# Jawahar Education Society’s

A. C. Patil College of Engineering

# Department of Artificial Intelligence And Data Science Engineering

Plant Disease Detector

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**Abstract**

Early detection of plant diseases is crucial to preventing harmful effects on crop yields. Convolutional neural networks (CNNs), particularly in the realm of deep learning, have become widely used for tasks like image recognition and pattern detection. Numerous researchers have developed different deep learning models aimed at identifying plant diseases. However, these models typically involve a large number of parameters, which leads to longer training times and makes them challenging to deploy on devices with limited computational power.In this paper, we present a new deep learning model that integrates inception layers and residual connections to address these challenges. To reduce the number of parameters, we utilized depthwise separable convolutions. The proposed model was trained and evaluated using three distinct plant disease datasets. It achieved an accuracy of 99.39% on the PlantVillage dataset, 99.66% on the rice disease dataset, and 76.59% on the cassava dataset. Despite using fewer parameters, our model demonstrates higher accuracy when compared to leading deep learning models.

## Introduction

Diseases in crops, primarily caused by bacteria and fungi, can significantly reduce both the quality and yield of crops. One of the main challenges in protecting crops is the timely and early detection of disease symptoms. In many developing countries, visual inspection by experts or agronomists is still the most common method used, but this approach is both time-consuming and expensive. An alternative and more efficient method is the use of smart devices to automatically identify diseases, which can help lower costs and improve efficiency.

In recent years, deep learning, particularly convolutional neural networks (CNNs), has gained popularity in agriculture for tasks such as plant detection, fruit detection, disease identification, weed detection, and pest recognition. The reason for CNN's widespread use is its ability to automatically extract relevant features from data. Well-known deep learning models like AlexNet, GoogleNet, VGGNet, ResNet, and DenseNet have been developed for identifying plant diseases.

Real-time applications of deep learning for disease detection are becoming increasingly important. However, one of the main challenges of these models is the large number of parameters and the high computational costs involved, which depend on the model's depth and the number of filters used. These resource-heavy models are difficult to implement on small devices with limited computational power. Most of the research in this area relies on powerful devices like GPUs and servers, which are not practical for widespread agricultural use due to their high cost. This creates a demand for more efficient models that use fewer parameters, require less computational power, and are suitable for devices with limited resources.

To address this issue, we have developed a lightweight deep learning model for identifying plant diseases. This paper introduces a new CNN architecture that combines Inception and ResNet to achieve high performance with fewer parameters. The Inception architecture extracts more relevant features using multiple filters of varying sizes, while the ResNet structure helps prevent the vanishing gradient problem by using residual connections. Instead of traditional convolutions, we used depthwise separable convolutions to reduce the number of parameters and computational complexity, without sacrificing performance.

The datasets used include the PlantVillage dataset, which consists of images captured under controlled conditions with a uniform background, a rice disease dataset with real-time field images, and a cassava disease dataset with field images containing multiple leaves. We compared our model’s performance with other state-of-the-art deep learning models, and the results show that our proposed model outperforms them.The rest of the paper is structured.

Our model was trained on three different plant disease datasets, and its performance was evaluated. The key contributions of this paper are as follows:

* We propose a new CNN architecture that combines Inception and residual connections, enabling better feature extraction and improved performance.
* We replace standard convolutions with depthwise separable convolutions, which significantly reduce the number of parameters while maintaining high accuracy.
* Our model uses fewer parameters and is faster than traditional deep learning models.
* We tested the model’s robustness on three different plant disease datasets to ensure its generalizability.

## Related Work

## This section provides an overview and analysis of recent research focused on identifying plant diseases using deep learning models. Mohanty et al. used AlexNet and GoogleNet to detect 26 diseases across 14 different plant species. They trained these models using both transfer learning and from-scratch methods, achieving a maximum accuracy of 99.34% with GoogleNet.

## Similarly, Ferentinos applied five pre-trained deep learning models, including VGG, AlexNet, AlexNetOWTBn, Overfeat, and GoogleNet, to identify 58 different plant leaf diseases. Another study by Geetharamani and Pandian employed a nine-layer deep CNN to detect plant diseases, achieving an accuracy of 96.46%.Building on the architectures of AlexNet and GoogleNet, Liu et al. developed a model that replaced AlexNet's fully connected layer with an inception layer. This approach was used to identify four types of apple leaf diseases and reached an accuracy rate of 97.62%.

