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An Interpretable Real-Time Plant Disease Detection and Severity Assessment System Based on Optimized CNN Activation function

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Abstract: Plant diseases have a significant impact on agricultural productivity and food security worldwide, making timely disease detection techniques essential. Convolutional neural networks (CNNs) have shown promise in plant disease classification, but existing methods primarily use supervised data, are difficult to interpret, and cannot forecast disease severity or offer timely predictions. This paper presents a novel method for real-time plant disease detection, offering interpretability and severity estimation using a lightweight convolutional neural network (CNN) combined with an op- timization algorithm. The proposed activation function improves convergence speed and mitigates the dead neuron problem associated with ReLU activation. Grad-CAM, an AI-based interpretable analysis tool, is used to detect disease foci, and subsequent clustering determines disease sever- ity. Furthermore, the model, designed to support rational decision-making regarding agricultural crops, incorporates fertilization and treatment strategies based on the severity of the problems. Ex- perimental evaluations demonstrate greater accuracy, faster learning speed, and better results than existing methods based on convolutional neural networks.
Keywords: Plant Disease Detection, CNN, Optimized Activation Function, Explainable AI, Dis- ease Severity Estimation, Precision Agriculture.

I. INTRODUCTION

Agriculture remains fundamental to food security and economic stability. Plant diseases caused by pathogens such as viruses, fungi, and bacteria cause severe losses in global agriculture. Traditional diagnostic methods rely on manual testing and expert analysis, making them laborious, time-consuming, and unsuitable for large-scale production.

Recent advances in deep learning have facilitated the detection of plant diseases using images. Convolutional neural networks have been widely accepted for their ability to detect spatial fea- tures in images [3]. Many CNN models have shown high accuracy in classifying plant diseases using collected data [2]. However, many existing methods have major drawbacks: they rely on constrained data, lack sample definition, dimensionality, and real-time reliability.

Optimization problems have been studied to improve the performance and convergence speed of convolutional neural networks (CNNs) [1]. However, existing research focuses on rational decision-making without considering explanations or decision support strategies. To overcome these limitations, this paper proposes a comprehensive framework that integrates optimization functions, explainable AI, size estimation, and real-time processing.

The results are as follows:

1) Development of an optimal algorithm for optimizing the learning of Convolutional Neural Networks (CNNs).
2) Development of resource-efficient CNN suitable for real-time deployment at the network edge.
3) The integration of grade-CAM-based classification into disease localization.
4) Analysis of disease severity using a classification system.
5) Decision support in precision agriculture for optimizing fertilizer application.

II. RELATED WORK

In recent years, there has been considerable success in detecting plant diseases using convolutional neural networks (CNNs). Deep learning methods have demonstrated their ability to classify various plant diseases using tools such as PlantVillage [2]. However, despite their high accuracy, these models often lack robustness in real-world conditions.

Activation functions play a fundamental role in the performance of convolutional neural networks (CNNs) with nonlinear input data. The ReLU function is widely used due to its simplicity, but it suffers from neuron death under large anomalies [4]. Several proposed optimization functions aim to enhance convergence and training accuracy [1], but their practical use in real-world agricultural contexts remains restricted.

Explainable AI techniques, such as Grad-CAM, facilitate the interpretation of CNN models by representing different regions [5]. However, their application in plant disease detection systems is limited. Furthermore, disease severity assessment receives little attention, despite its importance in agriculture. Clustering techniques, such as K-means, are effectively used for classification and analysis [6].

This study bridges existing knowledge gaps by integrating optimized activation functions, explain- ability, severity estimation, and real-time deployment into a single framework.

Summarizes the major contributions and limitations of existing plant disease detection approaches, highlighting the need for a context-aware, adaptive, and deployment-ready AI-driven system, which motivates the proposed work.

