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Advanced Deep Learning Model for Plant Diseases Detection in Precision Agriculture

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Abstract

Plant disease detection is becoming a vital research area due to the need to achieve sustainable development goals. This study aims to introduce a new deep learning technique based on inception and a depthwise-separable convolution layer. This approach aims to reduce computational complexity, size, and parameter set without compromising performance. The proposed model was evaluated on two datasets to classify different crop diseases. The proposed model achieved the highest accuracy of 99.1 in the plant village and 98.5 in the potato dataset with the compared studies.

Keywords: Precision Agriculture; Artificial Intelligence; Deep Learning; Plant Diseases; Potato.

1 | Introduction

1.1 | Background

For global rural populations to have access to jobs and income as well as food security, agriculture is essential. However, the industry faces difficulties like rising food consumption, a lack of natural resources and arable land, climate change, and land degradation. Challenges also arise from an aging workforce and an expanding environmental imprint. This is in sync with another FAO report that predicts an increase in the world's food demand by 2050. Achieving resource efficiency and sustainability in agriculture through precision farming can guarantee food security and lessen its negative effects on the environment [1].

Artificial intelligence (AI) can optimize output yield, reduce costs, and minimize sustainability. AI enhances farming operations' profitability, social factors, and working environment. It can improve yields, quality, and crop stress management. Plant diseases can be efficiently and effectively detected by automated techniques. High computational performance has been attained while handling massive volumes of data using machine learning (ML) and deep learning (DL) algorithms. In crop disease identification applications, convolutional neural networks (CNNs) have demonstrated notable performance, obviating the necessity for complex image

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pre-processing. To show how CNN-based architectures are utilized for crop disease detection during crop growth, a review study is required [2].

Egypt stands to gain from DL publications and research in a number of ways, including increased food security, increased economic growth, environmental sustainability, and innovation. These advantages are consistent with Egypt's Vision 2030, which contributes to the country's long-term objectives by aiming to improve agriculture, lower poverty, and protect natural resources [3].

1.2 | Aims and Scope of this Work

In this study, we introduce a lightweight, inception-based model. The model was evaluated on two datasets: the PlantVillage dataset [4], and Potato dataset [5]. PlantVillage contains more than fifty thousand images from 38 categories. The 38 are divided into 14 categories of healthy people, and the rest are diseases. Potato dataset consists of around 4000 images divided into three classes.

Main contributions:

- A depth-wise separable convolution is used to reduce computational complexity, size, and parameter set without compromising the performance.
- The proposed model compared with novel studies such as [6-9].
- The proposed model achieved the highest accuracy of 99.1 in the plant village and 98.5 in the potato dataset.

2 | Literature Review

This section describes the methodology of the proposed model for plant disease detection.

2.1 | Preliminaries

2.1.1 | Convolutional Neural Networks (CNNs)

A fundamental component of DL models, particularly for tasks involving the interpretation of images and videos, is standard convolution. However, its real-time application may be limited by its computing demands. Eq. (1) provides the parameters and computational cost equations for standard convolution. Depthwise convolution, which independently processes input channels with different kernels and lowers parameters and computing costs, was introduced to address this problem. Depthwise separable convolutions (DWSC), which combine depthwise and pointwise (1x1) convolutions, are becoming a popular option for creating deeper neural networks with higher efficiency. Eq. (2) provides the computational cost and parameters for the DWSC.

$$\mathrm{cost\_sd} = \mathrm{K} \times \mathrm{K} \times \mathrm{C} \times \mathrm{N} \times \mathrm{H} \times \mathrm{W}$$

$$\mathrm{parm\_sd} = \mathrm{K} \times \mathrm{K} \times \mathrm{C} \times \mathrm{N} + \mathrm{N} \tag{1}$$

Where, $\mathrm{K} \times \mathrm{K}$ = Kernel size, C = Number of input channels, N = Number of output channels and $\mathrm{H} \times \mathrm{W}$ = Spatial Height and Width of input image or feature map (For simplicity we consider padding = same, and stride = 0 and $\mathrm{H} = \mathrm{W}$).

$$\mathrm{cost\_DWsConv} = \mathrm{Cost\_DW} + \mathrm{Cost\_PW}$$

$$\mathrm{cost\_DWsConv} = (\mathrm{K} \times \mathrm{K} \times \mathrm{C_{in}} \times \mathrm{H} \times \mathrm{W}) + (\mathrm{C_{in}} \times \mathrm{C_{out}} \times \mathrm{H} \times \mathrm{W}) \tag{2}$$

$$\mathrm{parm\_DWsConv} = (\mathrm{K} \times \mathrm{K} \times \mathrm{C_{in}} + \mathrm{C_{in}}) + (\mathrm{C_{in}} \times \mathrm{N} + \mathrm{N})$$

