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A Machine Learning Approach for Potato Disease Detection with Application of Image Processing (HSV Processing and OTSU Segmentation)

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ABSTRACT

Potatoes are among the most widely cultivated and consumed staple crops worldwide; however, they are highly susceptible to diseases such as early blight and late blight, which significantly compromise crop yield and quality. Traditional disease detection methods, which often rely on manual inspection, are labor-intensive, time-consuming, and prone to human error. In response to these limitations, the present study proposes a machine learning-based framework for the ac-curate classification of potato leaf diseases, using Convolutional Neural Network (CNN) architecture. The approach implements image processing techniques, in which RGB color space is converted to the HSV color space. To enhance the localization of infected regions, Otsu's thresholding method is employed, allow-ing for effective separation of diseased areas from the background. The model is developed on a dataset consisting of 3000 images divided into 3 classes: healthy, early blight, and late blight. With a batch size of 32, The model was trained for 50 epochs, achieving an accuracy of 97.12% on the original dataset, which further improved to 98.56% when trained on the segmented dataset. And finally, using different assessment metrics, the classification performance of the model was evaluated.

Keywords Potato disease, Convolutional neural network, OTSU Segmenta-tion, Machine learning, Image processing.

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INTRODUCTION

Agriculture is a vital sector of a country's economy and it plays an important role in globe's population. This sector contributes significantly to the GDP of the nation and offers employment to many people living in rural areas (Kumar and Patel 2023). Among the many crops that play a vital role in agriculture, the potato stands out due to its global significance and versatility. It is considered to be an efficient crop due to its higher yield of protein, dry matter and minerals per unit as compared to cereals (Khalifa *et al.* 2021). The Potato (Solanum Tuberosum) ranks as the third most significant food crop globally, following cereals and rice. Global production surpasses 300 million metric tons and serves as a crucial source of nutrition and calorie provider for humanity (Oppenheim and Shani 2017).

India holds a significant position in the world in terms of potato production, ranking as the second largest producer of potato in the world with an annual production of 51.31 million tons from 2.14 million hectares of cultivated land (Bordoloi and Lama 2022). Potato cultiva-tion is predominantly concentrated in the northeastern region of India, where the crop is grown year-round across various areas. This region accounts for approximately 10 percent of the total land area under potato cultivation in the country (Patel *et al.* 2025, Sah *et al.* 2011). Within the Northeastern Region (NER), Assam records the largest area dedi-cated to potato cultivation and ranks fourth among all crops in the state in terms of cultivated area (Borah *et al.* 2016).

This reliance makes the crop more likely to get diseases, which can seriously reduce both its yield and quality, leading to high economic losses. Among the diseases, early blight and late blight are espe-cially harmful (Radwan *et al.* 2024). Early blight in potatoes is caused by the fungal pathogen *Alternaria solani*, while late blight is caused by *Phytophthora infestans* and is also notorious for having caused the Irish Potato Famine in the 1840s. Both diseases originate on potato leaves and can seriously damage the crops, resulting in major economic losses for affected countries (Gold *et al.* 2020). This highlights the broader significance of potato dis-eases in global agriculture. Recognized as some of the most destruc-tive plant diseases world-wide, they greatly reduce the yield and quality of potato crops, thereby adversely affecting the livelihoods of individual farmers and posing challenges to the agricultural industry as a whole (Arshaghi *et al.* 2023). Thus, early detection of the diseases is essential to take preven-tive measures and reduce crop losses.

Traditionally, the identification of such diseases has relied heavily on visual inspection by the human eye, a method that has been used for decades (Singh and Kaur 2021). However, this method is frequently deemed unviable due to the long processing time, the limited availability of experts on farms, and the poten-tial for inaccurate results (Iqbal *et al.* 2020). There-fore, using computers-based techniques for inspection can be more effective and less expensive. Researchers have also widely studied the use of computer vision and machine learning for disease detection over the past twenty years. Machine learning based techniques particularly CNN can be used to identify and diagnose diseases in plant leaves (Tarik *et al.* 2020), ena-bling the system to learn from data and make decisions independently. Since visible symp-toms often appear on plant leaves, these patterns can be extracted using various image pro-cessing techniques (Sangar and Rajasekar 2025). These extracted features then can be com-pared with previously collected data to identify similarities and differences. Based on the comparison and with the help of the machine learning algorithms, it can classify the type of disease affecting the plant. Therefore, the integration of image processing and machine learn-ing is very effective in accurate clas-sification and identification of potato leave diseases.