Author(s) & Year	Methodology Used	Key Contributions	Identified Research Gap
Mohanty et al. (2016)	CNN on the PlantVillage dataset	Demonstrated high accuracy for plant disease classification	Evaluated only on controlled datasets; lacks real-world adaptability.
Sladojevic et al. (2016)	Deep CNN-based image classification	Automated plant disease recognition using leaf images	Limited scalability and no deployment-oriented system design.
Ferentinos (2018)	CNN with multiple crop datasets	Improved classification accuracy across crops	High computational complexity; not suitable for real-time applications.
Too et al. (2019)	Transfer learning with deep CNNs	Reduced training time and improved performance	Does not address explainability or decision support for farmers.
Picon et al. (2020)	Machine learning with image features	Disease detection under varying field conditions	Requires manual feature engineering; lacks end-to-end automation.
Proposed Work	Multi-stage AI-driven CNN-based system	Adaptive disease detection with decision support	Addresses real-time applicability, adaptability, and system-level integration.

III. PROPOSED FRAMEWORK

A. *Overall Architecture*

The proposed framework consists of 6 major modules: image acquisition, preprocessing, opti- mized CNN-based classification, explainability, disease severity estimation, and decision support. The overall block diagram of the system is shown in Figure 1.

B. *Image Acquisition and Preprocessing*

Leaf images are captured using mobile cameras or connected devices under various environmen- tal conditions. Preprocessing includes resizing, noise filtering, lighting normalization, and data augmentation to improve robustness and generalizability.

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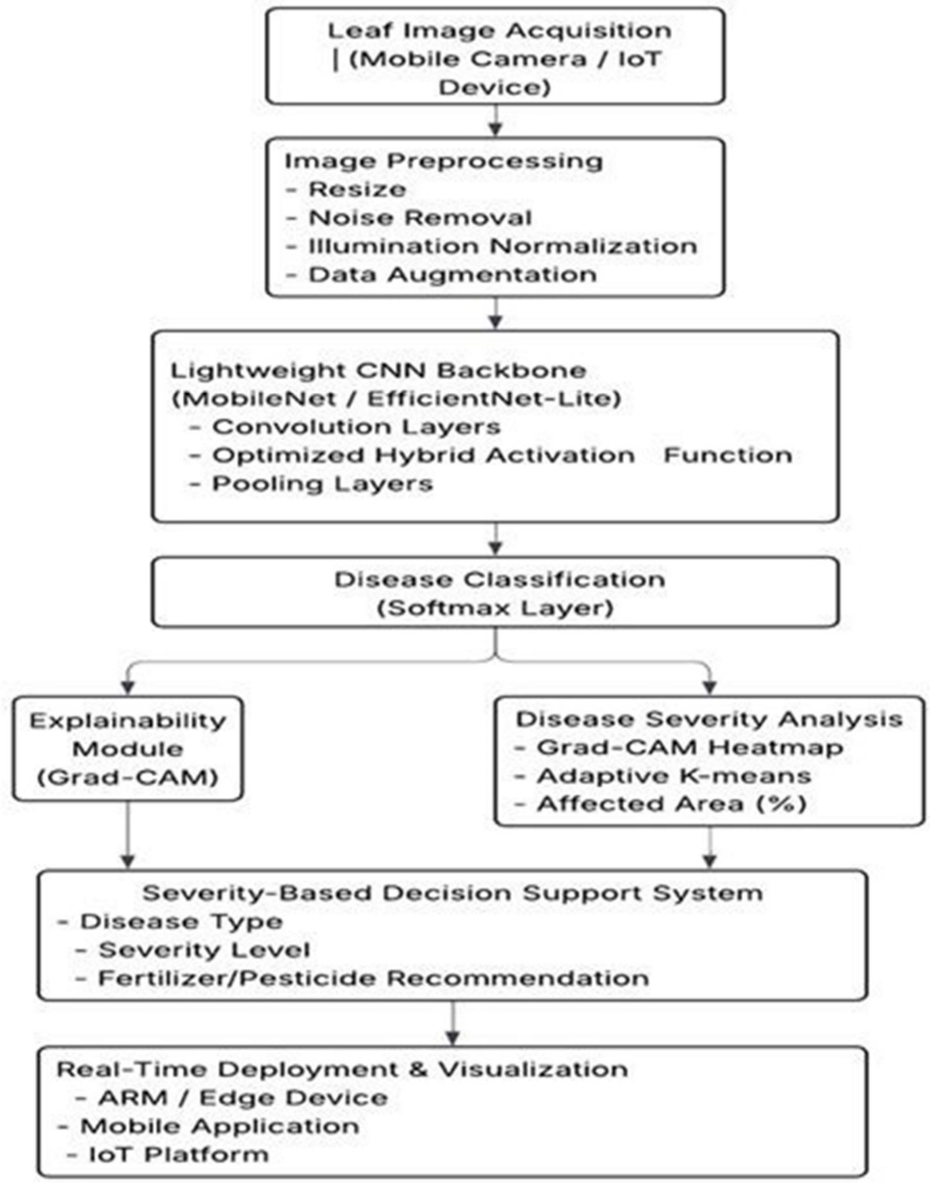