2.2 | Proposed Model

The proposed model utilize the inception block from the inception model [6]. Our proposed model improving some of the parameters that start, as it consisted of a convolution layer with kernel (1x1), (1x1) followed by convolution layer with kernel (3x3), (1x1) followed by convolution layer with kernel (5x5) and (1x1) followed by maxpooling layer (3x3) which are showed in Figure 1. The modified inception a DepthwiseSeparable convolution layer was applied, which consist of convolution layer with kernel (1x1), (1x1) followed by convolution layer with kernel (4x4), (1x1) followed by DepthwiseSeparable layer with kernel (4x4) and (1x1) followed by maxpooling layer (3x3). Figure 2 shows the structure of modified block. Figure 3 shows architecture for the proposed model. The model weights are updated with Adam optimizer with initial learning rate .0001 and 50 epoch.

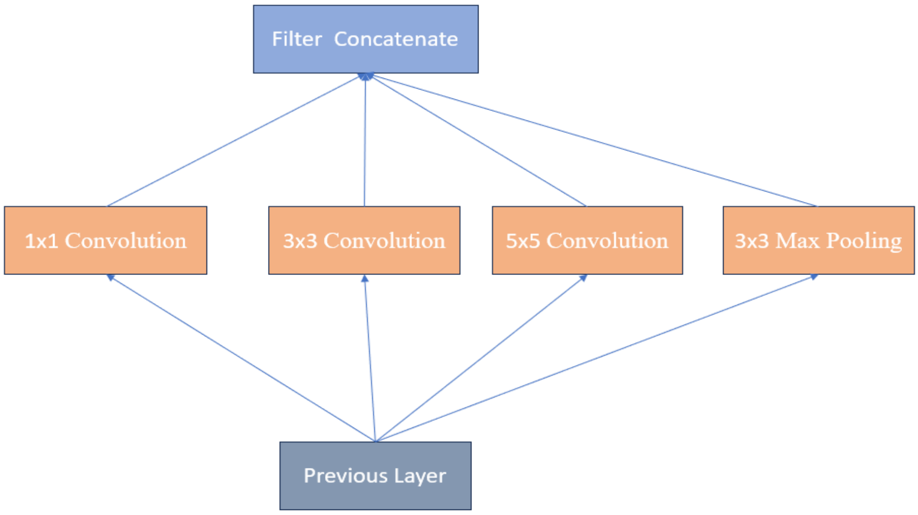

Figure 2. Structure of convolution block.

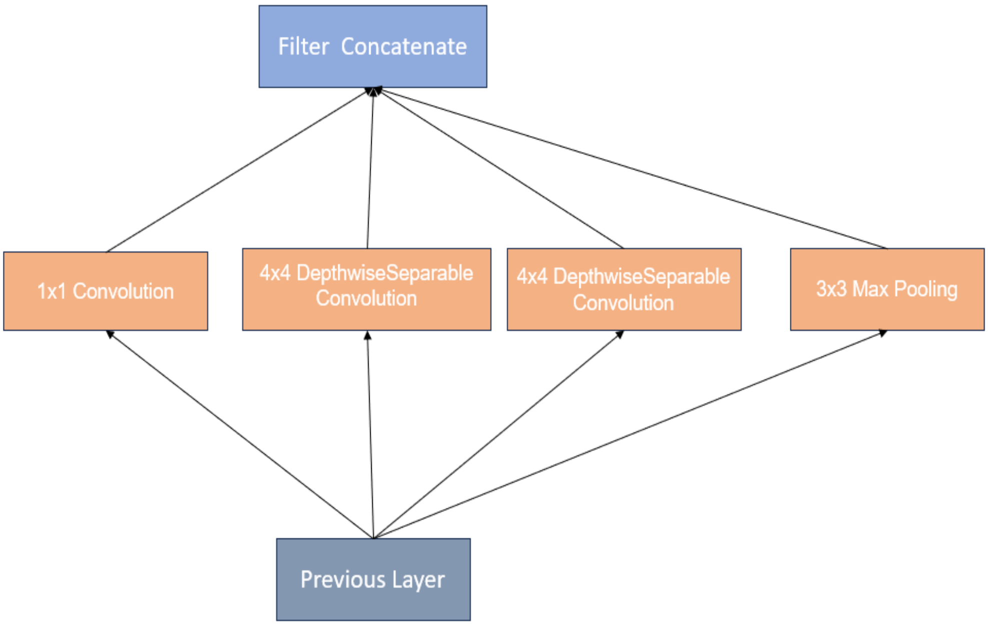

Figure 2. Structure of modified block after adding DepthwiseSeparable convolution.

