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# Deep Learning Approaches for Disease Detection in Groundnut Crops using CNN Models

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### Abstract

A major oilseed crop grown in tropical and subtropical parts of the world, groundnuts are a major crop in India. In the sixteenth century, groundnuts were likely transported from Brazil to West Africa, later making their way to India and the African east coast. According to earlier research, various strategies are employed to prevent diseases of groundnut leaves. The main methods include artificial intelligence (AI), machine learning (ML), convolutional neural networks (CNN), and more. Several CNN techniques for leaf disease identification and methodology will be employed in this study. Different CNN models, such as MobileNet, VGG-16, and EfficientNet, are compared to determine which model is most frequently used to identify leaf disease. The accuracy and precision will be computed and presented as a result of utilizing the dataset.

**Keywords:** Convolutional Neural Network (CNN), MobilNet, VGG-16, EfficientNet, Deep Learning (DL)

## 1. Introduction

Groundnut is the world's most significant crop of oilseeds and food legumes. In a growing population, sustainable groundnut production increases food security and reduces malnutrition. One such resource for long-term groundnut breeding is groundnut landraces.


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Collected from Peru, Mexico, and Brazil, agricultural races of hypogaea, hirsuta, fastigiata, vulgaris, peruviana, and aequatoriana demonstrate extensive genetic variety with reduced oil content, improved sweet characteristics, and the capacity to endure harsh climatic conditions. Farmers cultivated these landraces without the use of,fertilisers, or pesticides. To achieve the goals of farmers', these indigenous types must be preserved and properly utilized in a breeding program. Groundnut production is restricted by a number of biotic factors (such as fungal and foliar diseases, worms, & insect pests) as well as abiotic factors(such as salt, drought, and cold) [1].

There are a several plant diseases that can hinder the growth and yield of groundnuts. These include Early Leaf Spot, Late Leaf Spot, Rust, Stem Rot, Bud Necrosis, Alternaria Leaf Disease, and others. To combat these diseases, the plants will be treated with a variety of fertilizers and pesticides. Alternaria Leaf Disease is a common disease that causes the leaves of the plants to turn brown and twisted, causing the affected leaves to curl inward and become brittle. Affected leaves exhibit chlorosis and, in severe cases, turn prematurely senescent [7].

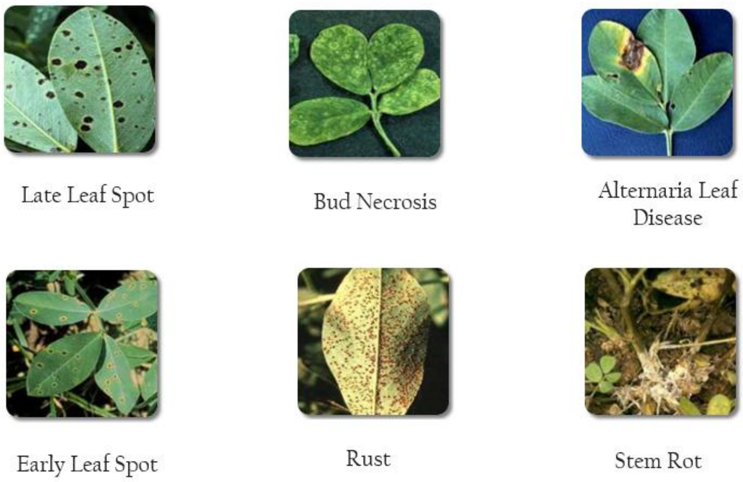



**Figure 1.** Different Kinds of Diseases that Affect the Leaves of the Groundnut

Cercospora arachidicola, commonly known as early leaf spot, infects leaves one month after planting. On leaflets, small chlorotic patches gradually enlarge, turn dark or black, and assume a subcircular form on the upper leaf surface. In severe cases, multiple lesions may merge, leading to early senescence. Peanut bud necrosis virus (PBNV) causes bud necrosis, characterized by the development of necrotic rings and streaks as well as chlorotic patches on immature leaflets. Terminal bud necrosis occurs at relatively high temperatures, with thrips serving as the primary vector for viral transmission. . Puccinia arachidis (Rust) initially appears on the lower surface, and in cultivars that are highly sensitive, colonies of additional pustules may encircle the original pustules. These rust pustules can occur on any aerial plant component except for the flower and pegs. Severe infection causes leaves to become necrotic and dry off, although they still cling to the plant. Figure 1 depicts the leaf diseases discussed earlier.

