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SPUDNET5-R3: A Lightweight Hybrid and Explainable CNN Model for Potato Leaf Blight Detection

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Abstract

Potato (Solanum tuberosum), the fourth most abundant food crop in the world, is subjected to significant challenges due to diseases such as late blight, causing global annual yield loss exceeding \$6.7 billion [1]. Current methods of detection are time-consuming and frequently fail to identify early-stage infections. Deep learning, and particularly the Convolutional Neural Networks (CNNs) provide fast and scalable automation of disease classification compared to traditional methods. In this work, potato leaf diseases were classified by many CNNs such as XceptionNet, DenseNet121, a 5-layer CNN, a 6-layer CNN, and a custom hybrid CNN model (SpudNet5--R3). The datasets we used are as follows: (1) PlantVillage dataset was used and (2) PLD dataset which contains healthy, early blight, and late blight potato leaves. A full preprocessing pipeline was carried out which includes resizing, colour normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE). Targeted data augmentation strategies were applied to tackle the class imbalance. The models were trained, validated, and tested individually on three datasets and the input images were resized to 224×224. We analysed performance measures such as accuracy, precision, recall, F1-score, and inference time for finding the best model. In addition, Grad-CAM visualization was used to provide interpretable insights into the model predictions, showing the particular leaf regions that contributed to the classification. Experimental results show the strong competitiveness of our custom SpudNet5-R3 architecture, obtaining testing accuracy of 99.07% and macro F1-score of 99% on the PlantVillage (D1) potato dataset. It achieved also the testing accuracy of 95.56% and a macro f1-score of

96% on PLD (D2) dataset, demonstrating the successfulness of CNN architectures customized for robust and accurate recognition of the potato diseases.

1. Introduction

Potato (Solanum tuberosum) is the fourth most important world food crop and is important for world food security. But its cultivation is seriously constrained by diseases such as late blight and early blight that severely affect yield and quality. Late blight, caused by the oomycete Phytophthora infestans, is one of the most severe diseases for potato cultivation. It is the causative agent of the Irish Potato Famine of the 1840s and continues to result in annual worldwide losses totalling over $6.7 billion [1]. Disease development is rapid with large crop losses as the pathogen grows well at low temperatures and in continuous moisture. Early blight, which is caused by Alternaria solani, is an additional serious threat, with yield losses ranging from 20% to 50% in vulnerable areas [2,3]. This disease is very common in warm temperate and tropical regions where it is aggravated by improper management of the disease and absence of resistant cultivars [4,5]. Conventional detection techniques for such diseases, including visual observation and laboratory diagnosis, are cumbersome and time-consuming, and cannot detect the infection at its early stage in most cases. On the other hand, deep learning algorithms, especially Convolutional Neural Networks (CNNs), have proved to be a valuable method for automated plant disease identification, providing fast and high accuracy in disease detection.

The objective of this study is to design and evaluate various custom hybrid CNN models, and suggest an optimal model for the classification of potato leaf diseases. Utilizing two open-access datasets and advanced pretreatment methods, the model will be a viable tool to increase the accuracy and efficiency in detecting diseases, for sustainable potato production.

Key Contributions of our research work are following:

- Leveraged two publicly available potato leaf disease datasets (PlantVillage subset and PLD dataset) with different train-validation-test splits to ensure robust model evaluation.
- Conducted a comparative analysis of multiple image enhancement techniques (CLAHE, gamma correction, tanh, Reinhard) and finalized CLAHE for improved feature extraction and model performance.
- Designed and implemented a custom five-layer hybrid CNN model with a residual connection at the third layer, balancing accuracy, complexity, and training efficiency.
- Trained and evaluated multiple architectures (XceptionNet, DenseNet121, multiple custom CNN variants) using precision, recall, F1-score, and inference time as key metrics, demonstrating the superior performance of the proposed model.
- Applied Grad-CAM visualizations to highlight critical leaf regions influencing classification decisions, enhancing trust and explainability in deep learning-based disease detection.

This paper is organized into six sections. Section one has been discussed as introduction. Section two reviews related work on plant disease classification. Section three outlines the datasets used, preprocessing techniques, model architectures, and training approach. Section four represents results and performance analysis. Section five covers Grad-CAM visualizations for interpretability. Section six concludes the study and suggests future directions.

2. Related Work

Recent advancements in deep learning have significantly improved the accuracy of plant disease detection, particularly for potato leaf diseases. Various models, including CNNs, hybrid architectures, and transformers, have been explored to identify and classify diseases like late blight and early blight. This section reviews the key studies and models developed for potato leaf disease detection, focusing on their methodologies, datasets, and performance metrics to highlight the current state-of-the-art.

Table 1. Literature survey of research works over potato leaf disease detection using DL and ML

Ref.	**Models proposed and used**	**Dataset**	**Results**	**Novelty**
Pasalkar et al. [6]	CNN (epochs: 37)	Potato leaf disease (600 images)	Accuracy: 97.4 % Precision: 100% Recall: 44 %, F1- Score: 61%	Used a CNN model with a publicly available dataset of potato leaf images, employing data augmentation and specific training parameters.
Rashid et al. [7]	PDDCNN (epochs 100)	Train: PlantVillage (Potato, 2152 images) Test: Potato Leaf Dataset (PLD, 4062 images)	Over PlantVillage (Potato) Accuracy: 96.75%, Precision: 97.6%, Recall: 95.33%, F1-Score: 96.33%	Proposed a PDCNN model for Potato Leaf disease detection using two datasets. Trained and tested the model over two datasets. Model trained over D1 is tested over D2 and viceversa.
Kothari et al. [8]	CNN,Resnet50, GoogleNet	PlantVillage (Potato, 2152 images)	Val Accuracies: (epochs 40) CNN: 97%, GoogleNet: 95%, ResNet50: 98%,	Conducted research on potato leaf disease detection using CNN, Resnet50, GoogleNet
Chang et al. [9]	RegNetY-400MF	Potato Leaf dataset (7 classes, 3076 images)	Accuracy: 89.87%, Precision: 90.24%, Recall: 89.87%, F1-Score: 89.83%	Introduced a RegNetY-400MF model for potato leaf disease setection.

Sofuoglu et al. [10]	Modified CNN	PlantVillage (Potato, 2152 images)	Weighted Average-Precision: 97.94%, Recall: 97.84%, F1-Score: 97.82%	Designed a new convolutional neural network (CNN) architecture specifically for potato leaf disease
Sharma, M. et al. [11]	Hybrid CNN	Potato Leaf dataset (7 classes, 3076 images)	Accuracy: 94.70%, Precision: 93.75%, Recall: 93.60%, F1-Score: 92.75%	Introduced a novel hybrid CNN architecture for Potato Leaf diseases
Adhikari et al. [12]	Vision Transformer (ViT)	PlantVillage (Potato, 2152 images)	Train Acc.: 99.54% Test Acc.: 99.55%	Presented a classification approach for potato diseases using ViT
Upadhyay et al. [13]	EfficientNetB0	PlantVillage (Potato, 2152 images)	Train Acc.: 99.66% Test Acc.: 99.05%	Proposed a classification-based methodology using EfficientNetB0
Grati et al. [14]	Att-MobileNetV2, Att-DenseNet and Att-InceptionV3	PlantVillage (Potato, 2152 images)	Accuracy & F-measure: Att-MobileNetV2: 0.99, 0.98 Att-DenseNet121: 0.98, 0.93 Att-InceptionV3: 0.94, 0.87	Investigated transfer learning for CNNs by modifying network structures and incorporating the Convolutional Block Attention Module (CBAM) into pre-trained models (MobileNet-V2, DenseNet121, InceptionV3) for identifying potato plant diseases.
Iftikhar et al. [15]	Modified CNN	PlantVillage (Potato, 2152 images) Epochs: 50	Training and validation 98.44% accuracy	Proposed a deep learning approach using a convolutional neural network to identify potato leaf diseases
Hazra S. et al. [16]	YOLOv8n	PlantVillage (Potato, 2152 images)	Accuracy: 97.02%, Precision: 94.57%, Recall: 94.164%, F1-Score: 94.36%	Investigated Potato leaf disease detection using YOLOv8n.
Anand S et al. [17]	DNN	a specialised dataset (450 potato leaf images)	Train and Test Accuracy: 98.52, 87.61%	Performance evaluation of the deep neural network (DNN) model for potato leaf disease (PLD)