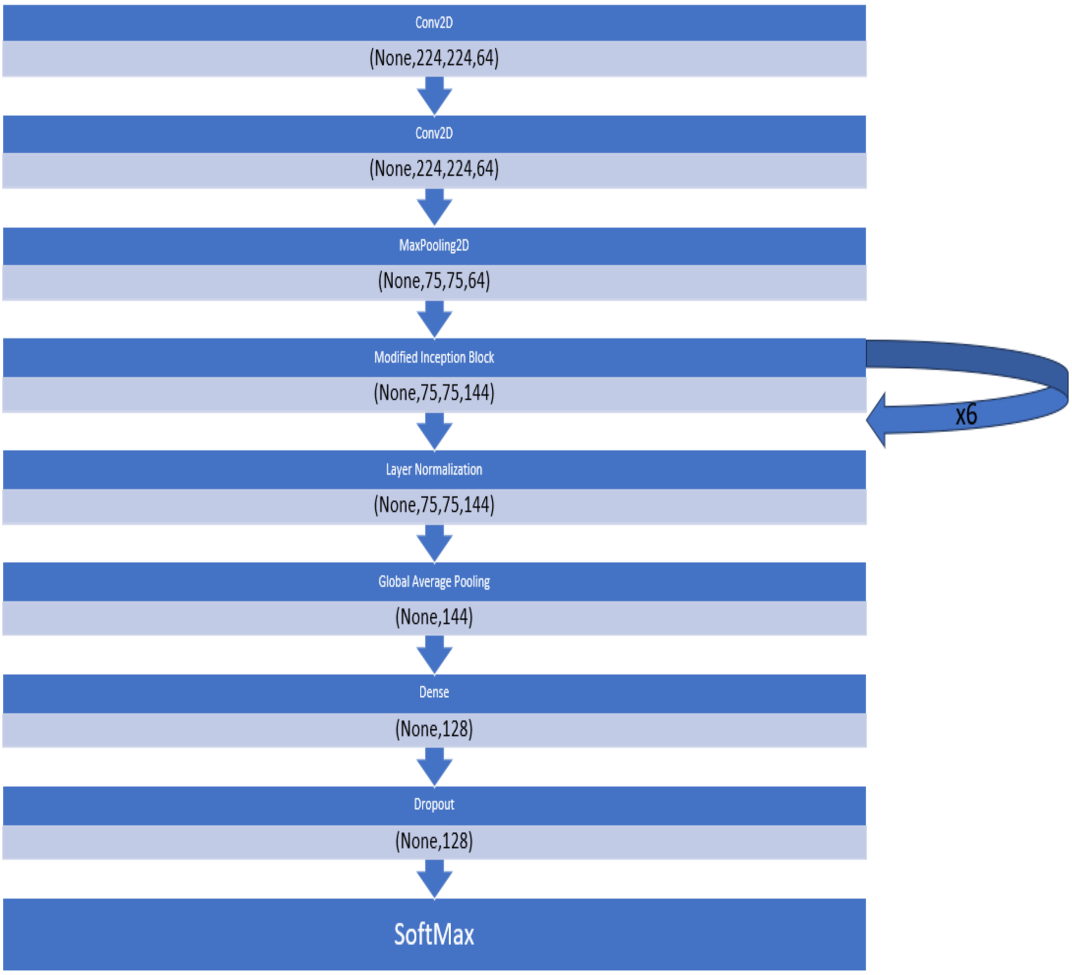

Figure 1. The proposed model.

3 | Experimental Setup

In this paper, we use two different data sets to make a comparison between the performance of a proposed model and a group of models. The first data set, PlantVillage, contains more than fifty thousand images from 38 categories. The 38 are divided into 14 categories of healthy people, and the rest are diseases. The second dataset is Potato dataset which consists of around 4000 images divided into three classes.

The training was obtained on GPU Nvidia Tesla P100 With Ram 16 GB, using Keras Version 2.3.1.

In this section, the proposed model was compared with ResNet152, EfficientNetB0, and studies from [6-9]. The proposed model performance was evaluated on two datasets, PlantVillage dataset and Pototo dataset. The comparisons are made through a set of metrics such as Accuracy, precision, recall, F1-score.