Thus, many leaf diseases will be identified by the application of various technologies that currently under development. Convolutional neural networks (CNNs) are predominantly used to identify leaf detection, when compared to other methods, CNNs consistently yield results with a high degree of accuracy. In this work, leaf disease is detected using several CNN models. This study compares and provides results for accuracy, precision, and recall for three popular models: The MobileNet, VGG-16, and EfficientNet models.

## 2. Literature Survey

Using a tri-CNN architecture made up of DenseNet169, Inception, and Xception—which have been pre-trained on the ImageNet dataset with two constructed non-linear equations based on decision scores from the previously mentioned base learners—we [2] developed a technique for disease identification and classification. The ensemble methodology described above produces final predictions for the test samples by combining the scores of four traditional evaluation metrics—recall, precision, accuracy, and f1-score—obtained from the base learners. The model is trained using the aforementioned CNN customized models in order to get better outcomes. The suggested method was assessed using a dataset of actual groundnut leaves. The proposed model achieved accuracy rates of 98.56%.

CNNs, the DL, and ML approaches covered in this work [3], are frequently preferred option for image recognition and classification because of their innate ability to independently gather relevant picture information and understand spatial hierarchies. However, the choice between traditional machine learning and deep learning depends on the specific issue, the availability of information and the available computing power. Because of this, DL—primarily using CNNs—is recommended in many complex image detection and classification applications when there is a sufficient amount of data and processing power available and when the results demonstrate strong detection and classification effects for their datasets but not on other datasets. Finally, by using a variety of image-processing methods used in the artificial intelligence (AI) field, the author hopes to keep future researchers informed about the performances, evaluation metrics, and outcomes of previously employed approaches to detect and classify various kinds of plant leaf or crop diseases.

In this research [4], we present a hybrid machine learning based IoT based real-time automated groundnut leaf disease detection and classification approach (GLD-HML). Using the improved crow search (ICS) method, we first divide the disease region from the leaf, which is a crucial step in the disease classification process. Next, we provide a feature extraction stage that utilises a multi-objective sunflower optimization (MSO) method to pick the best features from multiple retrieved features. Next, we demonstrate the use of a deep neural network based on moth optimisation (MO-DNN) for the multi-class classification of illnesses in groundnut leaves. In order to reduce unwelcome human delay, the Internet of Things idea is employed to communicate categorization results to the associated farmer through mobile for crop development. Lastly, the performance of the suggested GLD-HML technique may be examined using various standard datasets, and the findings should demonstrate the method's superiority over current approaches in the areas of accuracy, precision, F-measure, and precision.

We present an effective deep convolutional neural network (DCNN) approach that autonomously and independently identifies the salient features [5]. Leveraging deep learning, the DCNN technique can provide a detailed identification of plant diseases. Furthermore, the results of the DCNN testing and training procedure show an accurate diagnosis and categorization of groundnut illness. The plant village dataset is used to choose the number of photos of groundnut leaf diseases that are utilized in the training and testing phases. The dataset training process employs the stochastic gradient decent momentum approach, which has shown the enhanced performance of the suggested DCNN. From the comparative analysis, the sixth merged layer of suggested DCNN offers a 95.28% accuracy value.  The overall performance the suggested DCNN's for the groundnut disease classification yields 99.88% accuracy.

It is necessary to concentrate on certain methods for agricultural pest identification. The presentation provided a comprehensive summary of current research [6] on the identification of crop pests and diseases using machine learning techniques such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), and Naive Bayes (NB), as well as some deep learning techniques such as Convolutional Neural Network (CNN), Long Short-Term

Memory (LSTM), Deep Convolutional Neural Network (DCNN), and Deep Belief Network (DBN). The proposed approach ensures the highest level of crop protection, enhancing agricultural output and efficiency. This study offers information on various contemporary methods for monitoring agricultural fields for pest detection. It also includes a definition of plant pest detection that helps identify and classify pests of citrus plants, rice, and cotton, along with a variety of detection techniques. These techniques reduce human error and labour by enabling automated monitoring of large areas.