## Ahmad et al. used four different pre-trained deep learning models—VGG16, VGG19, ResNet, and InceptionV3—to identify various diseases in tomato leaves. By fine-tuning the network parameters, they achieved the best results with InceptionV3, which had an accuracy of 99.60% on laboratory images and 93.70% on field images. Similarly, Rangarajan and Purushothaman utilized the VGG16 model to detect eggplant diseases. They used VGG16 for feature extraction and employed a multiclass SVM for classification. To test the model's robustness, they worked with three different color image models: RGB, YCbCr, and HSV. The highest accuracy, 99.4%, was achieved using RGB images. Too et al. used several pre-trained deep learning models and fine-tuned their parameters to identify and classify plant diseases, achieving a maximum testing accuracy of 99.75% using the DenseNet architecture.

Sethy et al. combined deep features with an SVM classifier to detect rice leaf diseases. They extracted features using 11 different deep CNN models and found that ResNet50, paired with SVM, performed the best, with an f1-score of 98.38%.Rangarajan Aravind and Raja employed six different pre-trained deep learning models to identify 10 different diseases across four plant varieties. Among these models, VGG16 delivered the best accuracy of 90% on the test dataset. They used VGG16 for feature extraction and employed a multiclass SVM for classification.

**3.Materials and Methods**

**A. Convolutional Neural Network (CNN)**

A Convolutional Neural Network (CNN) is a type of neural network that is highly effective for various computer vision tasks, such as pattern recognition and image classification. One key advantage of CNNs is their ability to automatically learn and extract features from training images, unlike traditional methods that require manual feature extraction.

CNNs consist of several layers: convolutional layers, pooling layers, and fully connected layers. The convolutional layer is the most important part, as it extracts features from input images. It uses small matrices called kernels that slide over the input image to produce output known as feature maps. Different kernels are used to capture different types of features, and the number of convolutional layers depends on the size of the input images.

After the convolutional layers, pooling layers are used to reduce the size of the feature maps. Pooling helps lower the computational complexity by reducing the dimensions of the feature maps. There are different types of pooling, such as max-pooling, min-pooling, and average-pooling, each with its own method for downsampling the data.The output from the convolutional and pooling layers is then transformed into a one-dimensional vector in a process called a fully connected (or dense) layer. In this layer, every input is connected to every output by a weight. There can be multiple fully connected layers, with the final layer having the same number of outputs as the number of classes being classified.

**B. Residual Network**

Convolutional neural networks (CNNs) can achieve high performance in classification tasks, but as the network depth increases, the accuracy tends to plateau or even decrease. To solve this issue, He et al. introduced the Residual Network (ResNet) in 2015. ResNet helps address the challenges of training very deep networks by incorporating residual connections, which allow for more efficient training and help prevent the vanishing gradient problem—an issue that occurs as networks become deeper.

## As shown in Figure 1, the basic structure of ResNet uses a technique called a "skip connection" or "identity mapping." This method connects the output of one layer directly to a later layer, bypassing intermediate layers. The identity mapping does not add any additional parameters to the network, which enables ResNet to train deeper networks with lower complexity compared to other architectures, like VGG.

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## Figure 1.Basic Diagram of Residual Network.

## C. Depthwise Separable Convolution

## Depthwise separable convolution, first introduced by Chollet in the Xception model, was later used by Howard et al. in the MobileNet architecture. This technique breaks down the standard convolution operation into two parts: depthwise convolution and pointwise (1x1) convolution.In a standard convolution, both filtering and combining of input image values happen in a single step. However, in depthwise separable convolution, the process is split into two layers. The depthwise layer filters the input, and the pointwise layer combines these filtered outputs. Figure 2 illustrates this structure.

## The computational cost of depthwise separable convolution is calculated as: DK2×M×DF2+M×N×DK2D^2\_K \times M \times D^2\_F + M \times N \times D^2\_KDK2​×M×DF2​+M×N×DK2​

## In contrast, the computational cost for a standard convolution is: DK2×M×N×DF2D^2\_K \times M \times N \times D^2\_FDK2​×M×N×DF2​.

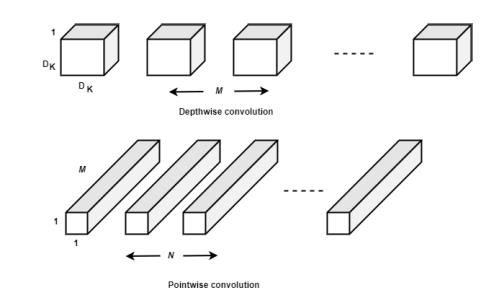
## By breaking down the operation in this way, depthwise separable convolution reduces computational complexity while maintaining efficiency in tasks like image processing.

Where:

* DFD\_FDF​ is the dimension of the input image (assumed to be square),
* DKD\_KDK​ is the dimension of the convolution kernel,
* MMM is the number of input channels, and
* NNN is the number of kernels or filters used.

