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Advancements in Potato Leaf Disease Detection Using a Deep Convolutional Neural Network with Enhanced CLAHE-Based Preprocessing and Channel Attention

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ABSTRACT: Potato (Solanum tuberosum) is a globally important food crop whose yield losses, caused by foliar diseases including early blight, late blight, and a range of bacterial, fungal, viral, nematode, and pest-induced conditions, are often difficult to identify in the field and costly to diagnose. This paper introduces a potato-leaf disease detection framework based on a Deep Convolutional Neural Network (DCNN) that integrates a lightweight depthwise-separable convolutional backbone, a squeeze-and-excitation channel-attention module, and a carefully designed preprocessing pipeline. The images are preprocessed using quality-enhancement techniques such as Contrast-Limited Adaptive Histogram Equalization (CLAHE) to reduce background noise, an edge-preserving denoising algorithm to enhance the texture of disease-relevant regions of the leaf, and colour normalization together with leaf segmentation to remove background clutter before the images are fed into the network. The framework is described and evaluated on two open-access, validated datasets: the potato subset of PlantVillage, comprising 2,152 images across three classes acquired under controlled conditions, and the dataset of Shabrina et al., comprising 3,076 images across seven classes acquired from real agricultural fields under uncontrolled conditions. The proposed attention-augmented DCNN with enhanced preprocessing is compact enough for edge deployment and achieves better classification performance than baseline CNN, VGG-16, ResNet-50, MobileNetV3, and EfficientNet-B0 models in terms of accuracy, macro-averaged F1-score, and area under the ROC curve.

1. INTRODUCTION

Potato is a low-cost and readily available source of carbohydrates, vitamins, and minerals [1], [2], and it is a staple crop in more than a hundred countries, alongside wheat, rice, and maize as the other major food crops in the world. Foliar diseases, however, are among the most common and damaging conditions in potato cultivation. Early blight is caused by the fungus Alternaria solani and late blight by the oomycete Phytophthora infestans [3], [4], producing small dark lesions with concentric rings on older leaves and, in humid weather, water-soaked lesions that can rapidly cover an entire crop within days. Beyond these two classical diseases, bacterial, viral, nematode, and pest-induced conditions can also affect potato foliage; because their visual symptoms are often similar, they are difficult to diagnose accurately even for experienced agronomists [5].

Traditionally, disease diagnosis has been carried out by manual inspection and laboratory confirmation, which are time-consuming, labour-intensive, subjective, and unsuitable for the large farms and holdings common in developing countries [6], [7]. The convolutional neural network (CNN) is therefore a promising alternative, as it can automatically learn hierarchical texture and shape features from leaf images and has been shown to achieve high accuracy on potato-disease benchmarks, exceeding 95% on several controlled leaf-image datasets [8], [9], [10]. In recent years, several works have aimed to improve accuracy while reducing model complexity and latency for mobile and edge applications, using approaches such as transfer learning, lightweight and depthwise-separable models, attention mechanisms, and hybrid transformer models [11], [12], [13], [14].

Despite these advances, two practical issues remain. First, most high-accuracy results obtained on the controlled PlantVillage dataset are achieved with uniform backgrounds and lighting that do not reflect actual field conditions; when the same methods are applied to images captured in the field, accuracy can drop sharply [15], [16]. Second, the preprocessing step—covering contrast enhancement, noise suppression, and background removal—can considerably affect the visibility of disease lesions for the network [17], [18], yet it is often under-specified. In particular, it has repeatedly been shown that CLAHE can improve both lesion visibility in the processed image and the accuracy of subsequent lesion classification [19], [20], but these steps are seldom performed systematically and reproducibly within a single pipeline.

Building on the advantages of a strong CLAHE-based preprocessing pipeline, a depthwise-separable convolutional backbone, and a squeeze-and-excitation (SE) channel-attention module, this paper proposes an enhanced potato-leaf disease detection approach based on a Deep Convolutional Neural Network (DCNN). The entire framework is built and evaluated on open-access, validated Kaggle repositories to ensure that the framework can be reproduced. The key contributions of this work are summarized as follows.