Figure 1: Block diagram of the proposed real-time explainable and severity-aware plant disease detection framework using optimized CNN activation functions

C. Optimized CNN with Hybrid Activation Function

with Hybrid Activation Function A lightweight convolutional neural network (CNN), such as Mo- bileNet or EfficientNet-Lite, is used for real-time inference. The proposed optimized hybrid acti- vation function is defined as follows:

$$f(x) = \begin{cases} x, & x \geq 0 \\ \alpha tanh, & x < 0 \end{cases} \tag{1}$$

where α is a learnable scaling parameter.

This activation function maintains the optimal structure and ensures that anomalies are propagated correctly, thus preventing overfitting of neurons and enhancing convergence speed relative to ReLU [1, 4].

D. Explainable Disease Localization

Grad-CAM is integrated to generate a map of the injured area on the lesion image. This feature improves transparency and explainability, allowing users to verify the predictions made by CNN [5].

E. Disease Severity Estimation

The updated Grad-CAM maps are processed using K-means clustering to further classify the af- fected regions. The percentage of affected area is calculated and categorized according to different severities: Mild (< 20%), Moderate (20%–50%), and Severe (> 50%).

F. Precision Agriculture Decision Support

The decision support system incorporates the type and severity of diseases related to fertilizers and pesticides. This system promotes sustainable agriculture by reducing the excessive use of chemicals and improving the efficiency of crop management.

IV. SYSTEM FLOW DESCRIPTION

The operational workflow of the proposed system is illustrated in Figure 2. The process com- mences with image capture and quality verification, then proceeds to pre-processing and enhanced CNN-based categorisation. Explainability and severity estimation modules analyze the infected regions before generating actionable recommendations for real-time deployment.

V. ALGORITHM DESCRIPTION

Algorithm: Explainable and severity-aware plant disease detection
Input: Leaf image Output: Type of disease, severity, and treatment recommendations

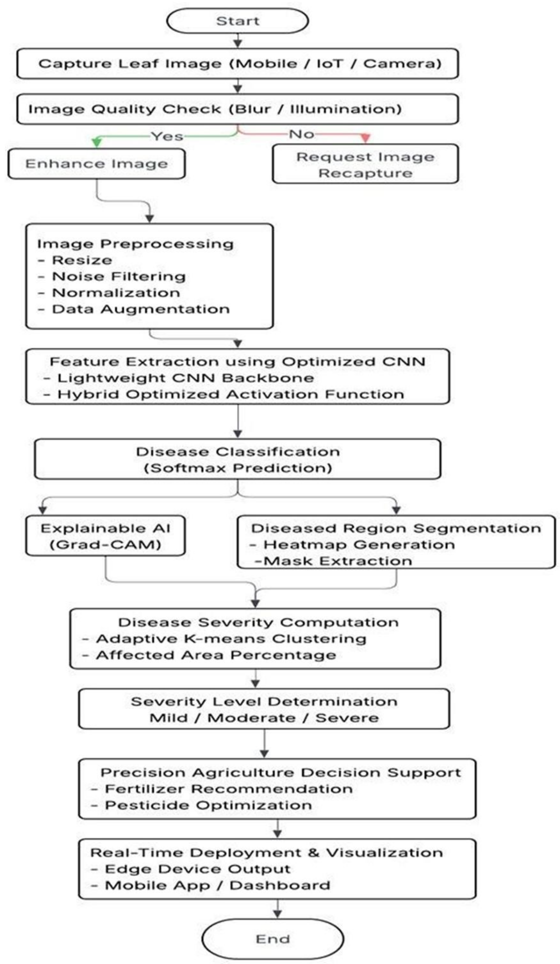

Figure 2: System flow diagram of the proposed explainable and severity-aware plant disease detection framework