Accuracy

This metric is calculated from the number of correct predictions for all categories to the total number of predictions which represented as follows:

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})}$$

Precision

This measure is calculated from the number of correct predictions for a category to the total number of predictions in the same category which represented as follows:

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

Recall

This metric is calculated by harmonic mean which represented as follows:

$$F1 \text{ Score} = 2 \times \frac{\text{recall} \times \text{precision}}{\text{recall} + \text{precision}}$$

4 | Results and Discussion

4.1 | Results in PlantVillage Dataset

The proposed model and the mentioned models were trained on 80% of the PlantVillage data, and the remaining images were tested. The image was resized to 224,224 and normalized to a division of 255. The proposed model achieves best accuracy with 99.1. Figure 4 shows the performance of models with different metrics. Table 1 and Figure 5 show comparison of models accuracy and Top-3 accuracy. Table 2 show precision, recall and F1-score obtained by proposed model each class in the PlantVillage dataset. The training curve and model loss curve are represented in Figures 6 and 7 respectively. Figure 8 represents the confusion matrix of proposed model.

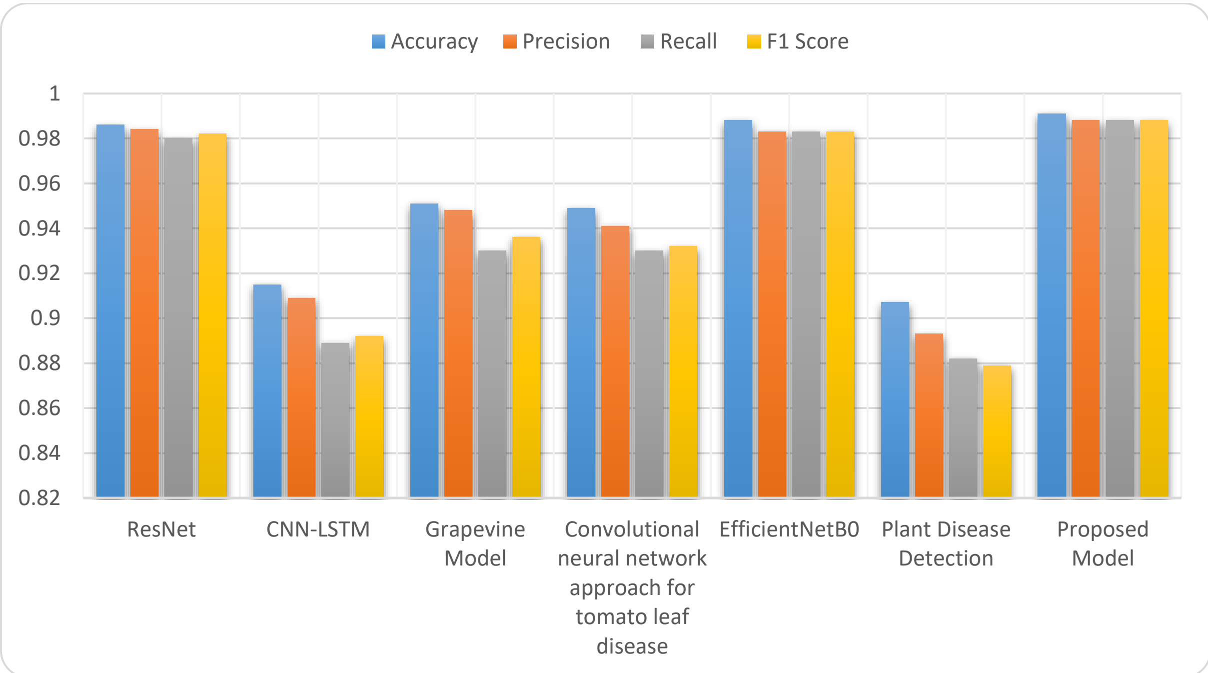

Figure 4. Performance of models with different metrics in PlantVillage dataset.

Table 1. Comparison of models accuracy and top-3 accuracy.

Model	Top 3 Accuracy	Accuracy
ResNet152	0.999	0.986
CNN-LSTM	0.985	0.915
Grapevine model [6]	0.993	0.951
Tomato disease detection model [7]	0.991	0.949
EfficientNetB0	0.999	0.988
Plant Disease Detection [8]	0.979	0.907
Proposed Model	0.999	0.991