## 3. Methodology

### 3.1 Convolutional Neural Network (CNN)

Currently, CNN is arguably the most well-known model and has proven its exceptional performance on several image classification problems in prestigious fields [8]. By identifying strong aspects in the photos and reducing the dissipating tendency issue, the concept of sharing loads in CNN creates a compelling image segment. Fig. 2 shows how a typical CNN is designed. Convolution, pooling, and fully related layers are all integrated into the CNN development process. The primary task of the convolutional layer, which functions as a channel, is to exclude characteristics from the insect pictures [9]. The pooling layer, which does downsizing and stores the essential data in the insect photos, comes after the convolutional layer. By reducing the spatial scale of the portrayal and the number of limitations, this layer keeps the model from overfitting and increases its capability. The last layer is the completely linked layers, which employ a ReLu establishment capacity to extract specific level components from insect photos and group them into distinct classes with labels [10].

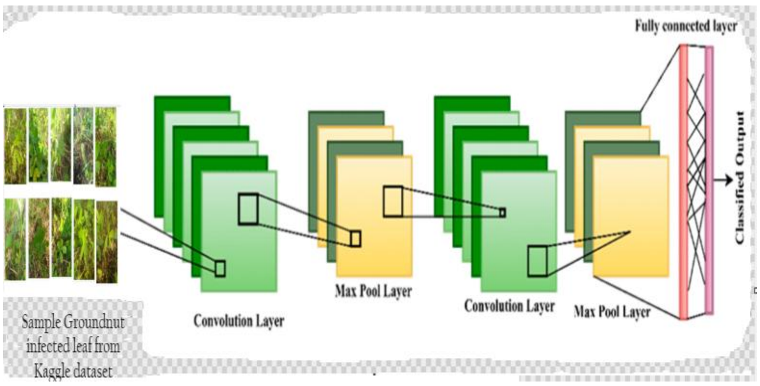



**Figure 2.** Convolutional Neural Network for the Leaf Detection Method

### 3.2 Multi-Class Classification

Multiple images of both healthy and diseased plant samples are stored in plant disease databases, and each sample is linked to a specific class. The features that are taken out of the source image are the only basis for classifying the target image. The testing phase output will categorise the precise label of the disease from all the four categories mapped under that specific class when a sample of a certain disease is retrieved as input. As a result, each category inside a class is regarded as a separate class in multi-label classification, classes in multi-class classification are mutually exclusive. If there are N classes, we may speak about N multi-classes; if there are M categories in the N classes, then every category inside the N classes is regarded as a class in and of itself.

### 3.3 VGG-16

The Oxford University Visual Geometry Group created the VGG-16 [11] network model, sometimes referred to as the Extremely Deep Convolutional Network for a large-scale Image Recognition. The depth is increased to 138 M parameters that can be trained and 16–19 weight layers. Additionally, by decreasing the convolution filter size to $3 \times 3$, the model's depth is increased. This model uses more disc space and takes longer to train.

### 3.4 MobileNet

MobileNet is type of CNN intended for embedded and mobile vision applications. They are based on a simplified architecture that can create lightweight deep neural networks with minimal latency for mobile and embedded devices using depth wise separable convolutions.

### 3.5 EfficientNet

Compound scaling technique is employed by EfficientNet, a neural network design, to enhance the performance. It achieves this by reducing the number of variables and Floating Point Operations per Second (FLOPs), aiming to improve computational efficiency while maintaining or enhancing performance.

## 4. Proposed work

The study methodology and the dataset utilised in the proposed method is described in this proposed section. A broad approach explaining the procedures involved in implementing the classification of groundnut leaf diseases using several convolutional neural network (CNN) architectures, such as EfficientNet, VGG16, and MobileNet, is provided. The proposed work is shown below in fig 3,