The major highlights of our work are:

To enhance image quality and facilitate region-specific feature extraction by converting images to the HSV color space and applying Otsu segmentation.

To design and implement a custombuilt Convo-lutional Neural Network (CNN) model tailored for the classification of potato leaf diseases.

To evaluate and compare the performance of the proposed model using various performance metrics, considering both the original and the segmented datasets.

In recent years, researchers worldwide have been working on AI-based tools to help farmers make better decisions and take the right actions to manage crop diseases (Pathak *et al*. 2024). The following section explores a range of models introduced by other scholars in the field to diagnose potato crop problems.

In 2021, Tarik *et al.* proposed an automated system for detecting potato diseases using machine learning and image processing techniques. The study utilized 2,034 images from the Plant Village dataset and achieved a high classification accuracy of 99.23% using pretrained models. However, despite the promising results, the datasets lack diversity, limiting the model performance in real-world agricultural environments (Tarik *et al.* 2021). In the same year.

In 2022, Chakraborty *et al.* (2022) focused on automating the recognition of potato leaf diseases using four prominent convolutional neural network (CNN) architectures: VGG16, VGG19, Mobile Net, and Res Net 50. The study used the Plant Village dataset, which included the images of healthy, late blight, and early blight-infected potato leaves. Among the models tested, VGG16 achieved the highest baseline accuracy of 92.69%, which was further improved to 97.89% through fine-tuning and parameter optimization. However, there was no analysis of class imbalance, which could bias the model towards majority classes in the dataset (Chakraborty *et al.* 2022). In the same year, Nishad *et al*. (2022) investigated the effectiveness of integrating K-means segmentation with deep learning for potato leaf dis-ease classification. They tested three CNN architectures VGG16, VGG19, and Res Net 50 and found that VGG16 achieved the highest accuracy of 97% (Nishad *et al.* 2022).

In 2023, Anim-Ayeko *et al.* (2023) introduced a deep learning model based on Res Net-9 for potato and tomato leaf disease detection, achieving remarkable results on the Plant Village dataset. The model achieved a test accuracy of 99.25%, with a precision of 99.67%, recall of 99.33%, and an F1-score of 99.33% (Anim-Ayeko *et al.* 2023). In the same year, Sadiq *et al.* (2023) utilized deep learning models such as VGG16, Efficient Net B4, InceptionV3, and Inception ResNetV2 to classify potato leaf diseases. Their results show that EfficientNet B4 outperformed the other models with a perfect accuracy of 100% (Sadiq *et al.* 2023).

Mahum *et al.* (2023) introduced a modified Dense Net-201 model for potato leaf disease detection, incorporating an additional transition layer and reweighted cross-entropy loss to handle data imbalance. Their model achieved an accuracy of 97.2%, significantly improving consistency and robustness, especially in small datasets (Mahum *et al.* 2023). Similarly, Nazir *et al*. (2023) proposed EfficientPNet, an optimized model built on EfficientNet-V2 which used the spatial-channel attention mechanisms for more precise disease identification. Tested on the PlantVillage dataset with over 10,000 images, Efficient PNet achieved a classification accuracy of 98.12% (Nazir *et al.* 2023). Also, Gupta and Shah (2023) integrated IoT with deep learning models to classify potato leaf diseases. By utilizing convolutional neural networks (CNNs) alongside K-nearest neighbors (K-NN) and IoT-based alert systems, the study achieved a detection accuracy of 90% (Gupta and Shah 2023).

In 2024, Anand *et al.* (2024) propose a deep learning combined with image segmentation approach to classify potato leaf diseases using the Plant Village dataset. Their methodology employed a K-Means clustering for disease region isolation and a deep neural network (DNN) for classification. The method achieved a higher accuracy of 98% (Anand *et al.* 2024). Similarly, Jha *et al.* (2024) proposed a transfer learning-based stacking ensemble mod-el combining Residual Network, Mobile Net, and Inception architectures for potato leaf disease prediction. Trained on an extensive dataset, the ensemble model achieved aclassification accuracy of 98.86% for potato leaf disease detection (Jha *et al.* 2024).

