# Leaves Disease Detection using Machine Learning Techniques: A Comparative Study

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**Abstract**

Deep Learning Neural Networks are at the core of a lot of recent research. Computer vision, natural language processing, health care, and autonomous predictions are only a few of the domains covered by their applications. The main goal is to analyze several deep learning network approaches employed in the biomedical industry, particularly for Leaves diseases. Through Deep Neural Networks, this study seeks to achieve the best prediction rate in leaver disease diagnosis systems. Specifically, an increase in the rate of recognition leads to an increase in the rate of diagnosis of these critical leaf diseases. Deep Neural Networks are a series of algorithms that endeavour to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. There are four Deep Neural Networks algorithms used in this study; they are CNN, Inception-V3, DenseNet-121, and VGG-16. For the evolution of these deep neural networks, some standard evaluation measures are used, such as F1-score, recall, precision, accuracy, and AUC. The overall outcomes show the better performance of Inception-V3 with an achieved accuracy of 95.5 %, as well as the performance of DensNet 121 with an accuracy of 94.4 %. However, VGG-16 performed well as well, with an accuracy of 93.3 %, and CNN achieved an accuracy of 91.9 %.

*Keywords:* , CNN, DensNet121, Inception V3, VGG 16, Leaves Diseases

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## 1. Introduction

Leaf diseases are the most common cause of agricultural loss. Diseases of the leaves, such as fungus, bacteria, and viruses, can cause sickness and form patches, making it difficult to determine if the source is fungal, bacterial, or virus. In agriculture, many diseases can result in various losses. Many agriculture professionals devote a significant amount of work to determining the diseases of a class (bacteria, fungus, viruses). Predicting leaf disease is critical for agricultural organizations to make the best possible leaf care decisions [1]. Incorrect judgments are likely to result in plant loss or delays in plant treatment. Furthermore, predicting the correct plant disease has long been considered a vital problem. Machine learning (ML) approaches have been developed. To handle this sort of agricultural care challenge, machine learning (ML) approaches have previously been created. Neural network groups have recently proved effective in a range of applications, including aiding in the treatment of leaves [2]. Through the training of a finite number of neural networks and then integrating their outputs, neural network ensembles can dramatically increase the generalization capacity of learning systems. Some agricultural professionals believe it is difficult to make disease-related judgments because they lack expertise in all agricultural areas. To address this problem, it is critical to establish a disease prediction system that integrates agricultural knowledge with an integrated system to deliver better and more accurate findings that benefit society [3].

Famine and starvation can result from plant disease losses, particularly in less developed countries where disease-control tools are limited and annual losses of 30 to 50 % of essential crops are not uncommon. Losses can be much larger in some years, which has severe effects on individuals who depend on the crop for their livelihood. [4]. Throughout history, major disease outbreaks among food crops have resulted in famines and huge migrations. In 1845, a severe outbreak of potato bacteria erupted in Europe. Due to its capacity to extract features, artificial intelligence using deep learning models plays a vital role in detecting a variety of plant diseases [5]. Multimodal analyses are automatically analyzed using DL models. Computer vision demonstrates how a computer obtains information from image and video processing using deep learning algorithms. Convolutional Neural Networks, VGG16, Inception V3, and DenseNet are some of the most advanced approaches currently available. AI applications also include medical domains such as cancer detection and classification, diabetes diagnosis, and so forth [5].

However, the primary goal of this research is to conduct a comparative analysis of several CNN approaches to identify the optimal methodology for plant diseases with the least number of mistakes and the highest accuracy. This study employs accuracy, precision, recall, F-measure, and AUC as assessment measures to evaluate existing approaches.