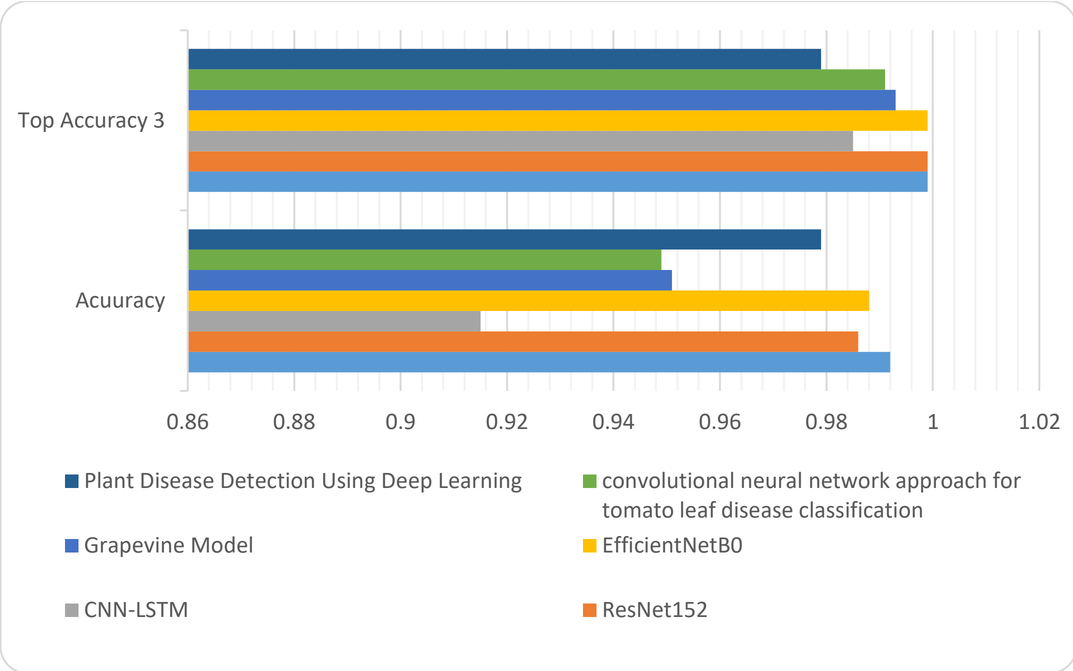

Figure 2. Comparison of models accuracy and Top-3 accuracy.

Table 2. Precision, recall and F1-Score obtained by proposed model each class in the PlantVillage dataset.

Class	Precision	Recall	F1-score	Class	Precision	Recall	F1-score	Class	Precision	Recall	F1-score
C1	1.00	1.00	1.00	C14	1.00	1.00	1.00	C27	1.00	1.00	1.00
C2	1.00	1.00	1.00	C15	1.00	1.00	1.00	C28	0.97	0.98	0.98
C3	1.00	1.00	1.00	C16	1.00	1.00	1.00	C29	0.96	0.96	0.96
C4	0.98	1.00	0.99	C17	1.00	0.99	0.99	C30	0.96	0.98	0.97
C5	1.00	1.00	1.00	C18	0.91	0.91	0.91	C31	1.00	1.00	1.00
C6	1.00	1.00	1.00	C19	1.00	1.00	1.00	C32	0.99	0.98	0.99
C7	1.00	1.00	1.00	C20	1.00	1.00	1.00	C33	.99	0.99	0.99
C8	0.94	1.00	0.97	C21	1.00	1.00	1.00	C34	0.99	0.99	0.99
C9	1.00	1.00	1.00	C22	0.97	0.93	0.95	C35	1.00	0.99	1.00
C10	1.00	0.97	0.98	C23	0.83	0.83	0.83	C36	0.97	1.00	0.99
C11	1.00	1.00	1.00	C24	1.00	1.00	1.00	C37	0.99	.99	0.99
C12	1.00	1.00	1.00	C25	1.00	1.00	1.00				
C13	1.00	1.00	1.00	C26	1.00	1.00	1.00				

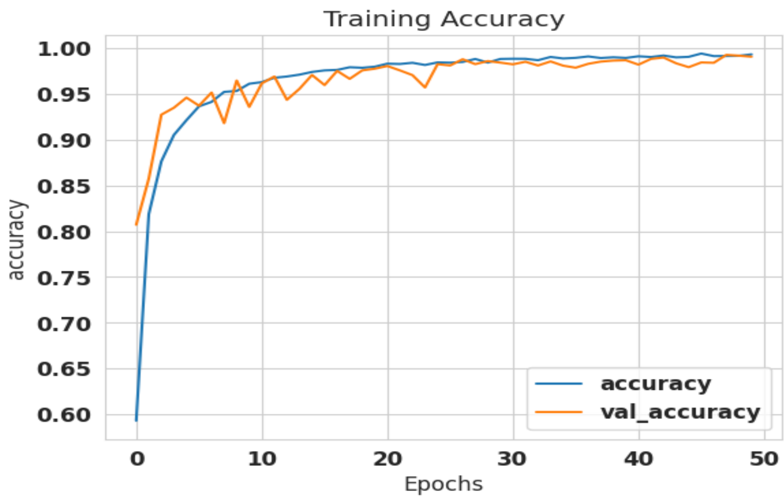

Figure 3. Proposed model training curve.