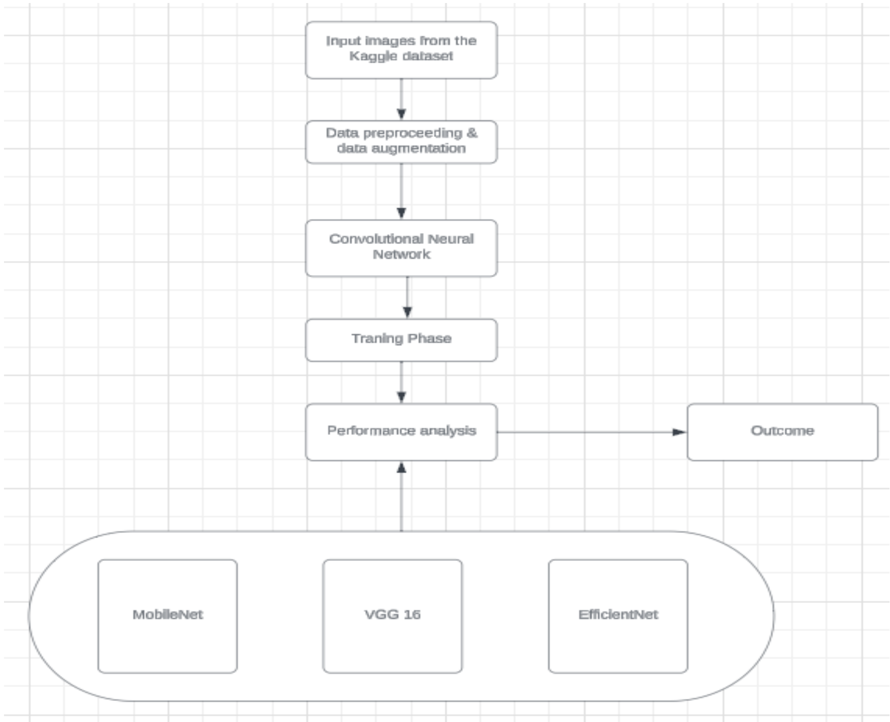


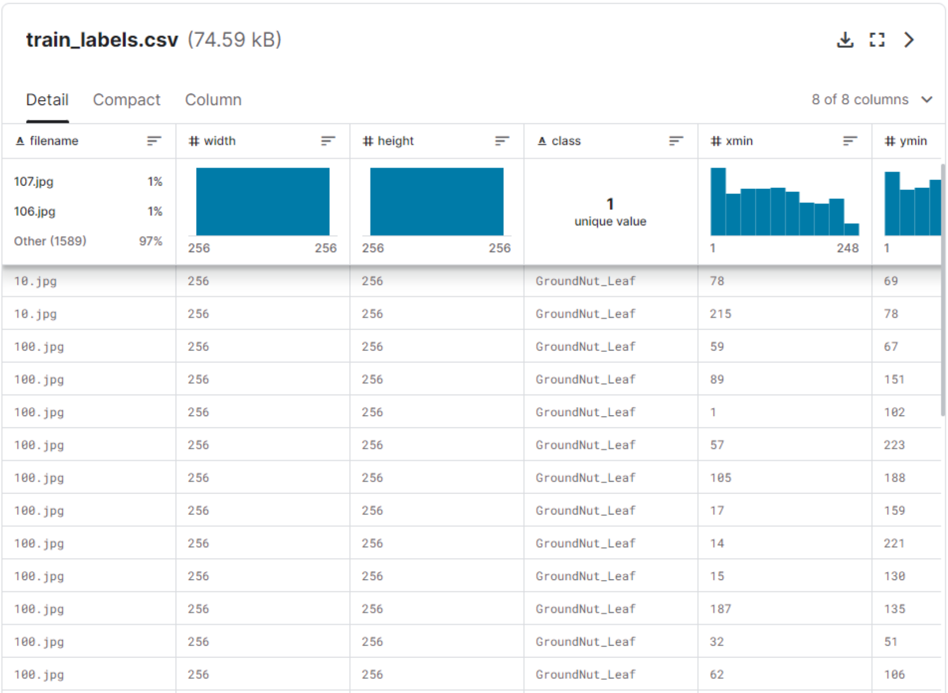

**Figure 3.** Proposed Flow Diagram

A groundnut leaf picture dataset [14] with labelled annotations for every disease is gathered from Kaggle. Every picture has a width and height of 256 × 256. The images in the dataset were prepared applying the preprocessing methods and the data augmentation process. TensorFlow or PyTorch, according to the requirement is installed before beginning the subsequent coding process with Python and Jupyter note book. In order to obtain the correctness of the whole task, images are imported and processed further for data segmentation and model development.

the models of CNN are selected from the libraries (MobileNet, EfficientNet, VGG-16) and complied using the proper optimizers (like Adam), evaluation metrics, and loss functions (such categorical crossentropy) and by importing the model's pre-trained images. Develop every model utilizing the training dataset, maintaining a focus on its performance with the validation set to avoid overfitting. Analyze the models' performance using the test dataset. Analyze measures like recall, accuracy, and precision.