## 2. Related Work

Arsenovic et al.[1], proposed a method to detect disease in plants by training a Modified LeNet VGG, VGG16, Inceptionv3, and Modified AlexNet. This CNN model is trained to identify healthy and affected plants of 42 diseases. These model achieved an accuracy Modified ALexNet 92.88% VGG 99.53%,VGG16 90.40%,Inception-v3 99.76%,Modified AlexNet 97.62%. Lili Li1 et al.[2], introduced a method to detect diseases in plants utilizing the captured image of the diseased leaf. VGG 16, VGG 19, Resnet, and Inception v3 are trained by properly choosing feature values to distinguish diseased plants and healthy samples.

Jobin Francis et al. [6], developed a method to detect diseases in the plant using image processing of the captured image of the diseased leaf. To identify leaf diseases, the leaves of the pepper plant are used as a set of leaves. Healthy and diseased plants can be distinguished using this method, which also yields better results. A cultivating farm's output can be increased and the quality of the pepper plants can be guaranteed by using this image analysis technology to remove good, healthy pepper plants. By examining the visual symptoms present on the plant's leaves, this algorithm aids in detecting the presence of diseases. Gunjan Chugh1 et al [3], proposed a work in which the author used a plant village dataset which has about 1000 leaf images of early blight and 152 images of healthy plants. For this model, the dataset has been divided into 2 parts, which are the training set and the test set. The training set comprises 80% of the dataset while the test set comprises 20% of the dataset. The pre-trained model used on this dataset for feature extraction is Inception V3. For classification, our CNN model provides an accuracy of about 90% based on the training and testing done on it.

Fatma Marzougui et al.[4], proposed a method that works based on ”resnet” criteria. It has an accuracy of 94.80% after training for 10 epochs. Finally, after implementation with the ”ResNet” architecture, the complete detection performance reaches 98.96%. Maryam Ouhami et al.[7] introduced a method which aims to identify the best machine-learning model for detecting tomato crop illnesses in RGB photos. They use the deep learning models DensNet161 and DensNet121 and VGG16 with transfer learning to solve this problem. For our research, images of infected plant leaves were separated into six categories: infections, insect assaults, and plant illnesses. The findings were encouraging With an accuracy of up to 95.65% for DensNet161, 94.93% for DensNet121, and 90.58% for VGG16, the findings were encouraging.

Peng Jiang1 et al.[5],By incorporating the GoogLeNet Inception structure , a novel apple leaf disease detection model based on deep-CNNs is suggested. Finally, the proposed INAR-SSD model is trained to identify these five frequent apple leaf illnesses using the hold-out testing dataset, which consists of 26,377 pictures of sick apple leaves. According to Sakshi Raina et al.[8], various scholars proposed the fundamentals of plant disease detection strategies. Based on diverse datasets and their preferences, tabular analysis provides identification, segmentation, and classification techniques. The recognition and learning rates of GPDCNN are greater. GANs have stronger evidence of information appropriation (more refined and clear images). A Multilayered Convolutional Neural Network that has deviated from its paradigms has the benefit of being able to recognize essential aspects without the need for human intervention. To put it another way, we gave a summary of the possible methodologies for solving the problem as well as the datasets.

Husnul Ajra,Mst et al. [9], the system obtains a total accuracy of 96.5% with AlexNet for the categorization of healthy and unhealthy leaves, whereas ResNet-50 achieves an overall accuracy of 97%. On the other hand, for leaf disease identification, ResNet-50 has an overall accuracy of 96.1 percent, whereas AlexNet has an overall accuracy of 95.3 percent. From all of the comparisons, it has been determined that Resnet-50 outperforms AlexNet.

## 3. Methodology

The goal of this study is to give a comparative examination of DNN techniques for detecting leaf diseases using datasets from each disease (fungus, bacteria, and virus). The technique is used to prepare the entire research. This is shown in Figure 1.