In 2025, Ramu *et al.* (2025) apply machine learning techniques, including K-Nearest Neighbours (KNN), Random Forest (RF), and Artificial Neural Networks (ANN), to detect late and early blight in potato and tomato plants. Using the Plant Village dataset, their findings indicate that the ANN model achieved the highest classification accuracy (98.5%) (Ramu *et al.* 2025). Similarly, Zhang *et al.* (2025) compared the performance of four deep learning models—VGG16, Mobile NetV1, Res Net 50, and ViT—on potato leaf disease classification. Among the models evaluated, VGG16 demonstrated the highest baseline accuracy of 97.26%. This performance was further improved to 97.87% through the development of a modified variant, VGG16S, which incorporated Convolutional Block Attention Module (CBAM), global average pooling, and the

Leaky ReLU activation function (Zhang *et al.* 2025). Further research in 2025 by Sangar and Rajasekar (2025) proposed an advanced Efficient Net-LITE model integrated with KE-SVM optimization for potato leaf disease detection. The model employed channel attention mechanisms in conjunction with one-dimensional local binary pattern (1D-LBP) features for enhanced representation learning, achieving an accuracy of 99.54% on controlled datasets and 87.82% on uncontrolled datasets (Sangar and Rajasekar 2025). Similarly, Alhammad *et al.* (2025) proposed a deep learning framework integrated with Explainable AI (XAI) techniques for potato leaf disease classification. The model employed pretrained neural networks alongside Gradient-weighted Class Activation Mapping (Grad-CAM) to enhance inter pretability. The framework demon-strated strong performance, attaining 97% validation accuracy and 98% testing accuracy, underscoring its reliability and inter pretability for effective agricultural disease detection (Alhammad *et al.* 2025).

Dey *et al.* (2025) proposed a lightweight deep convolutional neural network for real-time potato leaf disease classification, achieving an accuracy of 98.6%. With a parameter count of only 204,227, the model is well suitable for resource-constrained devices, and it outper-formed established architectures like VGG-16, AlexNet, and ResNet-50, thus making it ideal for deployment in field conditions (Dey *et al.* 2025). In a related study, Chen and Liu (2025) introduced CBSNet, a method designed to handle challenges such as tiny disease spots and noise in potato leaf images The architecture integrates a Channel Reconstruction Multi-Scale Convolution (CRMC) module and a Spatial Triple Attention (STA) mechanism, achieving 92.04% accuracy and 91.58% precision. This result demonstrates its ability to de-tect subtle disease symptoms and supporting large-scale disease prevention (Chen *et al.* 2025). Furthermore, Sujatha *et al.* (2025) proposed a hybrid approach that integrated ma-chine learning and deep learning techniques for plant leaf disease detection. The study em-ployed CNN architectures such as VGG19 and Inception v3 with SVM to extract features from potato leaf images, thereby achieving an accuracy of 62.6% in disease classification (Sujatha *et al.* 2025).

Despite the higher accuracies achieved in the previous reviewed studies, several limitations persist such as reliance on RGB color space, inadequate or non-robust segmentation methods, over-dependence on pre-trained models, and challenges related to class imbalance is-sues. Additionally, many models struggle to accurately isolate disease-affected regions ef-fectively, leading to reduced interpretability and increased noise. In contrast, our method employs HSV color space conversion combined with Otsu segmentation to enhance the extraction of region-specific feature. Furthermore, a custom-built model architecture was incorporated into the pipeline therefore addressing the key limitations of earlier methods and offers a more targeted and efficient disease classification strategy.

MATERIALS AND METHODS

Dataset

In this study, the Plant Village dataset, a widely recognized and publicly available benchmark resource, was utilized for evaluating the proposed approach. This dataset contains approxi-mately 54,000 labelled images of healthy and diseased plant leaves, captured under controlled conditions to ensure consistent lighting and a uniform background, thereby minimizing envi-ronmental noise. For the purpose of this work, which focuses specifically on potato leaf dis-ease classification, only the relevant subset of potato crop images was extracted. The dataset provides clearly annotated images categorized into three classes: healthy, early blight, and late blight. A total of 3000 images were used for development of the model, which were later augmented to increase the diversity and robustness of the dataset.