## 5. Result

The groundnut leaf disease dataset is gathered from Kaggle, from a total of 1586 pictures, 107 were selected for training. The example table utilized in this research study is shown in Fig. 4,


train_labels.csv (74.59 kB)

Detail Compact Column 8 of 8 columns

| filename | width | height | class | xmin | ymin |
|---|---|---|---|---|---|
| 107.jpg 1%; 106.jpg 1%; Other (1589) 97% | 256 – 256 | 256 – 256 | 1 unique value | 1 – 248 | 1 |
| 10.jpg | 256 | 256 | GroundNut_Leaf | 78 | 69 |
| 10.jpg | 256 | 256 | GroundNut_Leaf | 215 | 78 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 59 | 67 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 89 | 151 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 1 | 102 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 57 | 223 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 105 | 188 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 17 | 159 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 14 | 221 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 15 | 130 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 187 | 135 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 32 | 51 |
| 100.jpg | 256 | 256 | GroundNut_Leaf | 62 | 106 |

**Figure 4.** An Example Dataset of the Groundnut Leaf Disease Training Pictures

The constructed model is evaluated to determine the accuracy, precision and recall. Figure 5 shows the samples of images collected from the kaggle dataset.

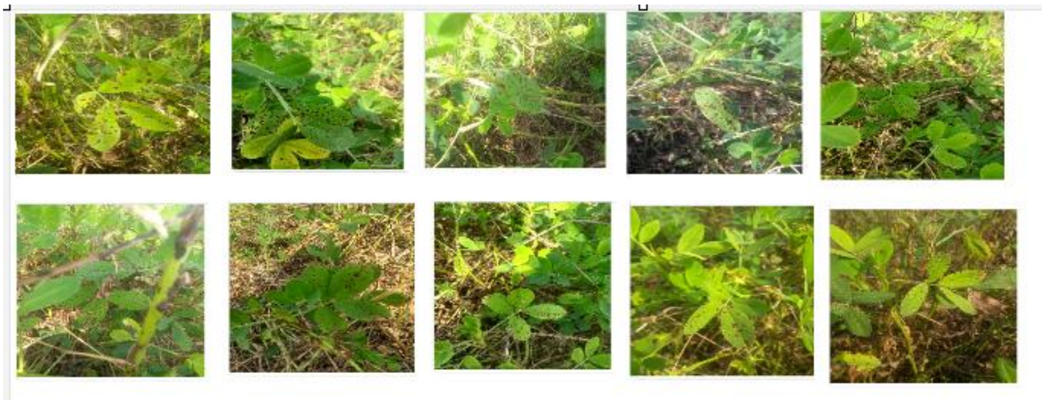


**Figure 5.** Sample Images of the Groundnut Infected Leaves Collected from the Kaggle Dataset

In this case, the VGG-16 total result from the data obtained is relatively best among the others. Common criteria for assessing the effectiveness of classification models, such as those used in leaf disease detection, include accuracy, precision, and recall. These indicators offer several viewpoints of how well the model predicts the future. Table 1 illustrates each model's performance along with the data that are needed for estimating the accuracy, precision, and recall functions.

**Table 1.** Performance of the Three Models of CNN

| | **Accuracy** | **Precision** | **Recall** |
|---|---|---|---|
| MobileNet | .92 | .87 | .82 |
| VGG 16 | .95 | .90 | .91 |
| EfficientNet | .89 | .82 | .81 |

## Accuracy

The percentage of accurate forecasts among all the guesses is called accuracy. An overall evaluation of correctness is provided by accuracy. However, while the model may obtain high accuracy by merely predicting the dominant class, it might not be appropriate for unbalanced datasets wherein one class is dominating. Figure 6 shown the overall accuracy of the research work. Although accuracy offers a broad indicator of correctness, unbalanced datasets might not be a good fit for it.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Prediction}$$