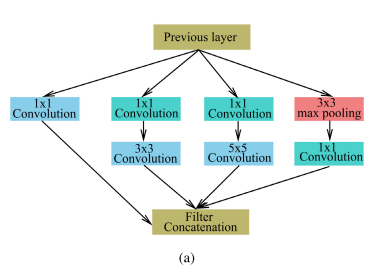
**D. Proposed Novel CNN Approach for Plant Disease Identification**

In this paper, we introduce a new lightweight Convolutional Neural Network (CNN) that combines elements of both Inception and Residual connections, designed with fewer parameters compared to models like InceptionV3, ResNet50, and other deep learning architectures. The Inception architecture, originally developed by Szegedy et al. in 2015 and known as GoogleNet (Inception-v1), was further refined into Inception-v3 by incorporating additional factorization techniques. The Inception architecture stands out from standard convolutional networks because it performs multiple convolution and pooling operations at the same time, enabling better feature extraction. It then combines the outputs of different convolution filters. Inception-v3 consists of various blocks, such as Inception A, Reduction A, Inception B, and Reduction B, as illustrated in Figures 3(a) and 4(a).



**Figure 2.Depthwise Separable Convolution.**

**Figure 3(a).Original Inception A- Block**

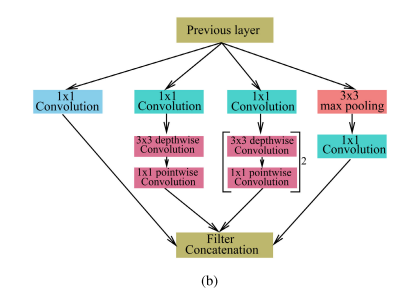
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* A 3×3 max-pooling layer followed by a 1×1 convolution.

In both blocks, 1×1 convolutions are used to reduce the computational load of the model.

The Reduction A block combines:

* A 3×3 max-pooling layer,

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**Figure 3(b).Modified Inception A- Block**

The Inception A block includes:

* A 1×1 convolution layer,
* A 1×1 convolution followed by a 3×3 convolution,
* A 1×1 convolution followed by a 5×5 convolution, and
* A 3×3 max-pooling layer followed by a 1×1 convolution.

The Inception B block has:

* A 1×1 convolution layer,
* A 1×1 convolution followed by a 7×7 convolution,
* A 1×1 convolution followed by two 7×7 convolutions, and
* A 3×3 max-pooling layer followed by a 1×1 convolution.

In both blocks, 1×1 convolutions are used to reduce the computational load of the model.

The Reduction A block combines:

* A 3×3 max-pooling layer,
* A 3×3 convolution layer, and
* A 1×1 convolution followed by another 3×3 convolution.

The Reduction B block includes:

* A 3×3 max-pooling layer,
* A 3×3 convolution followed by a 1×1 convolution, and
* A 7×7 convolution followed by a 3×3 convolution.

Figures 3(a) and 4(a) illustrate the structure of the Inception-A and Inception-B blocks in the Inception-v3 architecture, showing how these components are arranged to improve feature extraction while keeping computational demands low.

## 4.Conclusion

Deep learning has emerged as a powerful and advanced technique for image pattern recognition, making it particularly effective for identifying plant diseases. In this paper, we present a novel Convolutional Neural Network (CNN) model that combines the Inception and Residual connections to classify plant diseases with high accuracy. Additionally, we integrated depthwise separable convolution into the Inception architecture, reducing the number of parameters by 70%. This significantly lowers computational costs and decreases training time compared to standard CNNs.

Our experimental results demonstrate that the proposed model achieves high performance, with testing accuracies of 99.39%, 99.66%, and 76.59% on the PlantVillage, Rice, and Cassava datasets, respectively. In comparison, a previous study [25] reported accuracies of 52.87% and 46.26% using a standard CNN and a deep residual neural network on an imbalanced dataset. Another study [24] recorded 80.6% accuracy on a balanced dataset, while our model achieved 76.59% on the imbalanced Cassava dataset. For the rice dataset, Sethy et al. [1] achieved 98.25% accuracy, whereas our model surpassed that with 99.66% accuracy.

Looking ahead, we plan to extend our research to other agricultural applications such as weed detection and pest identification. Additionally, future work will explore using different plant disease datasets from various geographical regions. We also aim to investigate clustering-based unsupervised techniques for disease identification as another promising area of exploration.

Deep learning has emerged as a powerful and advanced technique for image pattern recognition, making it particularly effective for identifying plant diseases. In this paper, we present a novel Convolutional Neural Network (CNN) model that combines the Inception and Residual connections to classify plant diseases with high accuracy. Additionally, we integrated depthwise separable convolution into the Inception architecture, reducing the number of parameters by 70%. This significantly lowers computational costs and decreases training time compared to standard CNNs. In addition to these applications, we plan to investigate the use of unsupervised learning techniques, such as clustering, to further enhance the model's ability to identify plant diseases without relying solely on labeled data. This could potentially improve the model's adaptability and accuracy in diverse environmental conditions.

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