Image preprocessing

Image enhancement (HSV Conversion). In our work, Image Enhancement was performed by converting the RGB color space into HSV color space. This transformation was em-ployed as HSV effectively separates the color information (HUE) from intensity (Value), thereby facilitating the detection of subtle color changes caused by diseases like early blight and late blight. This improved color discrimination thus enhanced the accuracy of classification process in the disease detection pipeline.

OTSU-Segmentation. Otsu segmentation is a global thresholding technique widely used in image processing to automatically distinguish foreground regions of interest from the back-ground. The method determines an optimal threshold by analyzing the image histogram to minimize intra-class variance while maximizing inter-class variance between segmented re-gions. In the context of classifying potato leaf diseases into three categories, Otsu segmen-tation facilitates the isolation of diseased areas from healthy leaf tissue and background. This process enhances feature clarity and relevance by reducing background noise and directing the model's focus toward the affected regions.

Proposed CNN architecture

Fig. 1, illustrates the proposed convolutional neural network (CNN) model, which is de-veloped to classify images of potato leaves into three categories: Potato_Early_blight, Potato_Late_blight, and Potato_Healthy. The model consists of 8 convolutional layers, 5 max-pooling layers, 2 dense (fully connected) layers, 2 dropout layers, and one output layer. The overall architecture follows the structure: [{(2 Conv × 1 MaxPool × 1 Dropout) × 1} + {(3 Conv × 2 MaxPool × 1 Dropout) × 1} + {(3 Conv × 2 MaxPool) × 1} + 1 Flatten + 2 FC + 1 Output]. As shown in the figure, the model begins with taking in RGB images of size 255 × 255 × 3 and processes them through three main blocks of convolutional operations. Each convolutional layer utilizes a 3×3 kernel to perform localized, element-wise operations, enabling the extraction of essential spatial features. For reducing the spatial dimensions and also to maintain computational efficiency, Pooling layers were introduced after sets of convolutional layers in each block. The first, second and third blocks uses 32, 64 and 128 filters, respectively. A dropout layer was also utilized in the first and second block of the convolutional layers to reduce overfitting problems. Subsequently, two fully connected layers were employed with different weights and biases to link the features learned by the network, allowing it to combine this information and make accurate predictions for classifications. These fully connected layers then processed the flattened feature vector thus preparing the data for classification using standard mathematical methods. Finally, the Soft Max activation function was applied in the output layer to determine the class probabilities for the model predictions.

Experimental setup

The experiments were carried out in a local machine having as a processor, with 24 GB of RAM, the model training was done using a GTX 1650 GPU with 4 GB of VRAM. Visual studio code was used as an IDE, and various python libraries were used for image processing, model development and evaluation.

Performance evaluation of the proposed model

After the model training is completed, evaluation of the classification performance of the CNN model is

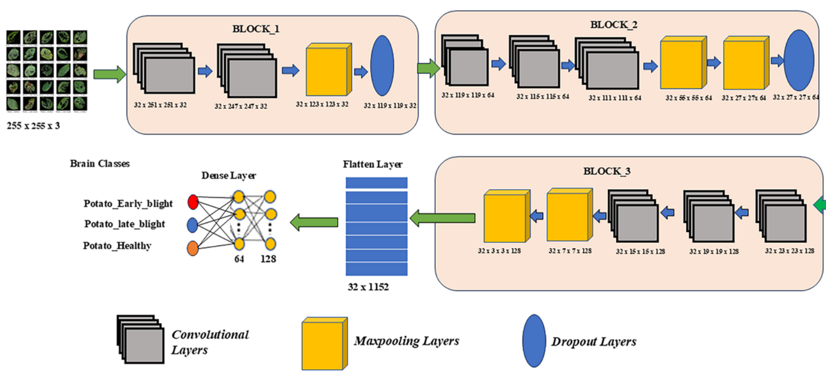

Fig. 1. Proposed CNN Architecture.

a very important step in any machine learning methodologies. In the proposed methodology, the dataset is partitioned into training (80%), testing (10%) and validation (10%) set. The training and validation set is used during the training phase, and the testing set is used to evaluate the model. Different set of assessment metrics such as Accuracy, Preci-sion, Sensitivity, and Specificity, etc. are used to assess the performance of the model. The equation for the different set of assessment metrics is displayed below (Eq 1-5).

$$\text{Accuracy} = \frac{T^{+}+T^{\prime}}{T^{+}+T^{\prime}+F^{+}+F^{\prime}} \quad (1)$$

$$\text{Precision} = \frac{T^{+}}{T^{+}+F^{+}} \quad (2)$$

$$\text{Sensitivity} = \frac{T^{+}}{T^{+}+F^{\prime}} \quad (3)$$

$$\text{Specificity} = \frac{T^{\prime}}{T^{\prime}+F^{+}} \quad (4)$$

$$\text{F1-Score} = \frac{2T^{+}}{2T^{+}+F^{\prime}+F^{+}} \quad (5)$$

Where T^{+} represents True Positive, $T^{\prime}$ is True Negative, F^{+} is False Positive and $F^{\prime}$ is False Negative.