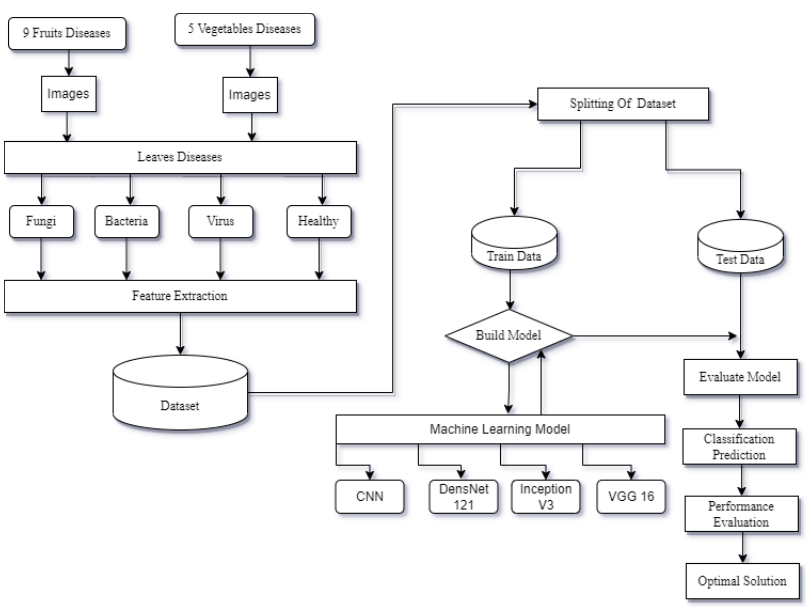


Figure 1: Research Methodology

Python and Colab are used for all of the experiments. Following the selection of the dataset. Then DNN approaches such as CNN, Inceptionv3, DenseNet121, and VGG16 are used in the dataset, and the results are evaluated using several assessment metrics to indicate which methodology performs best. The performance of DNN approaches on leaf disease datasets is evaluated using five assessment measures: F-measure, precision, recall, AUC, and accuracy

### *3.1. Dataset*

We have different leaf diseases in the agricultural area. But we mainly focused on leaves with major classes of bacteria, fungi, and viruses, in which we have 9 affected fruit leaves images caused by bacteria, fungi, or viruses and 5 affected vegetable leaf images [10]. Various categories of plant disease are shown in Figure 2.

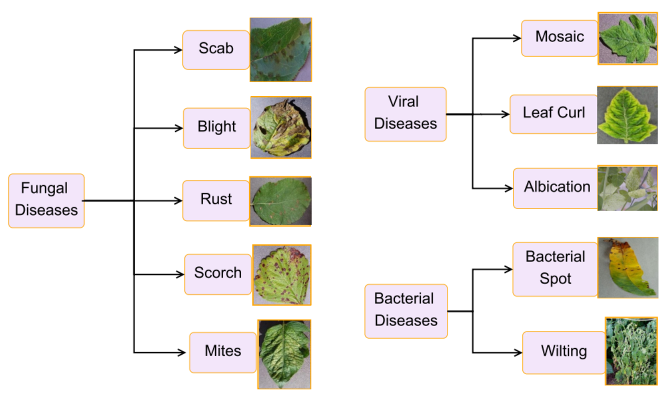


Figure 2: Various infections in plants with their categories in various crops

### *3.2. Leaves Disease Dataset*

This dataset is taken from Kaggle[1]. The dataset consists of 6753 leaves diseases images. The detail division of Diseases are presented in Table 1.
From the dataset, 80% was used for training and 20% was used for testing and validation.

[1]https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset

Table 1: Division of leaves diseases in Dataset.

| S. No | Disease | Description |
|---|---|---|
| 1 | Bacteria | 983 images |
| 2 | Fungi | 2720 images |
| 3 | virus | 1145 images |
| 4 | healthy | 1905 images |

## 4. Techniques Employed

Four classification systems, including CNN, VGG16, DenseNet 121, and Inception V3, have been utilized to identify methods with higher accuracy and reduced error rates. Each strategy is briefly described in the subsection.