			Precision: 89 %, F1-Score: 88%	

Several other research have been conducted to detect potato leaf diseases by means of deep learning-based models using different architectures and datasets to enhance the results in terms of accuracy and complexity. Pasalkar et al. [6] proposed a straight-forward CNN architecture with 600 potato leaf images obtaining a high accuracy of 97.4%. For their model, they reported poor recall at 44%, suggesting that more optimization is necessary. Rashid et al. [7] presented PDDCNN, trained and tested on two datasets, PlantVillage and Potato Leaf Dataset (PLD), which showed remarkable results having accuracy, precision and recall greater than 95%. Kothari et al. [8] explored several CNN models such as ResNet50 and GoogleNet on PlantVillage dataset and obtained accuracy results up to 98% for ResNet50. Similarly, Sofuoglu et al. [10] designed a novel CNN architecture for potato leaf diseases detection that demonstrated good performance with weighted average precision and recall of 97.94% and 97.84%, respectively. Sharma et al. [11] presented a hybrid CNN model, which obtained an accuracy of 94.7% also low precision and recall as compared to other models. On the contrary, Adhikari et al. [12] used Vision Transformer (ViT) to obtain close to perfect (99.55%) classification accuracy on the PlantVillage dataset. EfficientNetB0 of [5] proposed by Upadhyay et al. [13], also achieved excellent performance with a testing accuracy of 99.05%. Grati et al. [14], investigated transfer learning with attention modules (CBAM), and investigated pre-trained architectures such as MobileNetV2, DenseNet121, InceptionV3 for a highly-accuracy and F1-scores across in all models. More recently, Hazra et al. [16] used YOLOv8n model with precision classifier, and achieved the 97% accuracy and precision, Iftikhar et al. [15] introduced a CNN achieving a training and testing accuracy of 98.44% which even increases the penetration of deep learning approaches in this area. Anand et al. [17] employed a deep neural network (DNN) model on their own dataset, achieving the remarkable train accuracy of 98.52%; however, the test accuracy dropped significantly. These works prove the power of deep learning in potato disease diagnosis, but suggest that more efforts on adjusting architectural parameters and dataset should be made to improve detecting accuracy and model generalization.

3. Methodology

The complete pipeline flow for potato leaf disease detection with deep learning used in this work is described in this section. The study is based on two public datasets PlantVillage and Potato Leaf Disease (PLD) which contain images of three categories: Early Blight, Late Blight, and Healthy. The two datasets were divided into 80% training, 10% validation, and 10% testing. In order to improve the quality and uniformity of input data, different preprocessing methods were tested and CLAHE was chosen due to the enhancement of the contrast. Furthermore, data augmentation was performed to reduce any imbalance in class labels and to provide better generalisation. Many deep learning models were also tested, one such well-known architectures is XceptionNet and DenseNet121 architecture and custom made CNNs. We paid special attention to assess the performance of our proposed hybrid model, SpudNet-5R, which embeds residual connection into its third convolutional block. All of the models were trained under the same settings and assessed with principal performance measures including accuracy, precision, recall, F1-score and inference time. Additionally, the visual logits were analysed by Grad-CAM to interpret and understand the decision-making regions of the proposed model, indicating the explainability of the results.

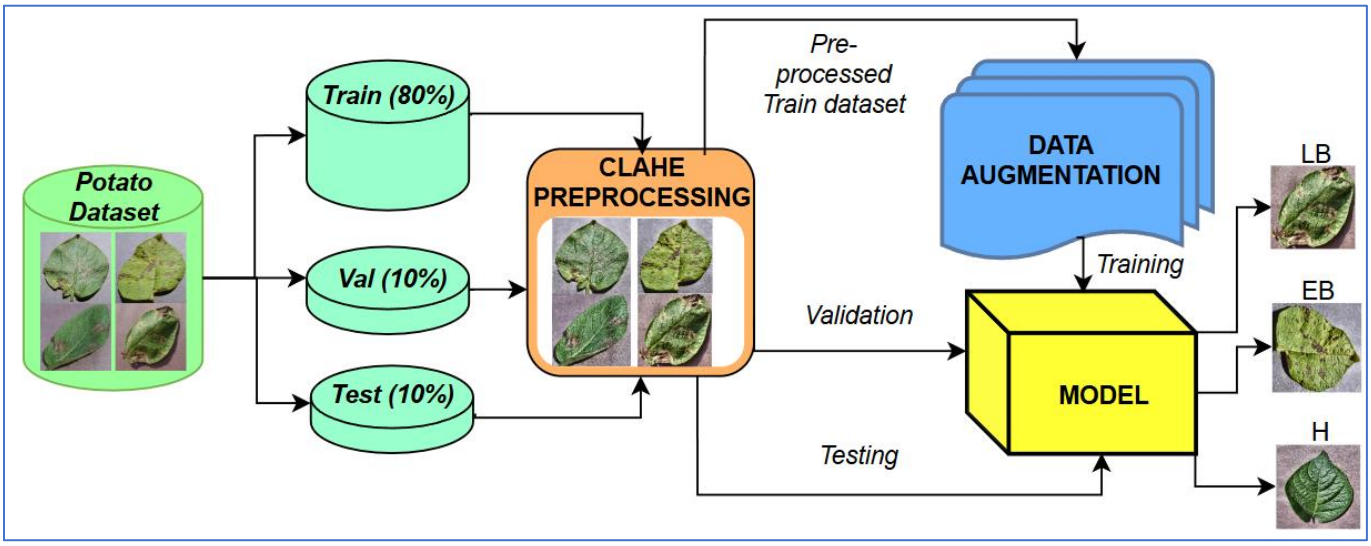


Figure 1: Proposed methodology diagram for classification of diseases in potato leaf diseases.

3.1 Dataset Description

In this work, we make use of two public datasets to study the classification of diseases in potato leaves. Dataset 1 (D1) This dataset includes 2,152 potato leaf images from the Kaggle-held PlantVillage dataset organized into 3 classes described as Early Blight, Late Blight, and Healthy. The DB comprises images of high quality, frame-grabbed under controlled conditions, with no background. And Dataset 2 (D2) Taken from the Kaggle Potato Leaf Disease (PLD) dataset, the dataset comprises 4,072 images, that are categorized into the same three aforementioned classes. The images in our dataset were captured in a variety of more natural and diversified scenarios, which is difficult and practical in testing models.

Figure 2: Sample potato leaf images from the datasets used in this study: (a) Early Blight (D1), (b) Late Blight (D1), (c) Healthy (D1), (d) Early Blight (D2), (e) Late Blight (D2), and (f) Healthy (D2).

For both datasets, an 80:10:10 division was used between training, validation, and test. This fair-split strategy provides consistent benchmarking and model comparison between these two datasets. The class distribution was evaluated after splitting and later augmented in order to compensate for any train imbalances. All images were resized to 224×224 pixels so that they are matched to pretrained deep learning models (e.g., Resnet) and can also be consistent among the experiments.

3.2 Pre-processing Techniques

To prepare the datasets for model training, a structured preprocessing pipeline was implemented to enhance image quality, ensure consistency, and address class imbalance. Initially, all images were resized to a fixed dimension of 224×224 pixels to maintain uniformity and ensure compatibility with the chosen deep learning architectures. Subsequently, various image enhancement techniques were evaluated on a subset of sample images to identify the most effective preprocessing method. Among the techniques tested—Gamma Correction, Tanh Transformation, Reinhard Normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE)—the CLAHE method produced the most visually informative results by effectively improving contrast while preserving important disease-related texture patterns as shown in Figure 3. Therefore, CLAHE was selected and applied uniformly across all images in both datasets.

To counter the issue of class imbalance observed in the datasets, data augmentation was employed selectively on the minority classes. This step not only expanded the training data but also introduced variability, which is crucial for improving the model's ability to generalize. A summary of the augmentation techniques and their parameters is presented in Table 2.

Table 2: Data Augmentation techniques and description

Augmentation Technique	Description
Rescaling	Pixel values normalized to [0,1] range (rescale=1.0/255.0)
Horizontal Flipping	Random horizontal flipping (horizontal_flip=True)
Brightness Adjustment	Random brightness variation (brightness_range=[0.8, 1.2])
Rotation	Random rotation up to 90° (rotation_range=90)
Shear Transformation	Shearing applied with shear_range=0.2
Zooming	Random zooming within 20% range (zoom_range=0.2)
Width & Height Shifting	Random shifts up to 20% (width_shift_range=0.2, height_shift_range=0.2)
Fill Mode	New pixel values filled using nearest neighbor interpolation (fill_mode='nearest')

3.3 Model Architectures

In this study, multiple deep learning architectures were explored to identify the most suitable model for potato leaf disease classification. The models considered include **XceptionNet**, **DenseNet121**, a custom **5-layer CNN**, a **6-layer CNN**, and our proposed hybrid architecture named **SpudNet5-R3**. While pre-trained architectures like XceptionNet and DenseNet121 are known for their strong representational capabilities, the goal of this research was also to design a lightweight and efficient model tailored specifically for the task, leading to the development of SpudNet-5R.