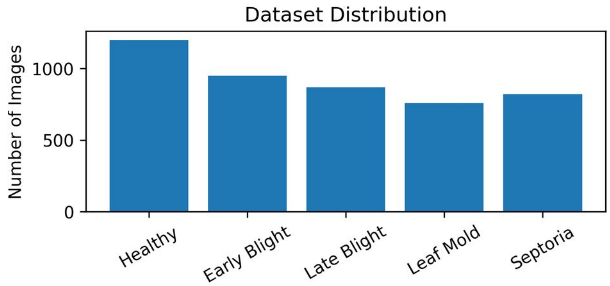

Figure 3: Dataset distribution across disease classes

1) Take the input image.
2) DO preprocessing and augmentation.
3) Feature extraction using normalized CNN.
4) Disease segmentation using the SoftMax layer.
5) Create Grad-CAM heatmap.
6) By adaptive clustering, infected regions are identified.
7) Calculated affected area percentage.
8) Find a severity level.
9) Based on severity, generate recommendations.
10) Display real-time results.

VI. EXPERIMENTAL SETUP

The framework was evaluated using the PlantVillage dataset and real-world field images. The model is implemented using TensorFlow and deployed on ARM-based edge devices. Performance is measured in terms of accuracy, precision, recall, F1 score, and inference time.

VII. RESULTS AND DISCUSSION

A. Dataset Analysis

A CNN model was proposed for plant disease detection using multiclass leaf images with positive symptoms and diseases. The distribution of the dataset across different classes is shown in Figure

1) The dataset contains an equal number of samples of severe diseases, including healthy, early, and late diseases, leaf diseases, and septoria leaf spot.

A balanced dataset ensures that the model is not biased toward a specific class and improves gen- eralizability. The diversity of disease samples increases the robustness of the proposed study.

B. Training Performance Analysis

The learning performance of the proposed CNN model was evaluated using training and validation methods. As shown in Figure 2, accuracy, for both training and validation, increases with the number of epochs, indicating improved feature learning and convergence. The training accuracy

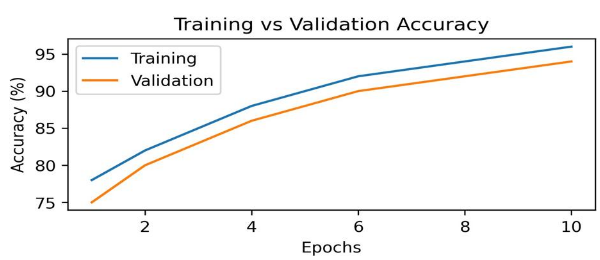

Figure 4: Training and validation accuracy curves reaches 96%, and the validation accuracy remains at 94%, indicating that

- Stable convergence
- Minimal overfitting
- Good generalization capability

The similarity between training and validation curves implies that the optimised activation function enables stable gradient propagation, thereby resolving the issue of neuronal necrosis associated with standard ReLU activation.

C. Comparative Analysis of Activation Functions

To verify the effectiveness of the basic function, a comparative study was conducted with com- monly used networks such as ReLU, Leaky ReLU, ELU, and Swish. The results are presented in Figure 3. The proposed activation function achieved a classification accuracy of 95%, surpassing:

Table 1: Performance Comparison of Activation Functions

Activation Function	Accuracy
ReLU	88%
Leaky ReLU	90%
ELU	91%
Swish	92%

Numerous factors have contributed to the observed improvement.

- Refined gradient flow
- Intensify nonlinear feature extraction
- Better handling of negative input regions