### *4.1. Convolutional Neural Networks*

Convolutional neural networks are composed of several artificial neuronal layers. Artificial neurons are mathematical operations that determine an activation value by computing the weighted sum of many inputs. The basic building block

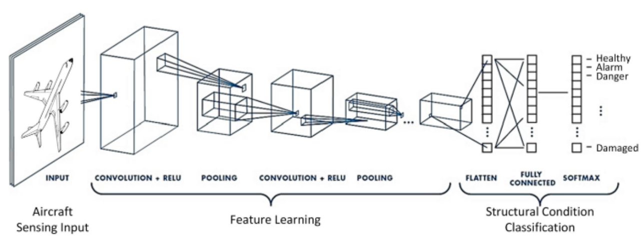


Figure 3: Convolutional Neural Networks

of artificial neural networks, the artificial neuron, has the following structure:[11] Each neuron's weights determine how it will behave. When supplied with pixel values, a CNN's artificial neurons can distinguish a variety of visual patterns. When you input an image to a ConvNet layer, it outputs numerous activation maps. Activation maps highlight the important components of the image. Each neuron multiplies the color values of a patch of pixels by its weights as input, sums them up, and then passes the output through the activation function.[12].

*4.2. Visual Geometry Group-16*

Convolutional neural network VGG-16. There are 16 layers. An image with dimensions is used as the network's input (224,224,3). Following a layer with 2 convolution layers that have 256 filter size and 3, 3 paddings, there are two layers with 64 channels of 3*3 filter size and the same padding, and then the (2, 2) stride. The image is then split into two sets of layers: a max pool layer and a set of three convolution layers. The resulting image is transmitted to the other layers after each of these has applied 512 filters of the same size. The size of the filters in these two layers differs in that AlexNet uses filters that is 3 by 3 while ZF-Net uses filters that are 7 by 7 in size. The network manipulates the number of inputs in some of the layers using a 1*1 pixel. To stop the spatial feature from impacting the image, padding is introduced after each convolution layer[13]. as shown in Figure 4.

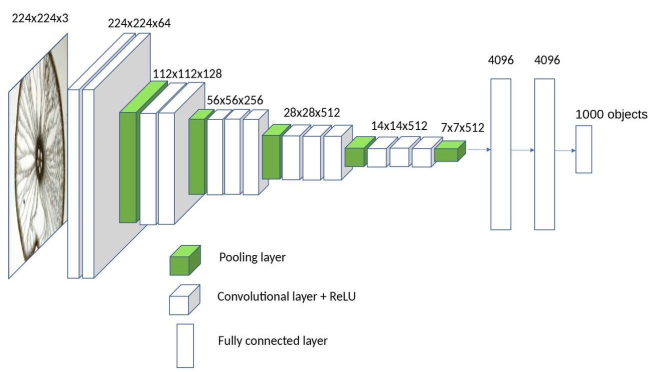


Figure 4: VGG-16

The convolution and max-pooling layers were stacked to produce a (7, 7, 512) feature map. In order to create a (1, 25088) feature vector, this output is flattened. The following three layers are all fully interconnected; the first produces a (1, 4096) vector using the last feature vector as input, the second produces a (1, 4096) vector as well, and the third generates 1000 channels for 1000 ILSVRC classes. The soft-max layer receives the output of the third fully connected layer after which the classification vector is normalized. The top five categories should be examined after the classification vector has been created. All hidden layers have ReLU as their activation function. Due to the fact that ReLU produces less data, it is more computationally efficient. There are two versions of VGG-16 (C and D). VGG utilizes (1, 1) filter size convolution rather than (3, 3) filter size convolution, which is the only significant difference between them. These two have, respectively, 134 million and 138 million parameters.

### *4.3. DenseNet121*

It is one of the most recent advancements in visual object recognition using neural networks. Although there are some significant differences, DenseNet and ResNet are relatively comparable to one another. ResNet utilizes an approach (+) to add the previous layer (identity) with the upcoming layer, whereas DenseNet uses an approach (.) to concatenate the output of the previous layer with the output of the subsequent layer.[14].