Proposed Architecture: SpudNet5-R3

SpudNet-5R is a custom five-layer Convolutional Neural Network (CNN) architecture enhanced with a **residual connection at the third convolutional block**, which aims to stabilize training and preserve feature integrity during deep propagation. The model accepts RGB images of size 224×224×3 as input and follows a sequential architecture of five convolutional blocks, each followed by max pooling.

- **First Convolutional Block**: The input image passes through a convolutional layer with 64 filters of size 3×3, using ReLU activation and L2 regularization, followed by a 2×2 max pooling layer.
- **Second Convolutional Block**: This block consists of 128 filters of size 3×3, again followed by ReLU activation, L2 regularization, and a 2×2 max pooling operation.
- **Third Convolutional Block with Residual Connection**: A convolutional layer with 256 filters processes the output. To enhance gradient flow and feature reuse, a residual shortcut connection is introduced from the output of the second convolutional block using a 1×1 convolution (to match dimensions), which is added elementwise to the third block's output. This mechanism helps mitigate the vanishing gradient problem and allows the model to retain important mid-level features.
- **Fourth Convolutional Block**: Similar to the previous blocks, this layer uses 256 filters of size 3×3 with ReLU activation, followed by max pooling.
- **Fifth Convolutional Block**: This final block increases the number of filters to 512, followed by ReLU activation, L2 regularization, and max pooling.

After the convolutional feature extraction stage, the model transitions into a fully connected stage:

- **Flattening**: The final feature maps are flattened into a 1D vector.
- **Dense Layers**: Two fully connected (Dense) layers follow — the first with 512 neurons, and the second with 256 — both activated using ReLU and followed by 40% dropout layers to prevent overfitting.
- **Output Layer**: A final dense layer with a SoftMax activation function is used to classify the images into their respective categories based on the number of disease classes in the dataset.

This architecture was deliberately chosen to achieve a trade-off between complexity and performance, so that it can be applied to critical scenarios that require precision and efficiency. Adding a residual connection in the middle layers is the main novelty and leads to improved learning dynamics.

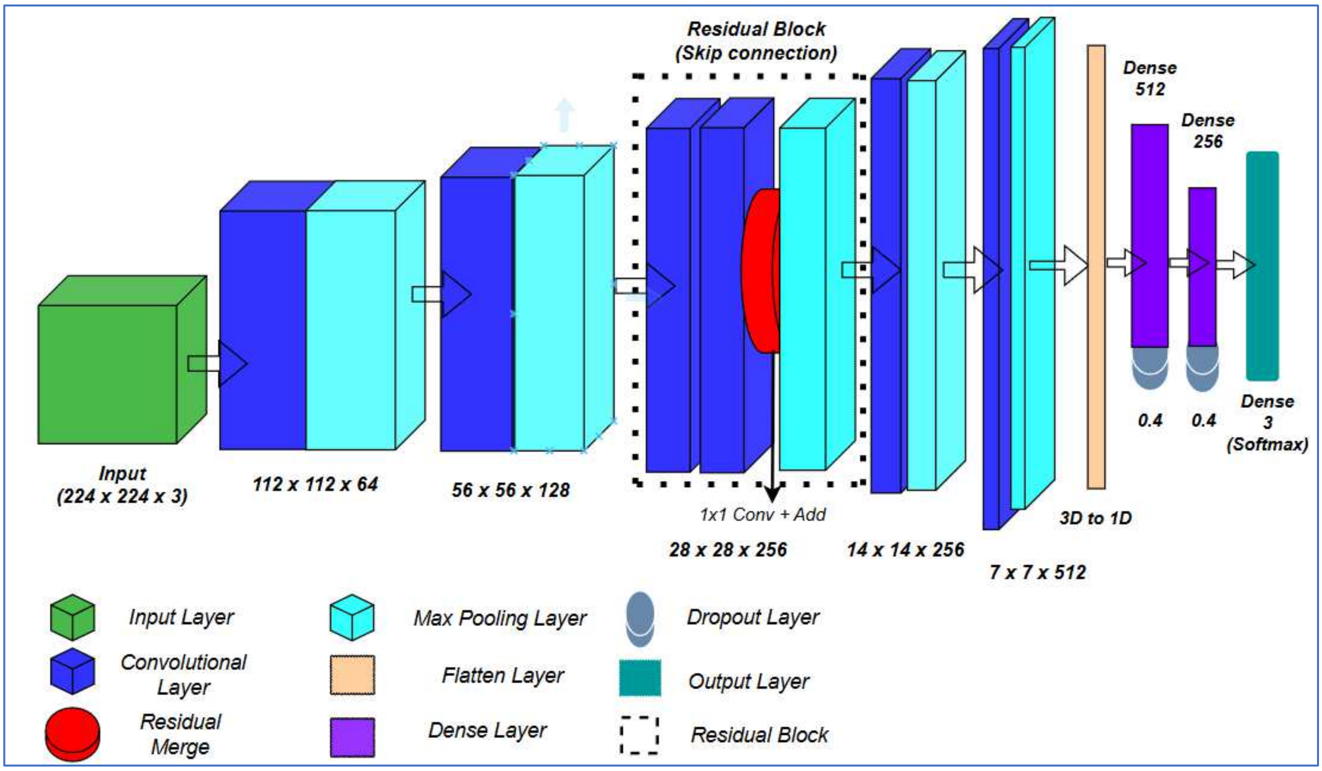


Figure 3: Proposed Hybrid CNN model (SpudNet-5R) for the classification of leaf diseases in tomato.

In this paper, we design a novel hybrid CNN architecture, SpudNet5-R3. In order to be consistent with the previous benchmarking, in the result's tables we use the name SPUDNET5-R3. The experiments were carried out using 2 datasets: D1, the PlantVillage Potato sub-dataset with 2,152 images, and D2, the PLD dataset with 4,072 images.

3.4 Algorithm: Hybrid-CNN-5R3 (Proposed Model - SpudNet5-R3)

Input: Image I$\in R^{224\times224\times3}$
Output: Class prediction $\hat{y} \in R^{C}$ (C = number of classes)
Preprocessing: CLAHE enhancement + normalization: $I' = \frac{I}{255}$

Feature Extraction:

1. $x_1 = MaxPool(ReLU\left(Conv_{3\times3}^{64}\ (I')\right))$
2. $x_2 = MaxPool(ReLU(Conv_{3\times3}^{128}\ (x_1)))$
3.
   a. Main: $x_3' = MaxPool(ReLU\big(Conv_{3\times3}^{256}\ (x_2)\big))$
   b. Residual: $r = ReLU\big(Conv_{1\times1}^{256}\ (x_2)\big)$
   c. Merged: $x_3 = MaxPool(x_3' + r)$
4. $x_4 = MaxPool(ReLU\big(Conv_{3\times3}^{256}\ (x_3)\big))$
5. $x_5 = MaxPool(ReLU\big(Conv_{3\times3}^{512}\ (x_4)\big))$

Classification Head:

- Flatten: x_f = Flatten (x_5)
- Dense-1: $x_{fc1} = Dropout_{0.4}(ReLU\big(W_1\, x_f + b_1\big))$
- Dense-2: $x_{fc2} = Dropout_{0.4}(ReLU\big(W_2\, x_{fc1} + b_2\big))$
- Output: $\hat{y} = Softmax\big(W_3\, x_{fc2} + b_3\big))$

Loss:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Optimization: Adam optimizer, learning rate η=0.0005
Training: 25 epochs, batch size = 32, using categorical cross entropy loss.

4. Result Analysis

The comparative analysis of different deep learning models over the PlantVillage (D1) and PLD (D2) is presented in Tables 3 and 4. The experimental results show that the model performance varies significantly with the architectures and data properties, in which our hybrid CNN variants exhibit comparable results.

4.1 Results on PlantVillage Dataset (D1)

To assess the flexibility of the presented Hybrid CNN-5(R3) model on PlantVillage dataset (D1), performance trends were observed from various parameters such as accuracy-loss curve, confusion matrix and ROC curve. Figure 4 shows the accuracy and loss through 25 epochs. The model demonstrates a steep rise in training and validation accuracy, which becomes more than 95% during the initial 10 epochs. A high training accuracy that reached approximately 99.6% and a validation accuracy of ~95-96% has been obtained, which demonstrates good learning and no signs of overfitting.