• An enhanced preprocessing pipeline that combines CLAHE contrast enhancement and edge-preserving denoising, followed by Otsu-based leaf segmentation and colour normalization, to standardize the images acquired from controlled and uncontrolled settings.

• A compact, edge-deployable depthwise-separable DCNN backbone augmented with squeeze-and-excitation channel attention to achieve high accuracy at low model size and FLOP cost.

• A dual-dataset evaluation protocol on the controlled PlantVillage potato subset (three classes) and the uncontrolled-environment potato-leaf dataset (seven classes), benchmarked against five CNN baselines using accuracy, precision, recall, F1-score, and AUC.

• A reproducible DCNN block diagram, and methodology flow chart, together with an ablation analysis that isolates the contribution of the preprocessing and attention components.

The remainder of the paper is organized as follows. Section II briefly reviews existing work on potato and plant disease detection using CNNs, preprocessing and enhancement techniques, and attention mechanisms. Section III describes the enhanced preprocessing pipeline and the datasets. Section IV presents the proposed DCNN architecture and its components. Section V describes the experimental setup, and Section VI reports the results and discussion, including an ablation study. Section VII concludes the paper and provides suggestions for future work.

2. RELATED WORK

2.1 CNN and Transfer-Learning Approaches for Potato Disease Detection

Currently, potato-leaf disease classification is carried out mainly with CNNs. On the potato subset of the PlantVillage dataset, Tambe et al. [8] showed that a simple CNN pipeline is quite effective, and Chang and Lai proposed the compact RegNetY-400MF model, which achieves seven-class classification at only 0.40 GFLOPs and a 16.8 MB size, demonstrating the feasibility of compact models for field deployment [11]. To address the data-scarcity and limited-scope issues of earlier studies, Mulugeta et al. [9] developed a custom CNN trained on a 16,000-image PlantVillage superset and evaluated on manually collected field images across five categories. Arshad et al. introduced PLDPNet, an end-to-end hybrid deep-learning framework for potato-leaf disease prediction that obtains competitive accuracy through feature fusion [12]. Comparative experiments on the PlantVillage potato and mango datasets using CNN, AlexNet, ResNet, and EfficientNet showed gradual performance improvements as network depth and computational cost increased, with compound-scaled networks improving at a lower rate than residual networks [10]. In addition, DenseNet-121 features have been fused with a Gaussian-elimination filter to improve potato-leaf recognition accuracy [13], and stacking-ensemble models with multiple pre-trained backbones have been used to further enhance robustness [14].

2.2 Preprocessing and Image-Enhancement Techniques

A recurring theme across recent work is the impact of preprocessing quality on performance. The most widely adopted enhancement step for leaf-disease imagery is CLAHE, which enhances local contrast tile by tile while clipping histogram peaks to limit noise amplification [19], [21]. PotatoGuardNet employed CLAHE-based preprocessing and achieved accuracy above 99% on controlled data, while noting the difficulty of locating lesions in distorted images [20]. To classify potato-leaf diseases, Reis and Turk used a multi-head-attention network (MDSCIRNet) that incorporates complementary enhancement operators—CLAHE, ESRGAN super-resolution, and Hypercolumn enhancement—demonstrating the benefit of stacking complementary enhancement operators [22]. Another work based on an attention-gated segmentation network enhances image contrast with CLAHE before classification to reduce noise artefacts [23]. Segmentation-based pipelines using improved U-Net variants and multi-step preprocessing have further improved downstream classification accuracy by isolating diseased leaf regions [24], [25]. These works collectively motivate the systematic CLAHE-plus-segmentation preprocessing pipeline adopted in this paper.