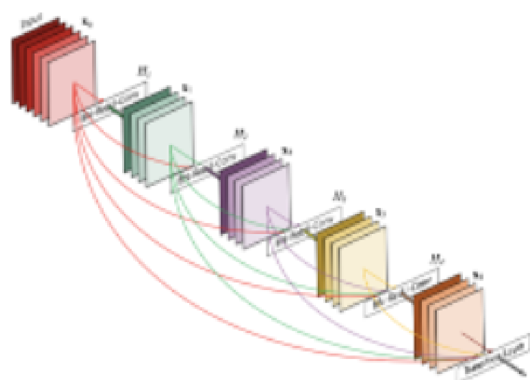

Figure 5: Simple DenseNet121

DenseNet is classified as a traditional network. An output from the first layer becomes an input for the second layer when the composite function operation is used. This composite procedure consists of the convolution layer, the pooling layer, the batch normalization layer, and the non-linear activation layer. As a result of these links, the network contains L(L+1)/2 direct connections. The letter L stands for the number of levels in the architecture. DenseNet is available in many different configurations, including DenseNet-121, DenseNet- 160, DenseNet-201, and others. The neural network's layer count is shown by the numbers [15]. This is how you get the number 121: 5+(6+12+24+16)*2=121

- Classification Layer(16)
- Dense Block (1x1 and 3x3 conv)
- Transition Layers (6,12,24)
- Convolution and Pooling Layer

### *4.4. Inception V3*

It is a deep learning model for image classification that uses Convolutional Neural Networks. The Inception V3 [16] is a more advanced version of the core model Inception V1, which was initially released in 2015. It features a lower mistake rate and a total of 42 layers. Following are the main modifications made to Inception V3:[17].

- Factorization to Smaller Convolutions
- Asymmetric Convolutions through Spatial Factorization
- Auxiliary classifiers' use
- Reduce Grid Size Effectively

## 5. Results and Discussion

First, the performance of DNNs is examined in terms of precision, recall, F1-score, AUC, and accuracy.Following that, the results are analyzed to determine which strategy performed better and why.

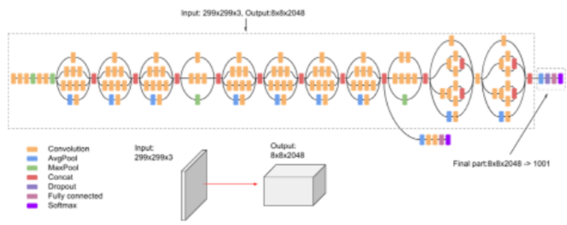


Figure 6: InceptionV3

The results from the examination of classification algorithms are presented in this section. The following metrics were used to rate these classifiers: precision, recall, F1-score, AUC, and accuracy. CNN, DenseNet121, VGG16, and Incep- tionV3 were four classifiers evaluated on bacteria, fungi, viruses diseases, and healthy plant leaves. We use standard deviation to tabulate the following numerical data in Tables 2- 6 of the employed techniques CNN, VGG-16, Inception-v3, and DenseNet-121 respectively show the Classification Report. We use standard deviation to tabulate the following numerical data in Tables 2 -6 of the employed techniques CNN, VGG-16, Inception-v3 and DenseNet-121 respectively show the Classification Report.

Table 2: CNN Classification Report

| **Diseases** | **Precision** | **Recall** | **F1 Score** | **Support** |
|---|---|---|---|---|
| Bacteria | 0.77% | 0.82% | 0.79% | 197 images |
| Fungi | 0.91% | 0.90% | 0.91% | 544 images |
| Healthy | 0.94% | 0.94% | 0.94% | 381 images |
| Virus | 0.96% | 0.95% | 0.96% | 229 images |

We use area under score to tabulate the following numerical data in Figures 7 - 9 of the employed techniques CNN, VGG-16, Inception-v3 and DenseNet-121 respectively show the Area under curve score. To determine the accuracy of each classifier, experiments were conducted on a dataset of images of bacteria, fungus, and viruses in Table 6 shows the results, shows the accuracy CNN,