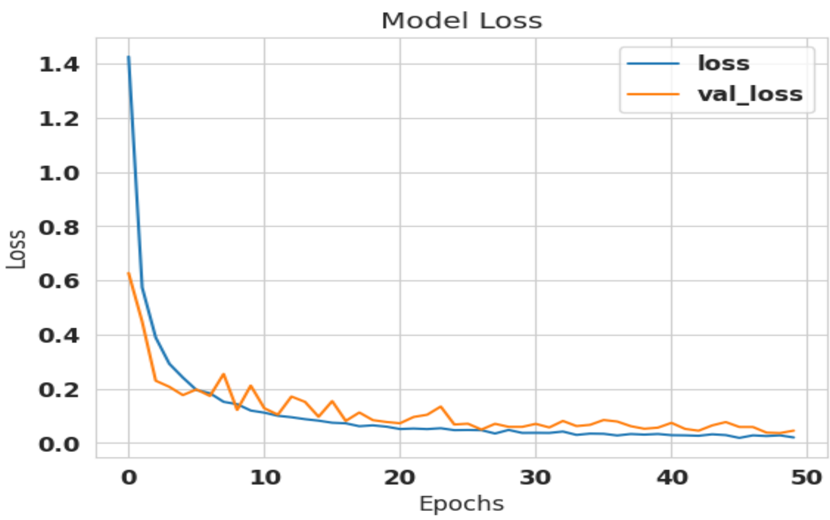

Figure 4. Proposed model loss curve.

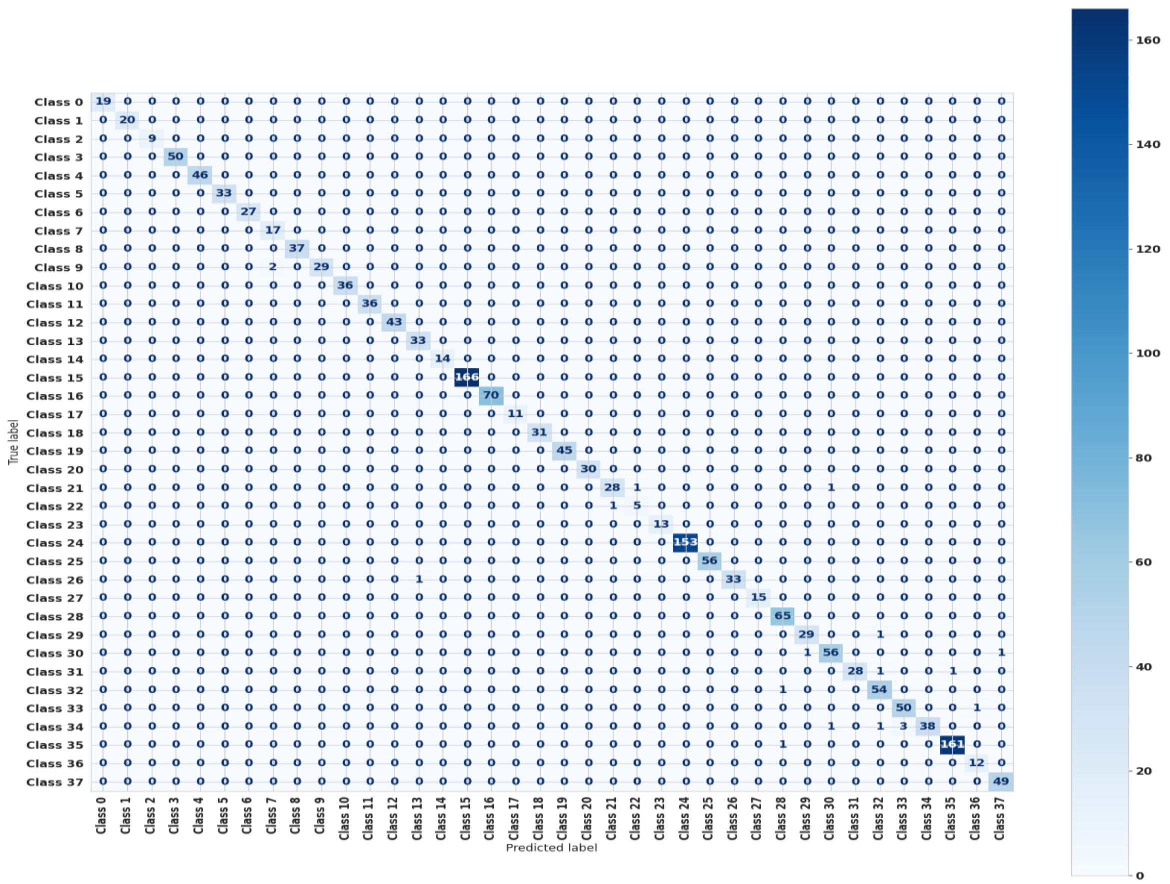

Figure 5. Proposed model confusion matrix.