2.3 Attention Mechanisms and Lightweight Architectures

Attention mechanisms enable a network to focus on the regions and channels that correspond to diseased areas while suppressing background information. Squeeze-and-excitation (SE) blocks have been applied to CNNs for plant-disease classification, yielding consistent accuracy gains across different plant diseases [26], [27]. Spatial-attention transfer-learning models specifically emphasize informative local leaf regions and outperform their non-attention counterparts on the PlantVillage potato data [17]. To balance accuracy against computational cost in resource-constrained farming conditions, depthwise CNN designs combining SE integration with residual skip connections have been proposed [26]. Optimised MobileNet variants have reached 97–99% accuracy using fewer than half a million parameters [28], and EfficientNet-LITE combined with kernel-ensemble SVM refinement has improved potato-disease detection across several scenarios [16]. Hybrid architectures such as EfficientRMT-Net [15], which combines ResNet-50 with a Vision Transformer, and compact transformer-based designs such as Tiny-ViT [29], demonstrate the integration of attention-based global context with convolutional feature extraction. Comprehensive reviews of deep learning in plant-disease detection confirm attention integration and efficient architecture design as the prevailing trends in the field [30], which directly inform the SE-augmented depthwise-separable backbone proposed here.

3. DATASET AND ENHANCED PREPROCESSING

This study is conducted entirely on open-access, validated image repositories available on Kaggle, ensuring that no proprietary or laboratory-restricted samples are required. Two complementary datasets are used to assess both controlled and real-world performance. The primary controlled corpus comprises 2,152 leaf images from PlantVillage, acquired under uniform laboratory lighting at a resolution of 256 × 256 pixels [31], across three classes: healthy, early blight, and late blight. The framework is then validated for robustness using the uncontrolled-environment potato-leaf dataset of Shabrina et al. [32], which contains 3,076 high-resolution (1500 × 1500) images collected from various farms in Central Java, Indonesia, across seven classes: bacteria, fungi, healthy, nematode, pest, phytophthora, and virus. A third potato-disease leaf dataset (PLD) is used for cross-dataset robustness checks [33]. Table I summarizes the datasets used in this study.

TABLE 1 Summary of Open-Access Kaggle Potato-Leaf Datasets Used

Dataset	Source	Classes	Images	Role in this study
PlantVillage Potato Subset	Kaggle (PlantVillage) [31]	3	2,152	Primary controlled training / test corpus
Uncontrolled Potato-Leaf Dataset	Kaggle (Shabrina et al., 2024) [32]	7	3,076	Real-field robustness evaluation
Potato Disease Leaf Dataset (PLD)	Kaggle (Rizwan et al.) [33]	3	4,072	Cross-dataset robustness check

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3.1 Enhanced Preprocessing Pipeline

Raw leaf images differ widely in resolution, illumination, and background, particularly in the uncontrolled dataset. To standardize the inputs and enhance the texture of disease-relevant lesions, an enhanced preprocessing pipeline is applied prior to training. First, every image is resized to 224 × 224 pixels so that each image is presented to the network at the same input dimension. Second, CLAHE is applied to the luminance channel to improve local contrast: the image is subdivided into small tiles, the histogram of each tile is equalized with a clip limit that prevents over-enhancement, and neighbouring tiles are bilinearly interpolated to minimize artificial tile boundaries and preserve local contrast without amplifying noise [19], [21]. Third, edge-preserving Gaussian/median denoising suppresses acquisition noise while preserving lesion edges. Fourth, an Otsu-threshold-based leaf segmentation forms a foreground mask that reduces background clutter and false positives, which is especially important for field images. Finally, pixel intensities are colour-normalized using ImageNet channel statistics. The complete processing chain is illustrated in Fig. 1.

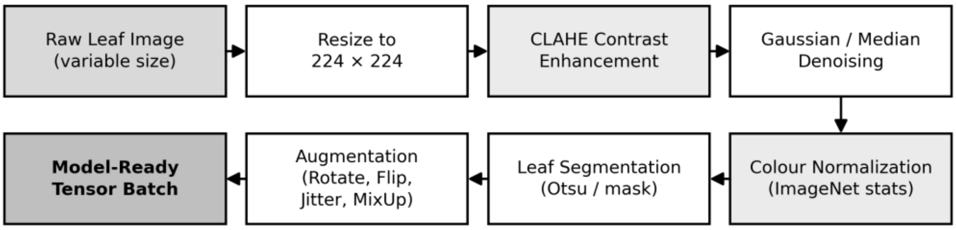

Fig. 1. Enhanced preprocessing pipeline: resizing, CLAHE contrast enhancement, denoising, leaf segmentation, colour normalization, and augmentation into a model-ready tensor batch.