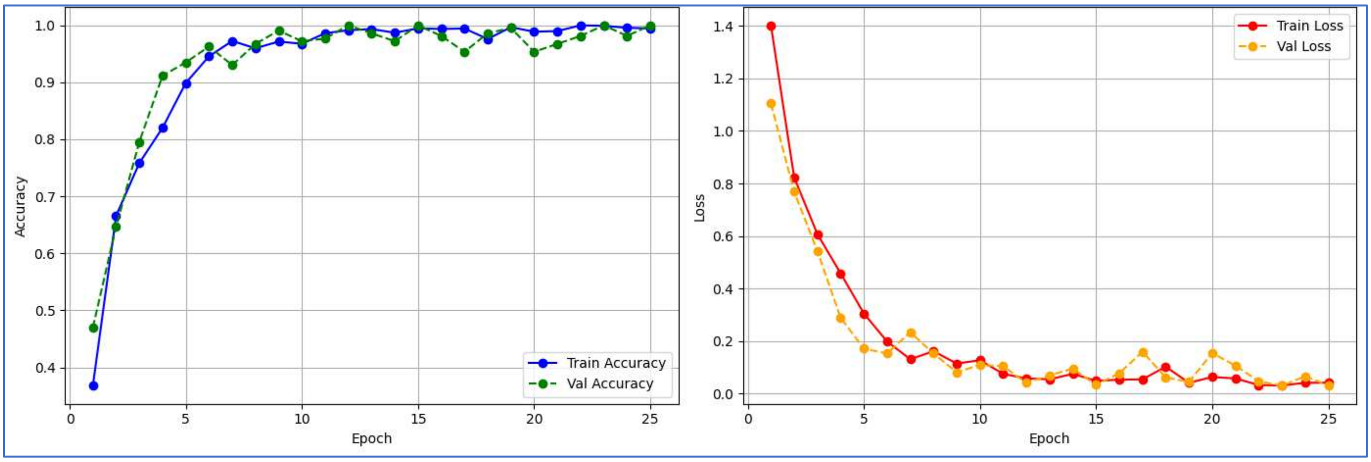


Figure 4: Accuracy vs Epochs and Loss vs Epochs plots of SPUDNET5-R3 (proposed model) over D1.

Corresponding loss curves (right panel of Figure 4) show consistent convergence for both training and validation loss, further confirming the model's stability and generalization capacity. Figure 5 shows the confusion matrix on the D1 test set, comprising three classes: *Potato__Early_blight*, *Potato__Late_blight*, and *Potato__healthy*. The proposed model achieved near-perfect classification, with only **2 misclassifications** out of **300 total samples**, demonstrating the model's precision and recall across all classes. For example, the model classified 99 out of 100 samples correctly for both *Early_blight* and *Late_blight*, and all 16 *Healthy* samples were predicted accurately.

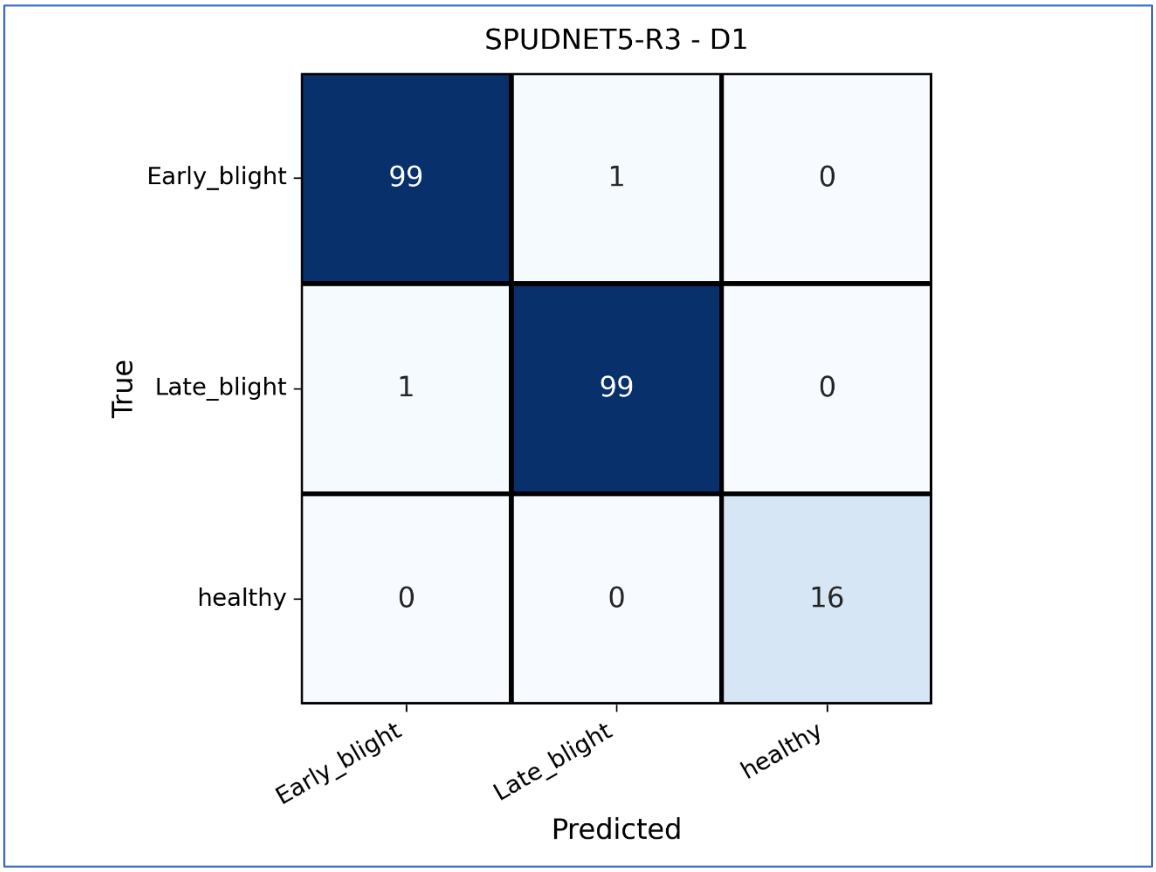


Figure 5: Confusion matrix of the SPUDNET5-R3 (proposed model) on the D1 test set.

Figure 6 illustrates the ROC curves for each class. The model achieved an **Area Under the Curve (AUC)** of **1.00** for all classes, confirming an excellent balance between sensitivity and specificity. This suggests the classifier makes highly confident predictions across the entire dataset. These results affirm the effectiveness of the proposed hybrid CNN in learning discriminative features from the well-curated and clean PlantVillage dataset. The consistent convergence, strong class separability, and perfect ROC performance underscore the model's suitability for scenarios involving well-annotated and homogeneous leaf image data.

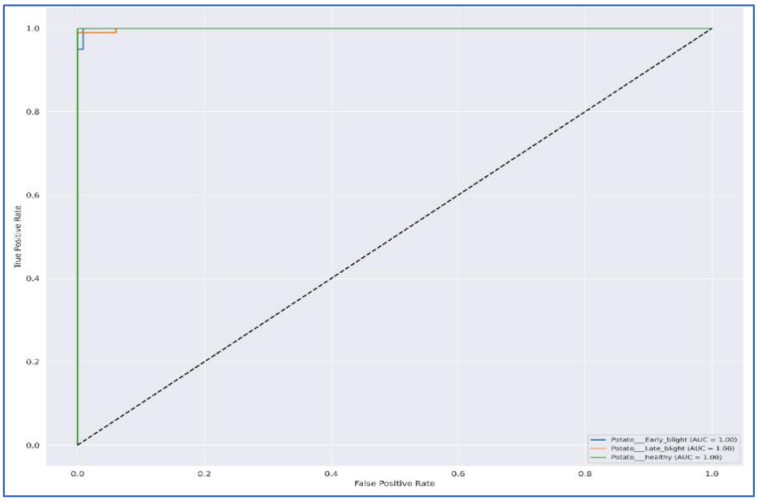


Figure 6. ROC curves for each class using the SPUDNET5-R3 (proposed model) on D1.