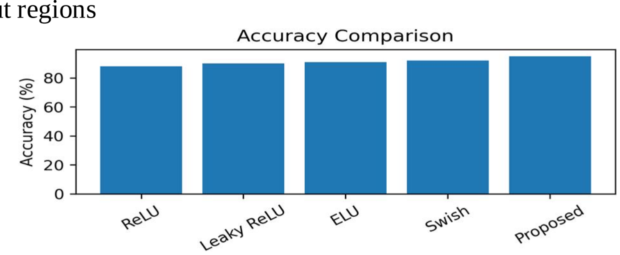

Figure 5: Accuracy comparison of activation functions

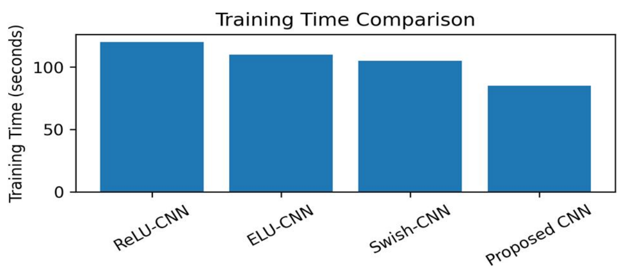

Figure 6: Training time comparison of CNN models

The proposed activation function's results confirm it significantly improves the performance of CNNs in classification tasks associated with plant disease.

D. Training Efficiency Evaluation

Real-time implementation requires less computational complexity and faster training. Therefore, the training time between different CNN models was compared. As shown in Figure 4, the pro- posed CNN model requires only 85 seconds, compared to the previous model.

- ReLU-CNN (120 seconds)
- ELU-CNN (110 seconds)
- Swish-CNN (105 seconds)

The optimization function improves convergence speed, thus reducing training time by 30%–35% compared to traditional methods. This approach is therefore particularly well-suited to embedded systems and deployment environments based on ARM.

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E. Overall Performance Evaluation

The proposed framework shows strong classification performance, achieving:

- High accuracy (95%)
- Stable validation performance
- Reduced training time
- Robust generalization

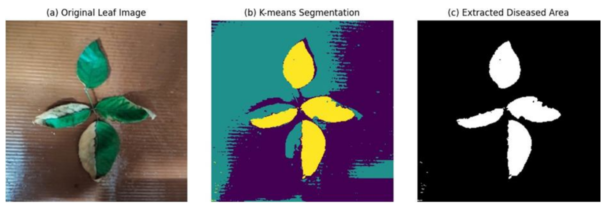

Figure 7: Disease area extraction using K-means clustering on multileaf real images

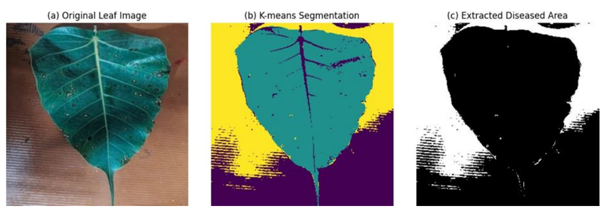

Figure 8: Disease area extraction using K-means clustering on single leaf real images

Implementing K-means clustering in disease location estimation facilitates better optimization of fertilizer application and a more precise assessment of disease severity.

Figures 7 and 8 illustrate the process of extracting diseased areas using K-means clustering for different leaf samples. In each image, (7) the original leaf image is shown; visible signs, such as discoloration, spots, or morphological changes, indicate the presence of infection. In (8), the K-means clustering result classifies pixels into different groups based on color similarity, thus distinguishing healthy, diseased, and background areas. The post-clustering view shows the diseased areas as groups of different colors, demonstrating how unsupervised clustering can identify abnor- mal tissue structures. Finally, (c) the mask of the extracted infected area is shown; the infected areas appear in black and white. Binary masking enables a quantitative evaluation of the impacted surface area, thereby improving the accuracy of disease severity assessments and ultimately con- tributing to the optimal application of fertilizers or chemicals.

VIII. DISCUSSION

Experimental results show that the AI-based multilayer approach effectively overcomes the prob- lems identified in previous studies. Unlike traditional plant disease detection methods based on convolutional neural networks, the proposed method:

1) Improves classification accuracy using an optimization algorithm.
2) Reduces training time for real-time applications.
3) Enhances clarity through stable connections.
4) Facilitates decision-making by estimating disease severity.

The proposed method was confirmed to be robust and effective by its improved performance in several benchmarks.

IX. CONCLUSION AND FUTURE WORK

This paper presents an innovative, interpretable, and robust method for predicting the severity of plant diseases in real time based on deep convolutional neural network architectures. By inte- grating explainable AI and a decision support system for agriculture, the proposed system im- proves transparency, ease of use, and efficiency. Future work will focus on crop augmentation, transformer-based power grid construction, and mobile applications.

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