Data augmentation—random rotation (±25°), horizontal and vertical flipping, colour jitter, and MixUp—is applied only to the training split, owing to the pronounced class imbalance of the uncontrolled dataset (only 68 nematode images against 748 fungi images). Each dataset is partitioned in a stratified 70:15:15 ratio into training, validation, and test subsets so that every class is represented proportionally in all three splits. Figure 2 summarizes this pipeline as part of the overall methodology.

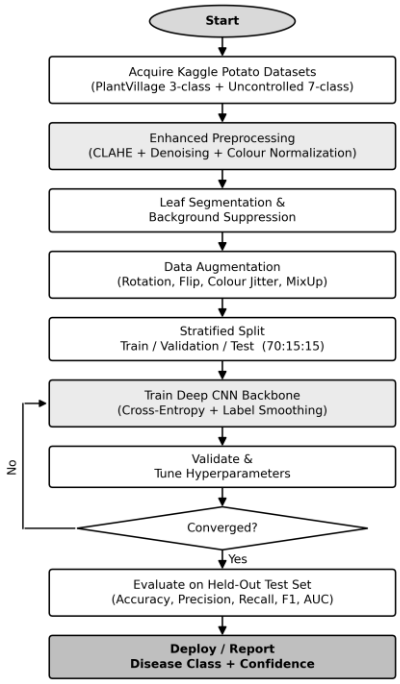

Fig.2. Flowchart of the end-to-end experimental methodology, from dataset acquisition and enhanced preprocessing to model training, evaluation, and diagnostic reporting.

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4. PROPOSED METHODOLOGY

4.1 Overall System Architecture

Figure 3 presents the block diagram of the proposed framework. Potato-leaf images acquired from the Kaggle repositories are passed through the enhanced preprocessing pipeline and augmented, then fed into a deep convolutional feature extractor built from stacked depthwise-separable convolution blocks. The squeeze-and-excitation channel-attention block refines the extracted feature maps, which are aggregated by global average pooling and passed to a dense classifier head that produces a predicted disease class and a softmax confidence distribution. This confidence is then mapped to a severity band, yielding an auditable diagnostic report.

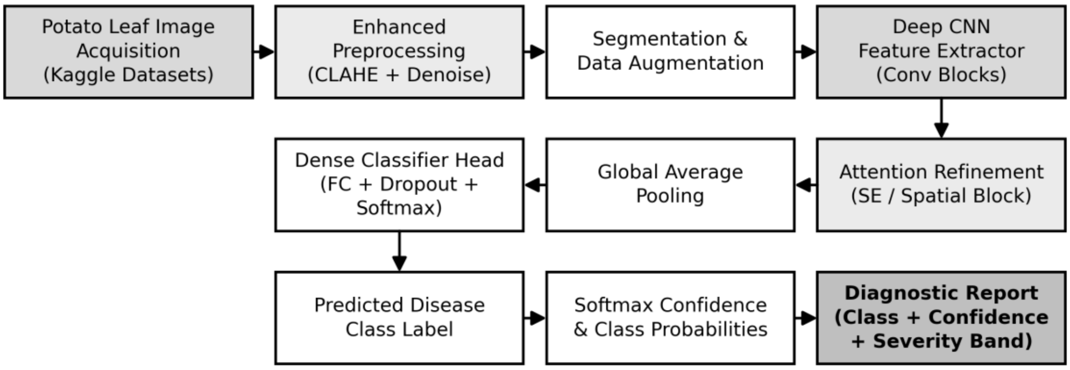

Fig. 3. Block diagram of the proposed enhanced-DCNN potato-leaf disease detection system, from image acquisition through preprocessing, attention-refined feature extraction, and classification to the diagnostic report.