RESULTS AND DISCUSSION

Output of the segmented images

In Fig. 2, the original dataset images were initially transformed from the RGB color space to the HSV color space. Subsequently, Otsu's thresholding method was applied to the HSV-converted images for segmentation. The resulting segmented images were then utilized for training the model.

Training and validation curves of the proposed model

In Fig. 3, the loss and accuracy of the model training and validation phase is plotted. With the help of the classification curves, we can observe if the model is underfitted or over-fitted during the training phase of the model. In Fig. 3, For the original dataset, both train-ing and validation accuracy show a steady increase, reaching accuracy above 95%, indicating linear learning capability. The loss curves also demonstrate a consistent decline with minimal fluctuations, though a few spikes in validation loss suggest minor overfitting or sensitivity to specific batches. Whereas, for segmented dataset, early and stable rise in accuracy suggests that Otsu segmentation helps the model focus on essential regions, reducing background noise and irrelevant details that could have otherwise distract the learning process.

Performance evaluation of the proposed model

In Table 1, the various evaluation metrics are calculated for the proposed model on original dataset and segmented dataset. From the confusion matrices depicted in Fig. 4, we calculate the number of True

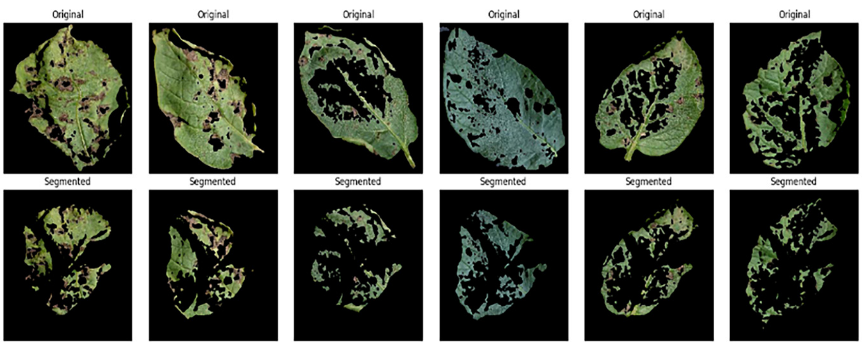

Fig. 2. Original and Segmented Image.

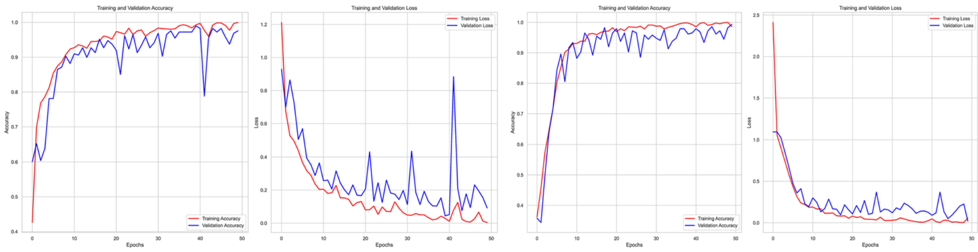

Fig. 3. Training and Validation Accuracy and Loss (a) Original Dataset (b) Segmented Dataset.

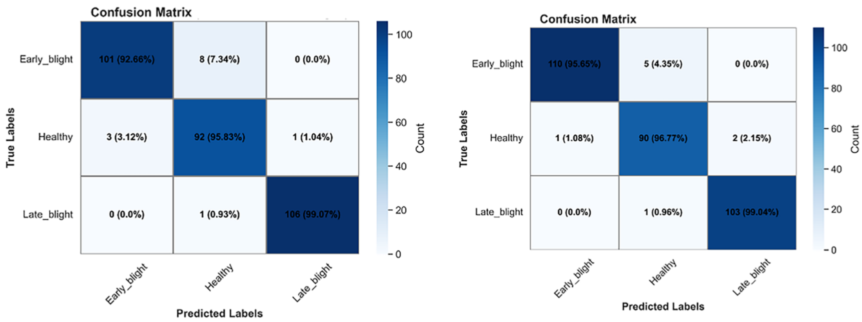

Fig. 4. Confusion Matrix (a) Original Dataset (b) Segmented Dataset.