Table 3: VGG-16 Classification Report

| Diseases | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Bacteria | 0.95% | 0.70% | 0.80% | 197 images |
| Fungi | 0.90% | 0.96% | 0.93% | 544 images |
| Healthy | 0.95% | 0.99% | 0.97% | 381 images |
| Virus | 0.96% | 0.97% | 0.96% | 229 images |

Table 4: Inception-V3 Classification Report

| Diseases | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Bacteria | 0.95% | 0.84% | 0.89% | 197 images |
| Fungi | 0.95% | 0.95% | 0.95% | 544 images |
| Healthy | 0.98% | 0.98% | 0.98% | 381 images |
| Virus | 0.92% | 0.99% | 0.95% | 229 images |

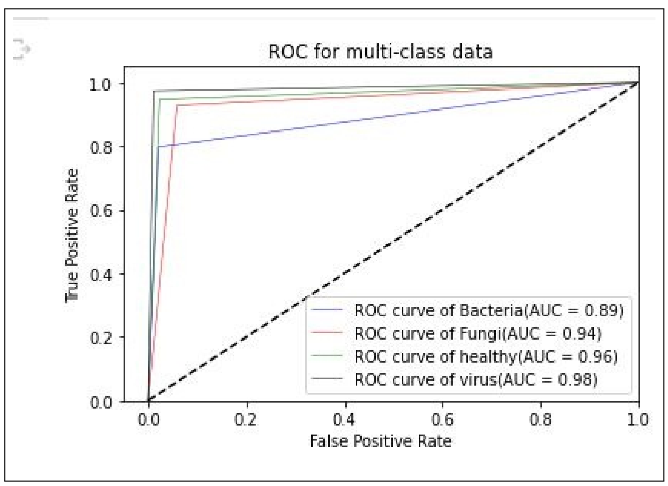


Figure 7: CNN AUC-ROC

InceptionV3, DenseNet and VGG-16 calculated throughout the experiments.

This study's primary objective is to examine DNNs' agricultural data, which includes information on various plant Diseases caused by bacteria, fungi, and viruses. The study shows that Inception V3 outperformed other approaches in

Table 5: DensNet-121 Classification Report

| **Diseases** | **Precision** | **Recall** | **F1 Score** | **Support** |
|---|---|---|---|---|
| Bacteria | 0.98% | 0.76% | 0.86% | 197 images |
| Fungi | 0.92% | 0.97% | 0.94% | 544 images |
| Healthy | 0.97% | 0.96% | 0.96% | 381 images |
| Virus | 0.91% | 0.99% | 0.95% | 229 images |

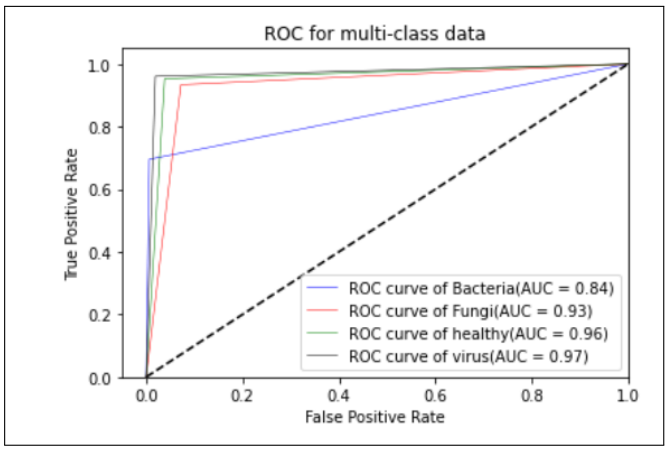


Figure 8: VGG-16 AUC-ROC

each of the aforementioned diseases. Additionally, Inception V3's competitors CNN, DensNet, and VGG-16 all produced results that were slightly better. In addition to achieving higher results in terms of accuracy, Inception V3 also did so in terms of precision, recall, F1-Score, and AUC.