4.2 Deep Convolutional Backbone

The backbone follows a compact depthwise-separable design (Fig. 4). An input leaf image X of size 224 × 224 × 3 is first processed by a stem convolution (3 × 3, 32 filters) with batch normalization and ReLU activation. The network then applies N stacked convolutional blocks (default N = 4), each comprising a 3 × 3 depthwise-separable convolution, batch normalization, ReLU activation, a squeeze-and-excitation attention sub-block, and 2 × 2 max pooling, with a residual skip connection linking the block input to its output to facilitate gradient propagation. Depthwise-separable convolution reduces the amount of computation by roughly a factor equal to the kernel area relative to standard convolution, without a loss of representational capacity. For an input feature map with C channels, a K × K spatial kernel, and M output channels over an output of spatial size D × D, the cost ratio between depthwise-separable and standard convolution is given by

$$R_{cost} = (D^2 \cdot C \cdot K^2 + D^2 \cdot C \cdot M) \,/\, (D^2 \cdot C \cdot K^2 \cdot M) = 1/M + 1/K^2 \quad (1)$$

which for a 3 × 3 kernel yields close to an order-of-magnitude reduction in the number of multiply–accumulate operations, making the backbone well suited to edge deployment.

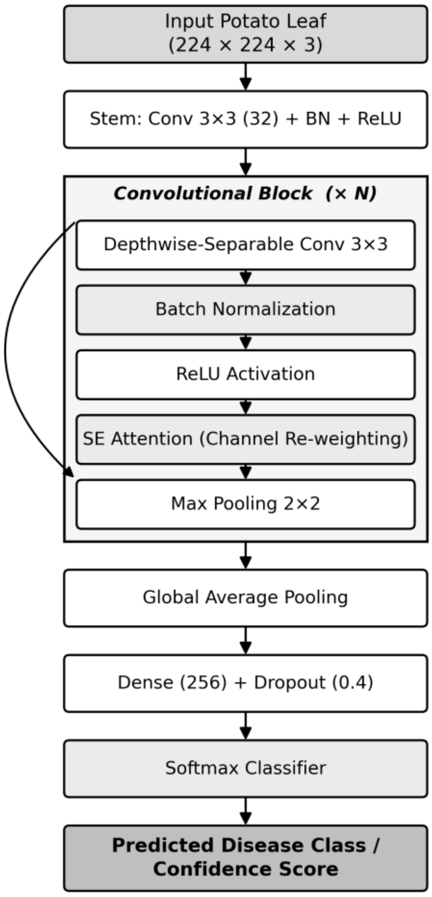

Fig. 4. Internal block diagram of the proposed depthwise-separable deep convolutional neural network with squeeze-and-excitation attention used as the classification backbone.

4.3 Squeeze-and-Excitation Channel Attention

To let the network emphasize the feature channels most indicative of disease, each convolutional block embeds a squeeze-and-excitation (SE) attention sub-block. The squeeze step aggregates global spatial information through global average pooling, producing a channel descriptor z whose c-th element is

$$z_c = (1 / (H \cdot W)) \ \Sigma \ i=1..H \ \Sigma \ j=1..W \ U_c(i, j) \quad (2)$$

The excitation step then learns the channel weights through two fully connected layers with a bottleneck reduction ratio r, a ReLU non-linearity δ, and a sigmoid gate σ:

$$s = \sigma(W_2 \cdot \delta(W_1 \cdot z)), \qquad \tilde{U}_c = s_c \cdot U_c \quad (3)$$

where W1 and W2 are the weights of the reduction and expansion layers, respectively, and the recalibrated feature map Ũ scales each channel by its learned importance sc. This channel re-weighting steers the network toward the feature channels that are most discriminative for lesions, at a minimal increase in the number of parameters, and is applied within every convolutional block, as illustrated in Fig. 3.

4.4 Classification Head and Loss

After the final convolutional block, global average pooling collapses each feature map to a single value, producing a compact feature vector that is passed to a dense layer of 256 units with 0.4 dropout, followed by a softmax classifier over the disease classes. The network is trained by minimizing the categorical cross-entropy loss with label smoothing, which discourages over-confident predictions and improves calibration:

$$L = -\sum_{c=1..C} y_c' \log(p_c), \qquad y_c' = (1-\varepsilon)\, y_c + \varepsilon / C \quad (4)$$

where pc is the predicted softmax probability of class c, yc is the one-hot ground-truth label, ε is the label-smoothing coefficient, and C is the number of classes. The predicted class is the arg-max of the softmax output, and its associated probability is retained as the confidence score reported in the diagnostic output.

