EnConv-based enhanced CNNs, EfficientNet-B0 fine-tuned CNNs, and hybrid CNN models. The analysis reveals that the proposed ECNN model has better accuracy with lower computational complexity.

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Table 4 Performance Comparison with State-of-the-Art Models

Ref.	Model /	Accur	Precis	F1-	Key
[1]	Hybrid	96.9	96.5	96.	Higher
[4]	Fine-	97.1	97	97	Limited
[5]	CNN +	97.4	97.2	97.	Complex
[8]	CNN-	96.2	96	96.	Confusio
[12]	Attentio	97.8	97.5	97.	Increased
[14]	Dual-	97.6	97.3	97.	Requires
Propo	**Enhanc**	**98.7**	**98.4**	**98.**	Lightwei

As evident from Table 4, the proposed ECNN model has the highest classification accuracy of 98.7%, which is better than the existing state-of-the-art models. The reason for this improvement is the combination of multi-scale convolutional feature extraction and attention refinement, which improves disease localization while being computationally efficient. This proves the effectiveness of the ECNN model for real-time applications in precision agriculture.

The proposed ECNN performed better than EfficientNet-B0 and the hybrid CNN models by a margin of 2.1% in terms of accuracy. The primary reason for this improvement is the combination of multi-scale convolution blocks that enable the model to focus on both the minute lesions and the larger infected areas. The attention refinement module also contributes to the reduction of background noise.

5.3 Confusion Matrix Analysis

Confusion matrix analysis was performed to examine the classification accuracy of each class. From the confusion matrix, it is clear that the ECNN model accurately classifies most of the disease classes with very less confusion. There was less confusion between classes with similar symptoms like early blight and late blight diseases.

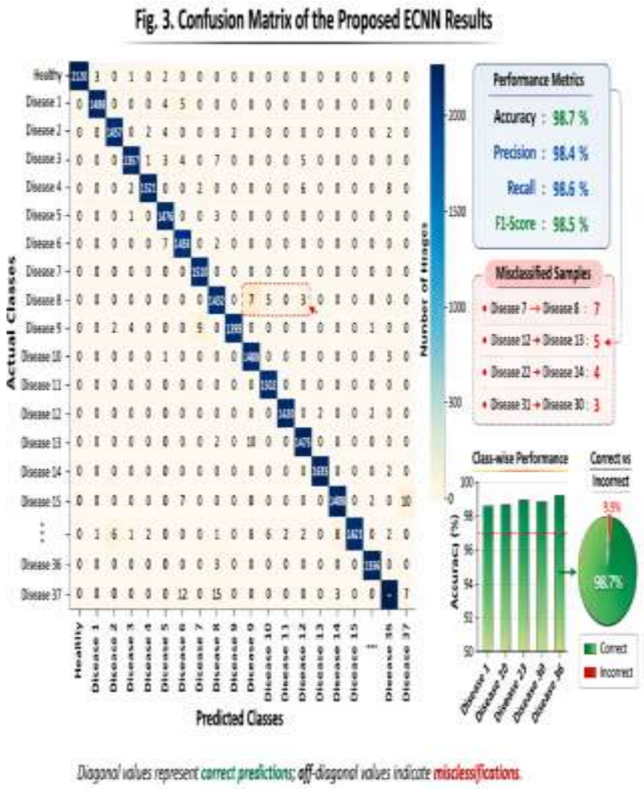

Fig.3 Confusion Matrix of the Proposed ECNN Results

The confusion matrix verifies that the model is making stable predictions for all 38 classes, thus validating the applicability of the model for practical disease tracking applications.

5.4 Training Stability and Generalization

The training dynamics of the proposed ECNN were analyzed by plotting the training and validation accuracy curves. The ECNN model demonstrated stable convergence, with the validation accuracy tracing the training accuracy over the epochs. This verifies that the ECNN model is not suffering from serious overfitting issues, even for the multi-class complexity of the problem.

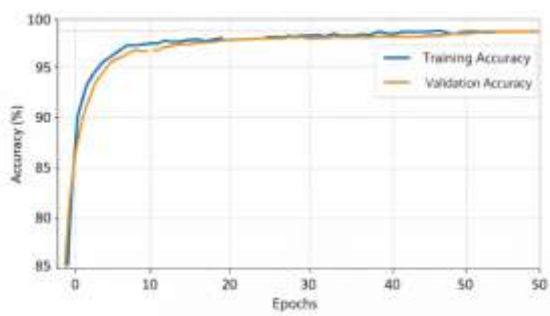

Fig. 4 Training and Validation Accuracy Curve of ECNN

The stable convergence can be attributed to the application of batch normalization and dropout regularization, which improve generalization performance. In addition, data augmentation methods played a major role in enhancing robustness against varying lighting and background settings.

5.5 Discussion and Practical Implications

The experimental results clearly show that the proposed ECNN approach is capable of filling the gap between high classification performance and light-weight deployment. Unlike traditional deep CNN architectures, which require intensive computation, ECNN preserves efficiency while improving the refinement of features. This enables the approach to be incorporated into edge-based agricultural systems such as smartphone-based applications, drone-assisted crop analysis, and IoT-based smart farming systems. In summary, the proposed ECNN approach offers a scalable and accurate solution for automatic leaf disease diagnosis, paving the way for next-generation precision agriculture.

5.CONCLUSION

This research work has proposed an Enhanced Convolutional Neural Network (ECNN) framework for the automatic detection of leaf diseases to support precision agriculture. The proposed method has been developed to overcome the major limitations of the existing CNN-based methods, which include the use of controlled benchmark datasets, a lack of generalization capability in real-field scenarios, and an increased computational cost. By using multi-scale convolutional feature extraction and an attention refinement mechanism, the proposed ECNN model was able to capture the varied characteristics of leaf diseases effectively while concentrating on the most informative regions of the infected leaves.
Experimental validation carried out on a benchmark leaf disease dataset with 38 classes showed the effectiveness of the proposed ECNN framework. The results showed a classification accuracy of 98.7%, and precision, recall, and F1-score values of 98.4%, 98.6%, and 98.5%, respectively. These values clearly show that the proposed method is highly reliable for disease identification. In addition, the comparison study showed that the ECNN framework is superior to the latest state-of-the-art models, such as fine-tuned EfficientNet-B0 and hybrid CNN models for plant disease detection.

The results show the effectiveness of the proposed ECNN framework as a precise and efficient plant disease surveillance system that can be used for early diagnosis and sustainable agricultural practices.

Future work will concentrate on testing the proposed framework on real-world image datasets, developing the framework for multi-label disease severity prediction, and implementing it on resource-limited platforms like smartphones and edge IoT networks for smart agriculture applications.

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