4.2 Results on PLD Dataset (D2)

To evaluate performance on more diverse and challenging real-world data, the proposed Hybrid CNN-5(R3) was tested on the PLD dataset (D2). This dataset introduces more complexity in terms of lighting, backgrounds, and variability in leaf appearances. As shown in Figure 7, both training and validation accuracies steadily improved, with training accuracy peaking near 99% and validation accuracy stabilizing between 94–96%.

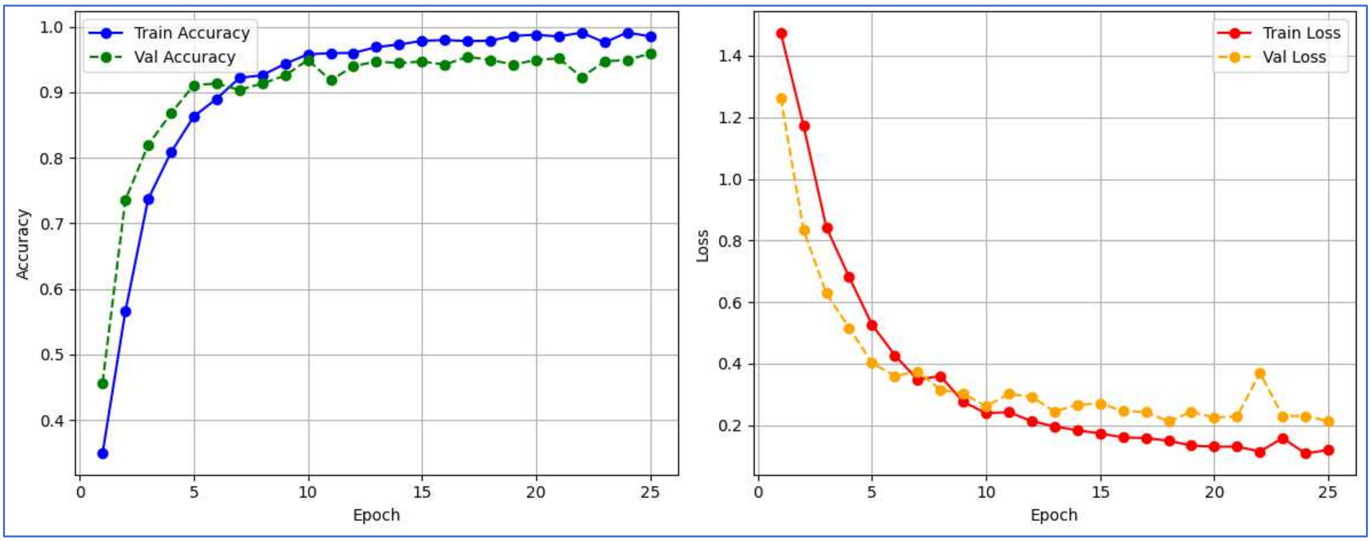


Figure 7: Accuracy vs Epochs and Loss vs Epochs plots of SPUDNET5-R3 (proposed model) over D2.

The validation loss curve reveals minor fluctuations toward the later epochs, hinting at mild generalization challenges possibly due to dataset complexity. However, the gap between training and validation curves remained relatively narrow, indicating controlled overfitting.The confusion matrix (Figure 8) reveals high classification accuracy for all three classes. Out of 404 test samples, only **18 samples** were misclassified. Specifically, *Early_blight* showed 148 correct predictions out of 162; *Late_blight* had 138 correct out of 141; and *Healthy* class was classified with **99% accuracy**, with only 1 misclassification. This performance confirms the model's robustness in distinguishing subtle inter-class differences, even under real-world imaging conditions.

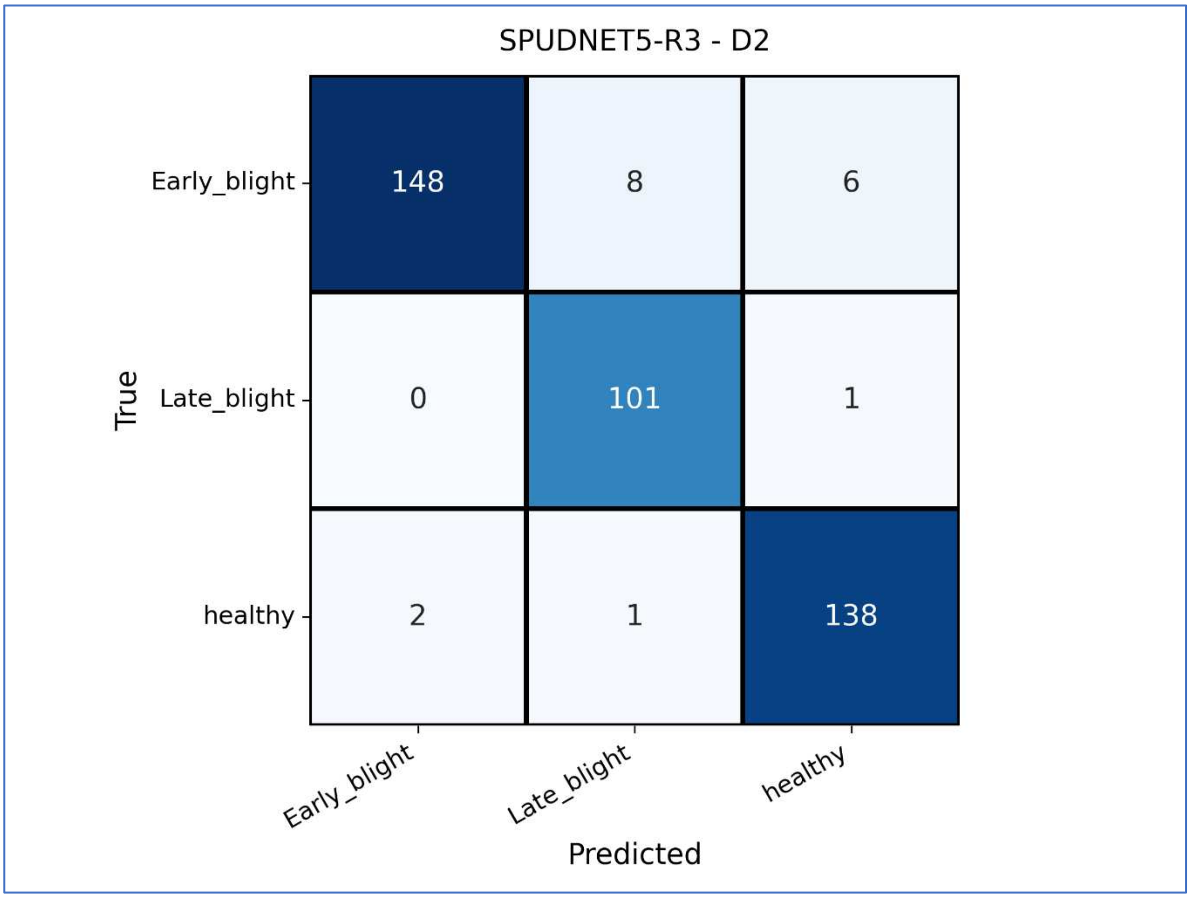


Figure 8: Confusion matrix of the SPUDNET5-R3 (proposed model) on the D2 test set.

The ROC curve (Figure 9) shows high AUC values for all classes: **1.00** for *Healthy* and *Late_blight*, and **0.99** for *Early_blight*, indicating strong discrimination. These results verify that the model retains high confidence in predictions even under distributional shifts. Despite the higher variability in image conditions, the proposed hybrid model delivered near state-of-the-art results. Minor misclassifications reflect the dataset's realistic challenges but do not significantly impact the overall performance. The near-perfect ROC scores reinforce the model's reliability across practical settings.

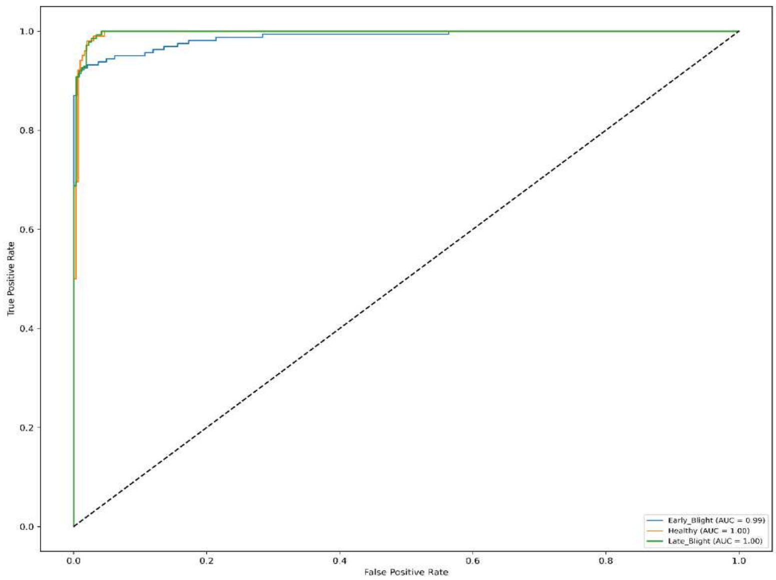


Figure 9: ROC curves for each class using the SPUDNET5-R3 (proposed model) on D2.