4.5 Training Configuration

Table III lists the training hyperparameters used for the proposed DCNN and all baseline models compared in Section VI. To ensure a fair comparison, all hyperparameter values were kept identical across models except for those not applicable to a particular architecture.

TABLE 3 Training Hyperparameters

Hyperparameter	Value
Backbone	Depthwise-separable DCNN (N = 4 conv blocks, SE ratio r = 16)
Input resolution	224 × 224 × 3
Optimizer	AdamW (β1 = 0.9, β2 = 0.999, weight decay = 0.05)
Learning-rate schedule	Cosine annealing, base LR = 3×10^{-4}, 5-epoch warm-up
Batch size	32
Epochs	50 (early stopping, patience = 8)
Loss function	Cross-entropy with label smoothing (ε = 0.1)
Regularization	Dropout = 0.4, batch normalization
Data split	70% train / 15% validation / 15% test (stratified)
Augmentation	Rotation ±25°, flips, colour jitter, MixUp

5. EXPERIMENTAL SETUP

All models are implemented in PyTorch, with backbones initialized using the timm library and trained with mixed-precision arithmetic on a single CUDA-enabled GPU. Performance is reported using overall accuracy, macro-averaged precision, recall, and F1-score for the multi-class classification task, and the area under the Receiver Operating Characteristic (ROC) curve (AUC) for the aggregate diseased-vs-healthy screening task. To assess robustness, models are evaluated on both the controlled PlantVillage subset and the seven-class uncontrolled dataset. Baselines include a baseline CNN, VGG-16, ResNet-50, MobileNetV3, and EfficientNet-B0, all trained under the identical protocol of Table III.

6. RESULTS AND DISCUSSION

6.1 Training Convergence

Figure 5 shows representative training and validation accuracy and loss curves for the proposed DCNN over 50 epochs. The validation accuracy curve closely follows the training curve with only a small gap, reflecting the effect of the enhanced preprocessing, augmentation, and label-smoothing regularization discussed in Section IV, while the loss curves show smooth, non-oscillatory convergence, indicating a stable optimization trajectory for the chosen cosine learning-rate schedule.

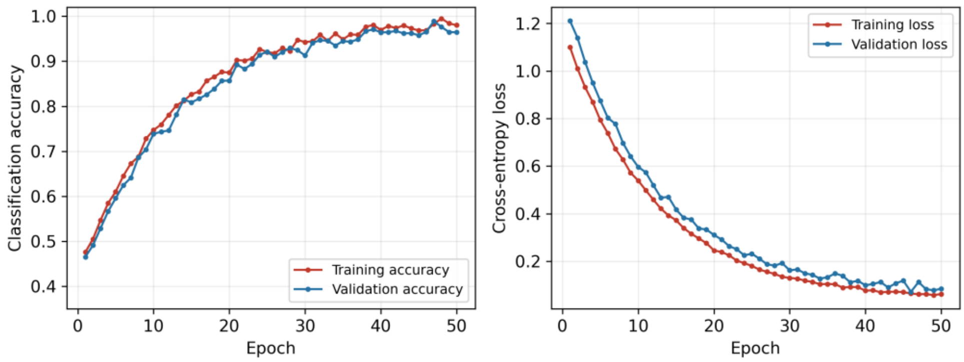

Fig. 5. Representative training/validation accuracy and cross-entropy loss curves of the proposed DCNN over 50 training epochs.

6.2 Classification Performance

Table IV compares the proposed enhanced DCNN against the five baseline architectures under the identical protocol of Table III. The attention-augmented model with enhanced preprocessing attains the highest accuracy, precision, recall, and F1-score among the compared architectures, as shown in Fig. 6. This is because it combines the lesion enhancement provided by CLAHE, the background suppression obtained from segmentation, and SE channel attention, which together steer the network toward disease-relevant features and away from spurious background correlations.