The advancement of the inceptionv1 is the inceptionv3. It improves him by using a variety of optimization techniques on its network. It operates more effectively. Compared to its previous edition, it features a deeper network and 42 layers with a low error rate. It uses asymmertric convolutions to replace 3x3 convolutions with 1x3 and 3x1, which reduces his computational cost and makes him 33% cheaper. With the aid of the convolutional filter size, it has the capacity to extract data from the input picture at various. scales. The network's feature capabilities are improved using 1x1 convolutional filters.

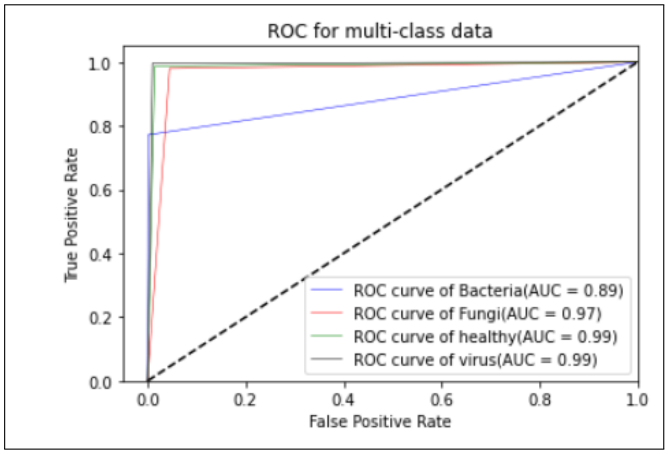


Figure 9: DenseNet-121 AUC-ROC

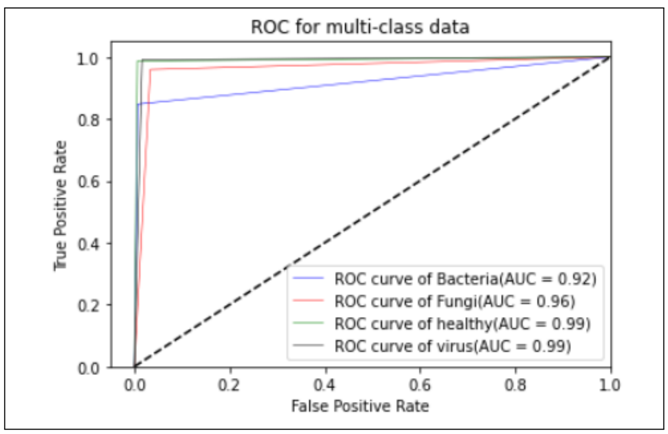


Figure 10: Inception-V3 AUC-ROC

## 6. Conclusion

The DNNs is an emerging research topic and it has got much attention in the last two decades. Many different disciplines have benefited from this research area. DNNs are advancing AI to the next stage while transforming business and daily life. DNNs-enabled technologies (including the smartphones and comput-

Table 6: Accuracy of CNN, Inception-V3, DensNet-121, VGG-16

| **Techniques** | **Accuracy** |
|---|---|
| Inception-V3 | 0.95% |
| DensNet-121 | 0.94% |
| VGG-16 | 0.93% |
| CNN | 0.91% |

ers that we use every day) are now trained to learn, detect patterns, and make predictions in a humanoid way, as well as solve issues in every business sector, by simulating the way linked brain cells behave. This research was to cover a comparative analysis of DNNs for leaf disease. It is observed from the literature that several kinds of research have developed techniques for prediction, but it is still a challenging task in terms of increasing accuracy. Despite the wide research done in this field, there is still room for improvement. This study focuses on improving the accuracy rate of prediction. The dataset for leaf disease from Kaggle is selected. The performance is evaluated using accuracy, precision, recall, AUC, and F1-Score. Overall outcomes show the better performance of Inceptionv3 in achieving high accuracy. As well as that, CNN, VGG-16, and DenseNet121 also have better performance, slightly less than InceptionV3. The recommendation of this study for prediction is InceptionV3 and CNN techniques.

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