4.3 Overall Performance Comparison

To analyse the learning curves and the capability of generalization of each model, we studied the Accuracy vs Epochs and Loss vs Epochs graphics for XceptionNet, DenseNet121, *SPUDNET5-R3* (proposed) and Hybrid_cnn_5_swish. These results are clear evidence of the differences in training stability and convergence capabilities between the model. XceptionNet continued to improve the accuracy in a slowly but the accuracy curve and loss curve were both fluctuated, indicating the slow convergence, instability, and overfitting as well. For DenseNet121, convergence is slightly faster and more smooth compared to XceptionNet, with loss drops drastically at the beginning, and training/validation accuracy also become better clustering. Nevertheless, small instability during the beginning of training suggests the proposed objective might have an initialization or learning rates sensitive. On the other hand, the training pattern of our proposed SPUDNET5-R3 model was more appealing because of its fast convergence, less deviation between training and validation accuracy, and consistent decrease in the loss. These trends suggest that there is successful learning and strong generalization. Similarly, Hybrid_cnn_5_swish also achieved early convergence and low loss, although its validation accuracy showed slight mid-epoch inconsistencies, implying comparatively less stability than the proposed variant. In general, other models were not as efficient and stable as the proposed model in terms of training, with reliable convergence and overfitting avoidance, which demonstrated the effectiveness of the proposed model for the plant disease classification in the PLD like complex dataset. The average values of accuracy, precision, recall, and F1-score across three target classes (Early Blight, Late Blight, and Healthy) are shown in Table 3. Between the models tested, the Hybrid CNN 5 - r3 had the best result consistently for both datasets (accuracy: D1: 99.56% and D2: 96.45%), as well as precision and F1-score. Densenet121 and 5-layer CNN models, facilitated competitive score as well, particularly for Dataset 1.

Table 3: Overall Performance Comparison of Deep Learning Models Across D1 (PlantVillage) and D2 (PLD)

Model	*Data-set*	*Testing Accuracy*	*Macro Precision*	*Macro Recall*	*Macro F1-Score*	*Weighted Recall*	*Weighted F1-Score*	*Inference Time (sec/image)*
XceptionNet	D1	0.963	0.96	0.96	0.96	0.96	0.96	0.3471
	D2	0.950617	0.95	0.96	0.95	0.95	0.95	0.581673
Densenet121	D1	0.9861	0.99	0.97	0.98	0.99	0.99	0.586554
	D2	0.97037	0.97	0.97	0.97	0.97	0.97	0.767655
5 Layer CNN	D1	0.9907	0.99	0.99	0.99	0.99	0.99	0.180737
	D2	0.945679	0.95	0.95	0.95	0.95	0.95	0.210494
Hybrid_CNN_6	D1	0.9491	0.95	0.96	0.95	0.95	0.95	0.2489

	D2	0.908642	0.91	0.92	0.91	0.91	0.91	0.132608
Hybrid_CNN_5_r4	D1	0.9583	0.92	0.97	0.94	0.96	0.96	0.153387
	D2	0.965432	0.96	0.97	0.97	0.97	0.97	0.09088
SPUDNET5-R3	D1	0.9907	0.99	0.99	0.99	0.99	0.99	0.186444
	D2	0.955556	0.95	0.96	0.96	0.96	0.96	0.098611
Hybrid_CNN_5_r2	D1	0.953704	0.91	0.97	0.94	0.95	0.95	0.46508
	D2	0.955556	0.95	0.96	0.96	0.96	0.96	0.092417
Hybrid_CNN_5_Swish	D1	0.643519	0.85	0.53	0.55	0.64	0.60	0.632609
	D2	0.9333	0.94	0.94	0.94	0.93	0.93	0.2

Interestingly, while XceptionNet exhibited relatively high accuracy on D1 (95.51%), its performance slightly dipped on D2 (94.28%), likely due to the increased complexity and variability in real-world images. On the other hand, Hybrid CNN 5 - Swish recorded the lowest accuracy on D1 (63.33%) despite a significant recovery on D2 (94.04%), suggesting instability in generalization when swish activation was used in certain configurations.

4.4 Class-wise Performance Analysis

Detailed class-wise metrics in Table 4 further reveal the robustness and limitations of each model across individual disease categories. Most models, including the proposed hybrid CNNs, maintained high F1-scores (≥0.94) for Late Blight, which appears to be the most consistently detected class across datasets. However, detecting Healthy leaves proved more challenging for several models. For example, Hybrid CNN 5 - Swish and Hybrid CNN 6 achieved only 0.40 and 0.88 F1-scores respectively for the Healthy class on D1, indicating difficulties in distinguishing disease-free leaves in the presence of heavy background noise or subtle features. In contrast, Hybrid CNN 5 - r3 and 5-layer CNN attained perfect scores (1.00) for the Healthy class on D1 and performed nearly as well on D2.

Table 4: Class-wise Performance Metrics (F1-Scores) of All Models o both the Datasets

Model	*Class*	*Precision (D1)*	*Recall (D1)*	*F1-Score (D1)*	*Support (D1)*	*Precision (D2)*	*Recall (D2)*	*F1-Score (D2)*	*Support (D2)*
XceptionNet	Early_Blight	0.98	0.96	0.97	100	0.99	0.92	0.96	162
	Late_Blight	0.95	0.97	0.96	100	0.93	0.96	0.94	141
	Healthy	0.94	0.94	0.94	16	0.92	0.99	0.95	102
Densenet121	Early_Blight	1.00	0.98	0.99	100	1.00	0.98	0.99	162
	Late_Blight	0.97	1.00	0.99	100	0.93	0.99	0.96	141
	Healthy	1.00	0.94	0.97	16	0.98	0.93	0.95	102
5-layer CNN	Early_Blight	0.99	0.99	0.99	100	0.97	0.91	0.94	162
	Late_Blight	0.99	0.99	0.99	100	0.92	0.99	0.96	141
	Healthy	1.00	1.00	1.00	16	0.94	0.94	0.94	102
Hybrid CNN 6	Early_Blight	0.94	0.96	0.95	100	0.98	0.81	0.89	162
	Late_Blight	0.96	0.93	0.94	100	0.94	0.96	0.95	141
	Healthy	0.94	1.00	0.97	16	0.79	1.00	0.88	102
Hybrid CNN 5 - r4	Early_Blight	0.96	0.99	0.98	100	0.98	0.94	0.96	162

	Late_Blight	0.99	0.92	0.95	100	0.97	0.97	0.97	141
	Healthy	0.80	1.00	0.89	16	0.94	1.00	0.97	102
SPUDNET5-R3	Early_Blight	0.99	0.99	0.99	100	0.99	0.91	0.95	162
(Proposed)	Late_Blight	0.99	0.99	0.99	100	0.95	0.98	0.97	141
	Healthy	1.00	1.00	1.00	16	0.92	0.99	0.95	102
Hybrid CNN 5 - r2	Early_Blight	0.96	0.98	0.97	100	0.97	0.93	0.95	162
	Late_Blight	0.98	0.92	0.95	100	0.96	0.97	0.97	141
	Healthy	0.80	1.00	0.89	16	0.93	0.98	0.95	102
Hybrid CNN 5 Swish	Early_Blight	0.56	1.00	0.72	100	1.00	0.84	0.91	162
	Late_Blight	1.00	0.35	0.52	100	0.85	1.00	0.92	141
	Healthy	1.00	0.25	0.40	16	0.97	0.99	0.98	102

It is also evident that the **proposed hybrid models** consistently outperform the baseline CNN architectures and pretrained models like XceptionNet in terms of both macro-averaged and class-specific metrics. The inclusion of optimized convolutional depth, hybrid feature blocks, and fine-tuned learning parameters contributed to improved generalization and recall, especially on the more challenging real-world dataset (D2). To holistically evaluate the performance of each deep learning architecture, Table 5 presents a comprehensive comparative analysis across multiple dimensions. This includes an overview of each model's architecture, class-wise performance on both datasets, computational efficiency during training, and their key strengths and limitations.