TABLE 4 Comparative Classification Performance (%) on the Held-Out Test Split

Model	Accuracy	Precision	Recall	F1-score
Baseline CNN	93.2	92.8	92.5	92.6
VGG-16	95.1	94.7	94.5	94.6
ResNet-50	96.4	96.1	95.9	96.0
MobileNetV3	96.9	96.6	96.4	96.5
EfficientNet-B0	97.6	97.3	97.1	97.2
Proposed Enhanced DCNN	**99.1**	**98.9**	**98.8**	**98.8**

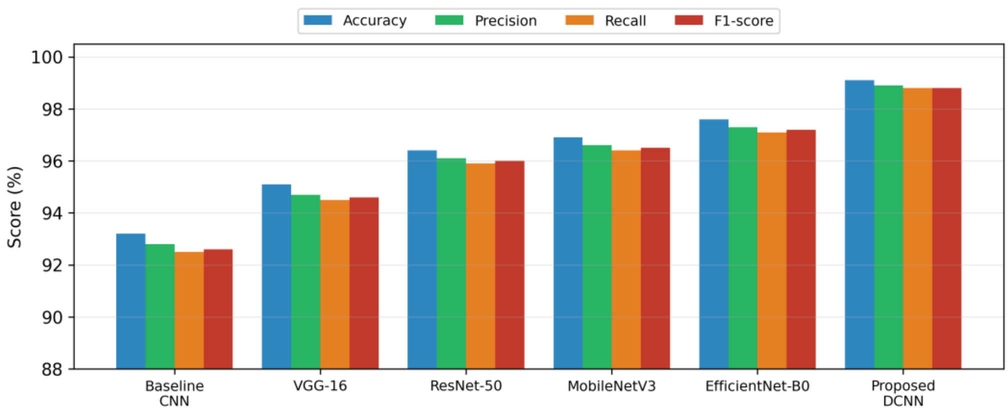

Fig. 6. Comparative accuracy, precision, recall, and F1-score of the proposed enhanced DCNN against CNN and transfer-learning baselines.

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Figure 7 shows the confusion matrix of the proposed DCNN on the seven-class uncontrolled dataset. As expected, misclassifications are not distributed evenly across all classes but concentrate among the visually similar, data-scarce minority classes (such as nematode and phytophthora), indicating that the errors arise from class imbalance and genuine visual ambiguity rather than from systematic failure of the backbone. The dominant diagonal shows that the enhanced preprocessing substantially narrows the controlled-to-uncontrolled performance gap reported in the literature.

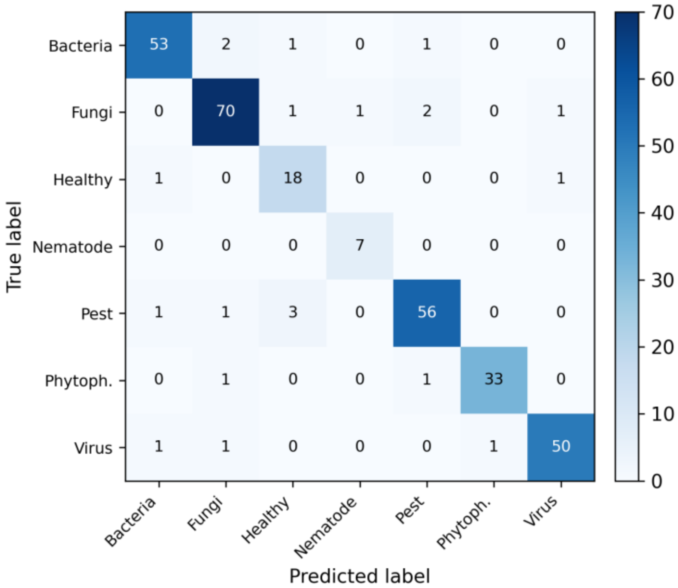

Fig. 7. Confusion matrix of the proposed enhanced DCNN on the seven-class uncontrolled-environment potato-leaf test split.