4.2 | Results in Potato Dataset

The proposed model and the mentioned models were also trained on 80% of the potato dataset, and the remaining images were tested. The image was resized to 224,224 and normalized to a division of 255. The proposed model achieves best accuracy with 98.5. Table 3 show performance of models with accuracy. Figure 9 shows performance of models with different metrics. Table 4 show precision, recall and f1score obtained by proposed model each class in the Potato dataset. The training curve and model loss curve are represented in Figures 10 and 11 respectively. Figure 12 represents the confusion matrix of proposed model.

Table 3. Performance of models with accuracy in Potato dataset.

Model	Accuracy
ResNet152	0.980
CNN-LSTM	0.849
Grapevine model [6]	0.967
Tomato disease detection model[7]	0.945
EfficientNetB0	0.977
Plant Disease Detection model [8]	.679
Proposed Model	0.985

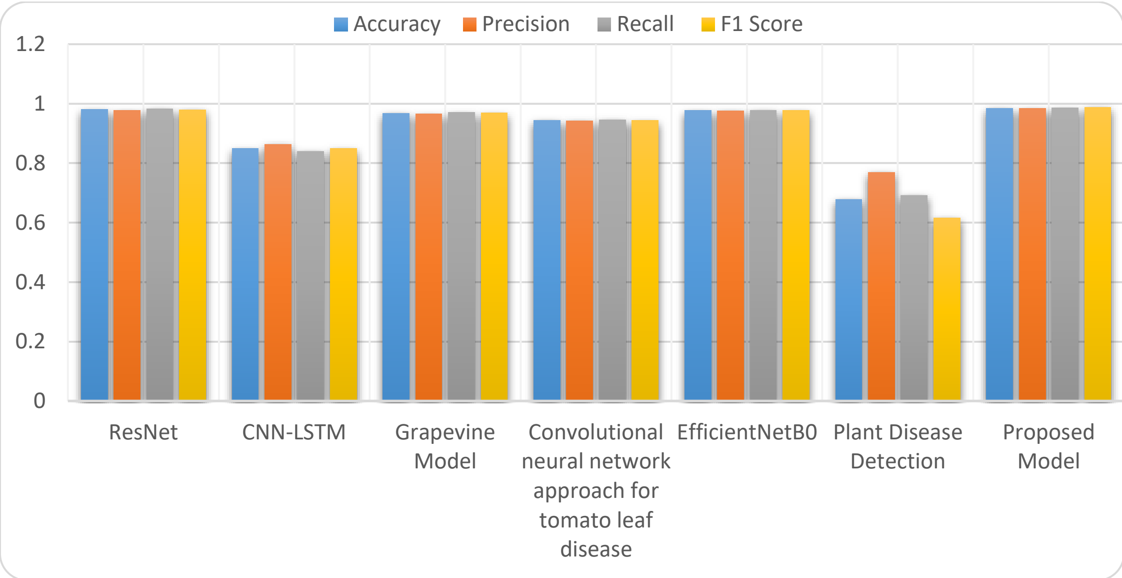

Figure 6. performance of models with different metrics in Potato dataset.

Table 4. Precision, recall, and F1-score obtained by the proposed model for each class in the Potato dataset.

Class	Precision	Recall	F1-score
Early_Blight	0.98	0.99	.98
Healthy	0.97	1.00	.99
Late Blight	1.00	.97	.99