Table 5: Comparative Analysis of CNN Architectures on Tomato Leaf Disease Classification

Model	***Model Overview***	***Class-wise Performance***	***Computational Efficiency & Training Behaviour***	***Strengths & Weaknesses***
XceptionNet	Pretrained architecture using depthwise separable convolutions	High F1-scores on most classes; slight drop in D2 recall for *Early Blight*	Moderate training time; good convergence; minimal overfitting	(+) Strong pretrained baseline. (-) Sensitive to real-world noise, esp. in *Early Blight* class
DenseNet121	Pretrained model with dense connections across layers	High, consistent F1 across all classes on both datasets	Efficient training; fast convergence due to pretrained features	(+) Excellent generalization, Strong on *Late Blight* *(-)* Slight dip in *Healthy* recall on D2
5-layer CNN	Lightweight custom architecture with ~5 conv layers	Excellent on D1; minor recall drop in *Early Blight* on D2	Fast training, low complexity, suitable for edge deployment	(+) Great for clean datasets. (-) Slightly overfits on D2; lacks deeper abstraction
Hybrid CNN 6	Hybrid model with residual block in layer 4	Strong on D1; F1 dips on D2, especially in *Early Blight*	Moderate training time; more complex to tune	(+) Diverse feature representation. (-) Overfitting risk and domain sensitivity
SPUDNET5-R3	Optimized 5-layer hybrid model	Outstanding across all classes on both D1 and D2	Fast convergence, robust to overfitting; optimal training time	(+) Best performer overall Consistent

	(residual links, tuned depth)			across datasets and classes
Hybrid CNN 5 - r4	Slightly modified with residual link at layer 4	Great across both datasets, especially *Healthy* class on D2	Similar to r3 in training behavior	(+) High *Healthy* recall. (-) Slightly behind r3 in overall F1
Hybrid CNN 5 - r2	5 layer CNN with residual link at layer 4	Balanced, slightly weaker than r3 and r4	Efficient and stable	(+) Reliable choice. (-) Doesn't outperform other hybrids in any one metric
Hybrid CNN 5 (Swish)	Variant using **Swish** activation instead of ReLU	Very poor performance on D1 (low F1 in *Late Blight*); surprisingly better on D2	Unstable training on D1; erratic loss curve; better convergence on D2	(+) Promising on noisy D2. (-)Highly unstable on D1, Inconsistent results require further tuning

The result analysis highlights that the ***SPUDNET5-R3*** architecture, with a balanced structure and training configuration, delivers the most consistent and high-performing results across both datasets. The model demonstrates excellent recall and precision, particularly for the Early Blight and Healthy classes, which are typically more error-prone in imbalanced or noisy datasets. This is developing also supported by the ROC curves. The ROC curve analysis is used to give an overall quantification of the class-wise discriminative performance of each model on both datasets. The SPUDNET5-R3 model outperformed all the other models in all classes on both the D1 and the D2 datasets, with almost perfect values of AUC (Area Under the Curve). On D1, the ROC curves are all clustered near the top-left corner, which shows high sensitivity and specificity for each class. Even on the challenging D2 dataset, the model achieved consistently high AUCs over 0.97, indicating its strong generalization and robustness against data complexity and quality. In comparison, XceptionNet and DenseNet121 achieve promising results on D1, where AUCs are around 0.98-1.0, but present some performance deterioration on D2. XceptionNet curves were more broadly distributed per class on D2, disproportionately affecting the minority classes, and DenseNet121, after a promising performance at lower resolutions, showing signs of class instability when evaluated across datasets. The 5-layer_CNN_swish reached almost perfect curves for D2, but failed to retain similar performance for D1, indicating that the model with fixed filters might bear limited generalization. Such results corroborate the better class-wise discrimination, stable generalization to different datasets, and reliable intra-class variations handling of the proposed model. As for the visual evidence, the roc curves of the SPUDNET5-R3 on both D1 and D2 are most representative and should be part of the paper to confirm it's stability and balanced prediction power.

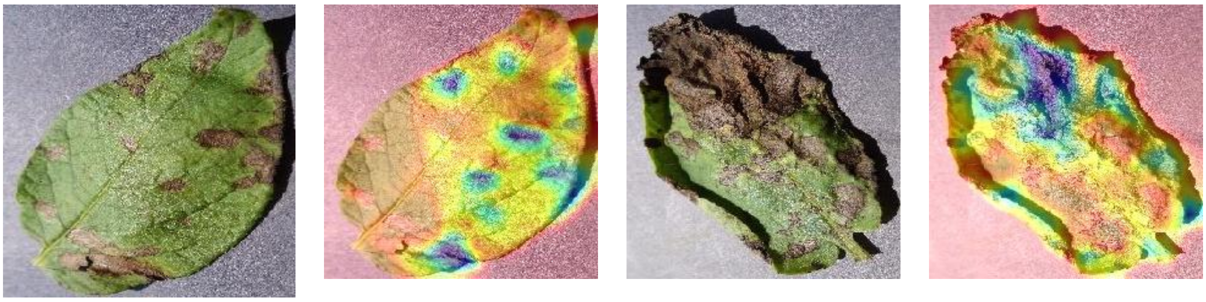
5. Explainable AI (XAI)

To enhance the interpretability of the deep learning model and ensure transparency in the decision-making process, we employed Gradient-weighted Class Activation Mapping (Grad-CAM) as an explainable AI (XAI) technique. Grad-CAM generates heatmaps that highlight the discriminative regions in an image that influence the model’s prediction, thus offering insights into what the model has learned. We applied Grad-CAM to visualize the class-specific activation maps over the original test images of the potato leaf dataset. This approach allows us to evaluate whether the model’s attention aligns with the visible disease symptoms such as lesion patterns, discolorations, or blight-affected areas. Figures 10 to Figure 15 illustrate Grad-CAM visualizations for three representative classes—Early Blight, Late Blight, and Healthy. Each visualization set contains the original image and its corresponding heatmap. The following observations can be made:

- **Early Blight**: As shown in Figure 12 and 15, the Grad-CAM heatmaps effectively localize dark, concentric lesion spots and surrounding yellow halos, indicating that the model focuses on biologically relevant regions for classification.
- **Late Blight**: In Figure 11 and 14, the visualizations highlight the irregular, dark patches typically associated with the disease. The attention regions are tightly clustered around the necrotic lesions, suggesting the model accurately distinguishes Late Blight characteristics.
- **Healthy**: As shown in Figure 10 and 13, the attention maps are more diffused and lack high-activation zones, which is consistent with the absence of disease symptoms.

These visual explanations confirm that the model bases its decisions on meaningful visual cues rather than background artifacts or noise. By using Grad-CAM, we demonstrate not only the high accuracy of the model but also its reliability and trustworthiness in real-world agricultural scenarios.

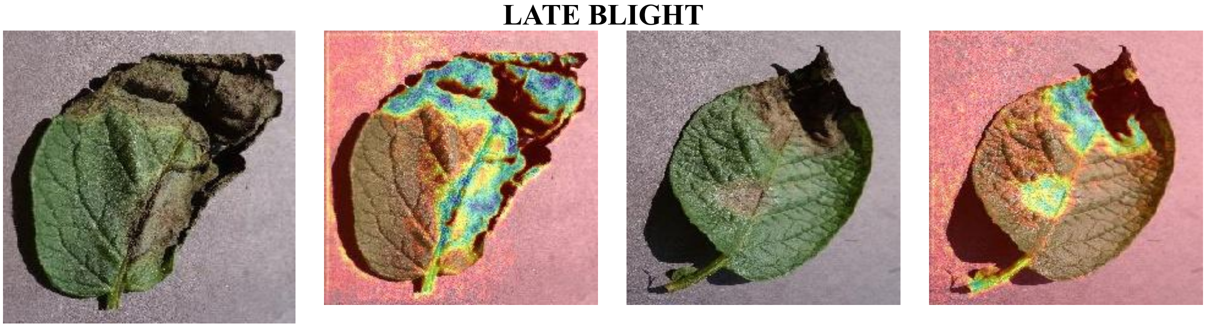
EARLY BLIGHT



(a) Original image (b) XAI-based heatmap (a) Original image (b) XAI-based heatmap

Figure 10: GRAD-CAM visualization of two samples from Early Blight class (Dataset D1).

LATE BLIGHT



(a) Original image (b) XAI-based heatmap (a) Original image (b) XAI-based heatmap

Figure 11: GRAD-CAM visualization of two samples from Late Blight class (Dataset D1).