Positive (TP), True Negative (TN), False Positive (FP), and False Nega-tive (FN), which are used to determine the various performance metrics for the model trained on original and segmented dataset. When comparing the performance of the model on original and segmented datasets at a learning rate of 0.0001, the segmented dataset consistently yields better results. Notably, improvements are observed in the Early Blight and Healthy classes, where precision and sensitivity increase significantly with segmentation (e.g., Early Blight precision improves from 0.97 to 0.99, and sensitivity from 0.93 to 0.96). Although Late Blight already shows high metrics with the original dataset, segmentation maintains this strong performance. Image segmentation enhances the model ability to distinguish important features in the input images, thus improving the classification performance of the model.

Classification: ROC Curve and AUC

In Figure 5, the Receiver Operating Characteristic (ROC) curve is displayed for the pro-posed model trained on (a) original dataset and (b) segmented data-set. The ROC curve helps us in evaluating individual class wise performance, compared to other classes Early blight, Healthy, and Late blight, for a multi class model. In the figure, we can observe that, the

Table 1. Performance evaluation of the proposed model on original and segmented dataset.

Performance	Learning rate	Early Blight Original	Early Blight Segmented	Healthy Original	Healthy Segmented	Late Blight Original	Late Blight Segmented
Accuracy		0.96	0.98	0.96	0.97	0.99	0.99
Precision		0.97	0.99	0.91	0.94	0.99	0.99
Sensitivity	0.0001	0.93	0.96	0.96	0.97	1.00	0.99
Specificity		0.99	0.99	0.96	0.97	0.99	0.99
F1-Score		0.95	0.97	0.93	0.95	0.99	0.99

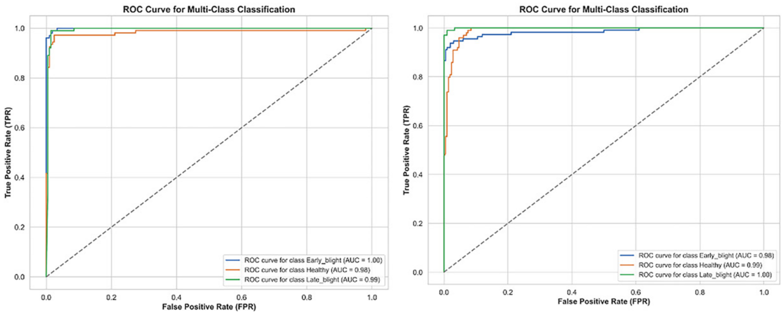

Fig. 5. ROC curve of the proposed model (a) Original dataset (b) Segmented dataset.

de-veloped model achieved quite similar performance for the original and segmented dataset. The minimal difference in AUC values between the original and segmented datasets deter-mines that segmentation has a marginal impact on classification performance, and the model maintains strong discriminative power in both scenarios.

CONCLUSION

A large volume of potato cultivation is affected by various diseases, thus significantly reducing its yield and quality. In the proposed study, using machine learning, a CNN model is developed for early detection and classification of potato leaf diseases. The application of HSV color space conversion and Otsu segmentation significantly enhanced the extraction of region-specific features, allowing the model to focus more precisely on disease-affected areas while reducing background noise. The proposed CNN model demonstrated strong classification performance, achieving an accuracy of 97.12% when trained on the original dataset. Notably, this accuracy improved to 98.56% when the model was trained on the segmented dataset, underscoring the effectiveness of the pre-processing steps in enhancing model learning and generalization. Performance improvements were particularly evident in the classification of early blight and healthy leaf samples, where precision and sensitivity showed marked gains. However, the model was trained on a limited dataset consisting of only 2 disease classes, and the model may fail to classify other class in real world settings. Future work will focus on deploying this model in real-time applications, such as mobile or edge-based systems, and expanding the dataset to include more diverse and uncontrolled field conditions.

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