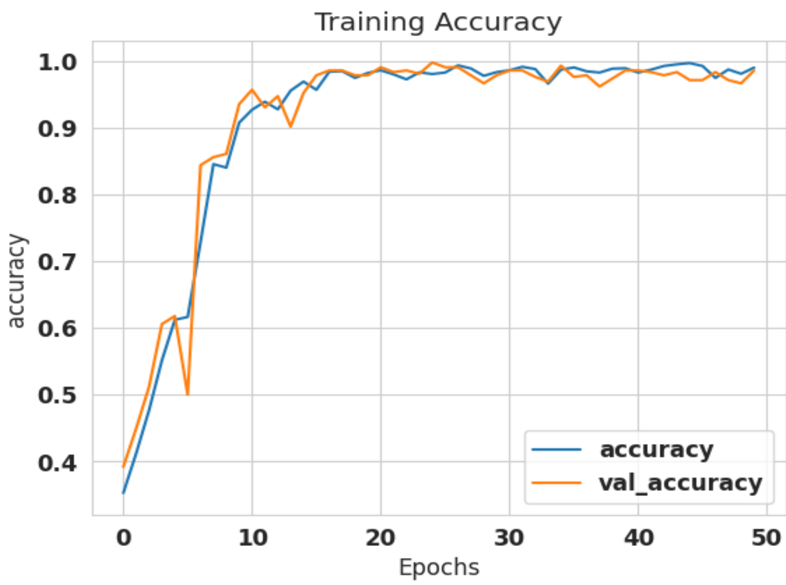

Figure 7. Proposed model training curve.

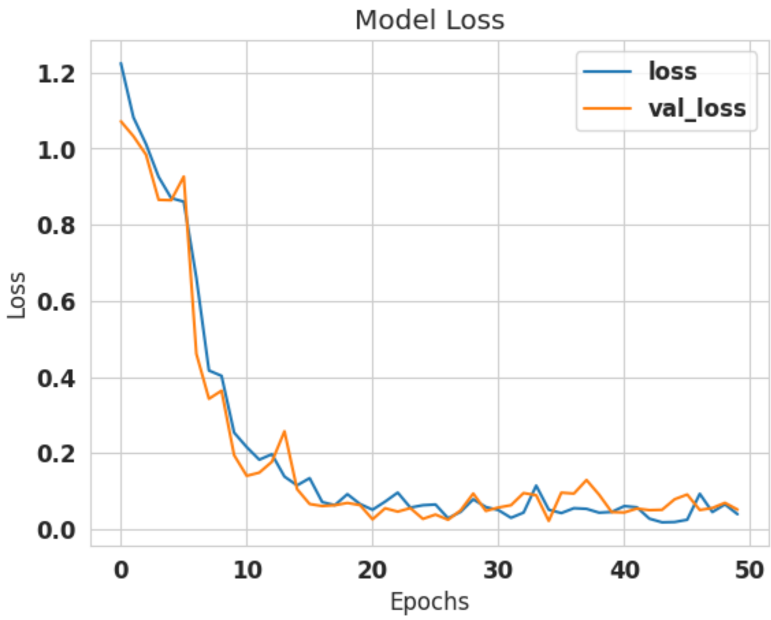

Figure 8. Proposed model loss curve.

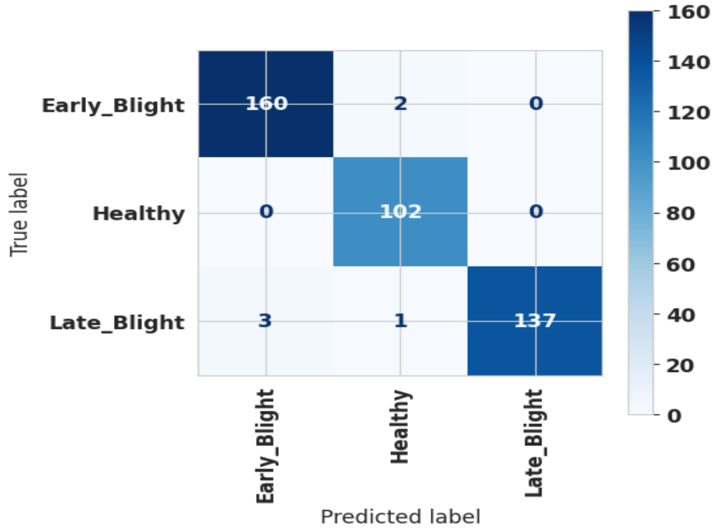

Figure 9. Proposed model confusion matrix.

5 | Conclusion and Future Work

In this study, we introduce a novel model that can classify different crop diseases. The proposed model is a lightweight model based on the Inception block. The model utilizes DepthwiseSeparable convolution layer, which can reduce computational complexity, size, and parameter set without compromising performance. The training and testing were obtained on two datasets: the PlantVillage and the Potato dataset. The model achieved the highest score of 99.1 in the plant village and 98.5 in the potato dataset. In the future, the suggested method's real-time performance can be verified on devices with limited resources, including smartphones and agricultural robots, to see how it affects the real-time detection of plant diseases.

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Author Contributaion

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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