HEALTHY

(a) Original image (b) XAI-based heatmap (a) Original image (b) XAI-based heatmap

Figure 12: GRAD-CAM visualization of two samples from healthy class (Dataset D1).

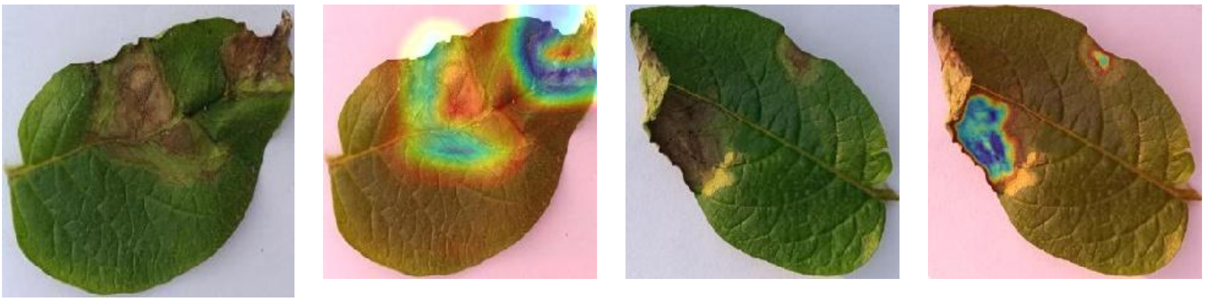
GRAD-CAM images over PLD dataset (D2)

EARLY BLIGHT

(a) Original image (b) XAI-based heatmap (a) Original image (b) XAI-based heatmap

Figure 13. GRAD-CAM visualization of two samples from Early Blight class (Dataset D2).

LATE BLIGHT



(a) Original image (b) XAI-based heatmap (a) Original image (b) XAI-based heatmap

Figure 14. GRAD-CAM visualization of two samples from Late Blight class (Dataset D2).

HEALTHY

(a) Original image (b) XAI-based heatmap (a) Original image (b) XAI-based heatmap

Figure 15: GRAD-CAM visualization of two samples from healthy class (Dataset D2).

6. Benchmarking

To evaluate the effectiveness of the proposed model, we conducted a comprehensive benchmarking analysis against several state-of-the-art models applied to potato leaf disease classification. As shown in Table 6, the proposed SPUDNET5-R3 model achieved superior performance across both datasets. On the PlantVillage dataset (2152 images), it attained a macro accuracy of 99.07%, with precision, recall, and F1-score all reaching 99%, outperforming previous methods such as Att-MobileNetV2 [14] and YOLOv8n [16]. On the more challenging PLD dataset (4072 images), it maintained strong performance with a 95.56% accuracy and an F1-score of 96%, despite increased data complexity. In contrast, existing models either reported high accuracy with limited class-wise recall [6] or lacked full metric disclosure [8,15]. These results affirm the robustness and generalizability of our approach across different datasets and conditions.

Table 6: Benchmarking Comparison with Existing Models on the Potato leaf disease detection

Model Name or Paper	***Model***	***Dataset***	***Accuracy (Macro) (%)***	***Precision (Macro) (%)***	***Recall (Macro) (%)***	***F1-Score (Macro) (%)***	***Training Epochs***
Pasalkar et al. [6]	CNN	Potato leaf disease (600 images)	97.4	100%	44%	61%	37
Rashid et al. [7]	PDDCNN	PlantVillage (Potato, 2152 images)	96.75	97.6	95.33	96.33	100
Kothari et al. [8]	CNN	PlantVillage (Potato, 2152 images)	97	-	-	-	40
Sofuoglu et al. [10]	Modified CNN	PlantVillage (Potato, 2152 images)	-	97.94	97.84	97.82	15
Grati et al. [14]	Att-MobileNetV2	PlantVillage (Potato, 2152 images)	99	-	-	98	-
Iftikhar et al. [15]	Modified CNN	PlantVillage (Potato, 2152 images)	98.44	-	-	-	50
Hazra S. et al. [16]	YOLOv8n	PlantVillage (Potato, 2152 images)	97.02	94.57	94.164	94.36	5
Khalifa et al. [18]	Modified CNN	Potato leaf blight (1722 images)	98	94.75	93.22	93.98	-

Sanjeev et al. [19]	FFNN	PlantVillage (Potato, 2152 images)	96.5	96.47	96.47	96.47	-
SPUDNET5-R3 (proposed)		PlantVillage (Potato, 2152 images)	99.07	99	99	99	25
SPUDNET5-R3 (proposed)		PLD (4072 images)	95.56	95	96	96	25

7. Discussion

The results obtained from the proposed SpudNet5-R3 model demonstrate a robust capability in classifying potato leaf diseases across diverse datasets and disease categories. When tested on the D1 (PlantVillage) dataset, the model achieved an outstanding macro average accuracy and F1-score of 99.07%, outperforming several state-of-the-art models, including those by Rashid et al. [7], Grati et al. [14], and Hazra et al. [16]. Similarly, when evaluated on the more complex and diverse D2 (PLD) dataset, SpudNet5-R3 maintained high generalization performance, achieving 95.56% accuracy and a macro F1-score of 96%. These results suggest that the model is highly adaptable to varying image acquisition conditions and dataset characteristics. In comparison with the benchmark models implemented in this study, SpudNet5-R3 significantly outperformed both DenseNet121 and XceptionNet on D1. While DenseNet121 showed relatively better performance on D2 in terms of accuracy, SpudNet5-R3 demonstrated more stable training behavior with smoother convergence in training accuracy and loss. Furthermore, SpudNet5-R3 achieved the lowest inference time of only 0.1864 sec/image on D1 and 0.098 sec/image on D2, whereas DenseNet121 required 0.5865 sec/image and 0.7676 sec/image, respectively. This highlights SpudNet5-R3's superiority not only in predictive accuracy but also in computational efficiency, making it well-suited for real-time agricultural applications. A notable strength of SpudNet5-R3 lies in its balanced precision and recall, particularly for the D2 dataset, where class imbalance has historically posed challenges. The model achieved nearly equal precision and recall scores, effectively addressing overfitting and underfitting concerns that were prevalent in previous studies. In addition, the model converged within just 25 training epochs, further underscoring its computational efficiency compared to deeper, more complex models that typically require longer training cycles. The incorporation of Explainable AI (XAI) through Grad-CAM visualizations validated that SpudNet5-R3 consistently focuses on meaningful lesion areas rather than irrelevant background noise. This interpretability is critical for real-world deployment, as it fosters trust and transparency in automated diagnostic systems. Overall, SpudNet5-R3 not only excels in performance but also proves to be a practical, reliable, and interpretable solution for automated disease detection in real-world farming environments.

8. Conclusion

This study introduced SpudNet5-R3, a lightweight and efficient hybrid CNN architecture designed for accurate and real-time classification of potato leaf diseases. Through extensive experimentation on two benchmark datasets—D1 (PlantVillage) and D2 (PLD)—the proposed model demonstrated exceptional performance, achieving 99.07% accuracy on D1 and 95.56% on D2, with consistently high macro F1-scores across all classes. Compared to existing models and popular deep architectures such as DenseNet121 and XceptionNet, SpudNet5-R3 not only delivered superior accuracy but also showcased faster inference speeds and stable training behaviour. A key strength of the model lies in its generalization capability across datasets with varying image quality and acquisition conditions, along with balanced precision and recall, even in the presence of class imbalance. Moreover, the integration of Explainable AI (Grad-CAM) added interpretability to the decision-making process by confirming that the model focused on relevant lesion areas, which is crucial for trust and real-world deployment. In summary, SpudNet5-R3 proves to be an effective and reliable solution for automated potato disease diagnosis. Its high accuracy, fast inference, and explainability make it well-suited for implementation in mobile-based or edge computing applications, ultimately supporting precision agriculture and timely disease management in farming systems.

Ethical Statements

Research Involving Human and /or Animals

Not Applicable.

Consent to Participate declaration

Not Applicable.

Clinical trial number

Not Applicable.

Consent to Publish declaration

Not Applicable.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The used datasets are online available on Kaggle repository, https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset (Dataset D1) and https://www.kaggle.com/datasets/rizwan123456789/potato-disease-leaf-datasetpld (Dataset D2).

Authors' Contribution

S.R., A.J., A.K.D., A.P., V.J., S.K. worked on Conceptualization, Data curation, Investigation, Software, Validation, Writing – original draft. M.A.S., S.M. reviewed and edited the manuscript and participated in validation.

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