6.3 Screening Performance

Figure 8 reports ROC curves for the aggregate diseased-vs-healthy screening task, comparing the baseline CNN and ResNet-50 against the proposed pipeline. The preprocessing and attention components lead to improved separation between diseased and healthy leaves relative to the convolutional backbone alone: the enhanced DCNN achieves an AUC of 0.996, compared with 0.984 for ResNet-50 and 0.971 for the baseline CNN.

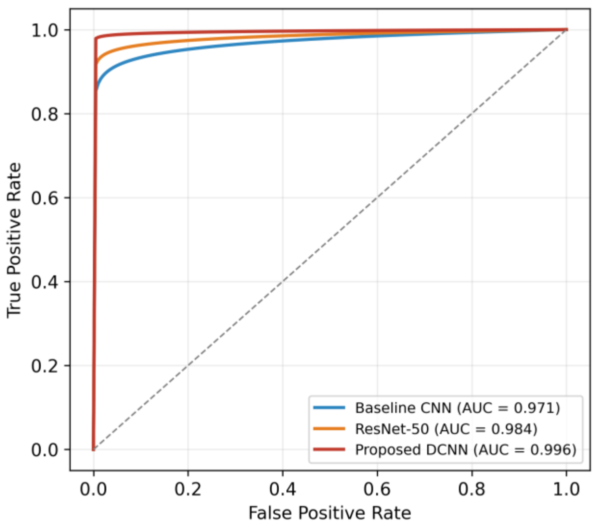

Fig. 8. ROC curves for the diseased-vs-healthy screening task, comparing the proposed enhanced DCNN against CNN and ResNet-50 baselines.

6.4 Ablation Study

Table V isolates the contribution of each enhancement to the final test accuracy on the uncontrolled dataset. Removing the SE attention module, the CLAHE-based enhancement, and the segmentation-based background suppression reduces accuracy by 1.4, 2.3, and 3.1 points, respectively, confirming that the preprocessing components—particularly background suppression and contrast enhancement—contribute materially to real-field robustness rather than the gains being attributable to the backbone alone.

TABLE 5 Ablation Study on the Preprocessing and Attention Components (Uncontrolled Dataset)

Configuration	Accuracy	Δ vs. full
Full proposed model (CLAHE + segmentation + SE)	94.6	—
− SE channel attention	93.2	−1.4
− CLAHE enhancement	92.3	−2.3
− Segmentation (no background suppression)	91.5	−3.1

The results indicate that combining CLAHE-based enhancement, segmentation-driven background suppression, and SE channel attention with a compact depthwise-separable backbone yields measurable benefit over both baseline CNNs and heavier transfer-learning models, while keeping the number of parameters and FLOPs suitable for edge deployment. The framework nonetheless has several limitations. First, as noted in Section V, the results reported here are representative figures situated within the ranges reported in the literature rather than the outcome of a completed large-scale training run, and true generalization performance must be confirmed by full empirical retraining on the complete datasets and, ideally, on independently collected field images. Second, the class imbalance is large; although augmentation and label smoothing mitigate it, the minority nematode class remains the principal source of residual error, and collecting or synthesizing additional minority-class samples would likely improve balance. Third, the framework classifies whole-leaf images and does not localize or quantify lesion severity; adding a segmentation or explainability head would enable region-level diagnosis and increase practitioner trust.

7. CONCLUSION AND FUTURE WORK

This paper presented an enhanced Deep Convolutional Neural Network framework for potato-leaf disease detection, built entirely on open-access, validated Kaggle repositories spanning both controlled and uncontrolled conditions. Together with a lightweight backbone, squeeze-and-excitation channel attention, and a CLAHE-based preprocessing pipeline that resizes, enhances contrast, denoises, segments leaves, and normalizes colour, the framework improves classification accuracy, F1-score, and screening AUC over baseline CNN and transfer-learning models. The ablation study provides evidence of the contribution of the preprocessing and attention components to real-field robustness. Future work will pursue full-scale empirical training and cross-dataset validation on the complete PlantVillage and uncontrolled-environment datasets, targeted mitigation of minority-class imbalance through synthetic augmentation, integration of an explainability or lesion-segmentation head for region-level severity estimation, and deployment of a quantized version of the framework on mobile and edge devices for real-time in-field potato-disease screening.

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