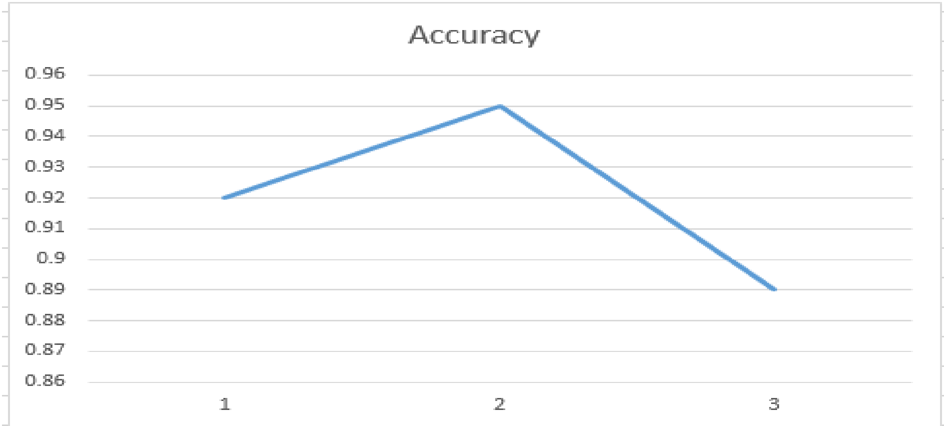



**Figure 6.** Overall Accuracy Performance of the Leaf Disease Detection

**Precision**

The percentage of accurate positive predictions within all the model's positive predictions is known as precision. The accuracy of optimistic forecasts is the main emphasis of precision. When the cost of false positives is substantial, such as when a healthy leaf is mistakenly classified as sick, it is a valuable statistic. Figure 7 shows the precision of those three models. Precision is helpful when false positives are expensive since it concentrates on the accuracy of the positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives\ +\ False\ Positive}$$

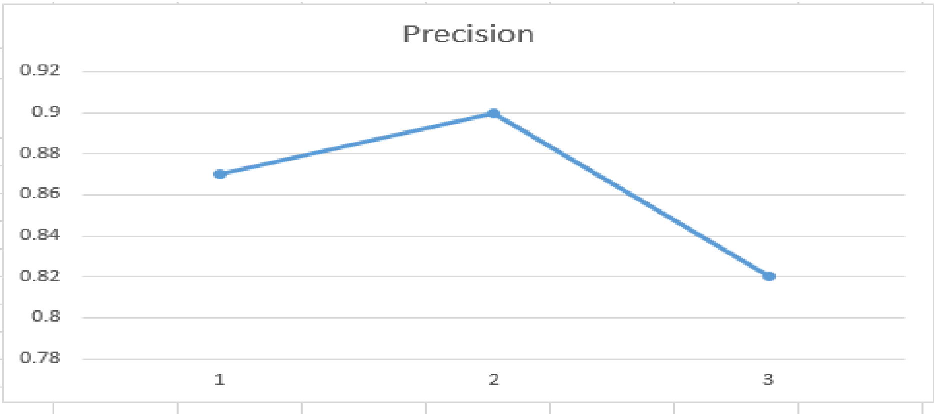



**Figure 7.** Overall Precision performance of the Leaf Disease Detection

## Recall

The percentage of accurate positive forecasts among all real positive occurrences is known as recall. The model's recall gauges its capacity to record all pertinent occurrences of the positive class. When the cost of false negatives is large, it is crucial (e.g., failing to detect a sick leaf). Figure 8 shows the recall performance in the leaf disease detection work.

$$Recall = \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives}$$

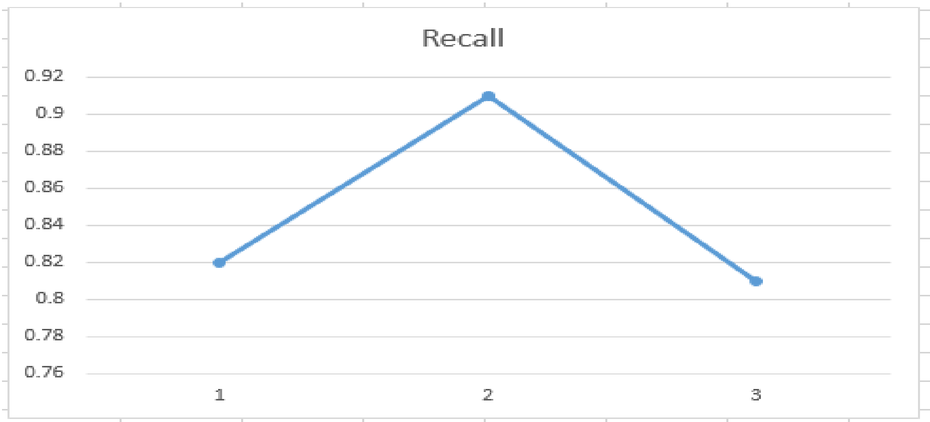



**Figure 8.** Overall Recall Performance of the Leaf Disease Detection

Recall is crucial because false negatives might be expensive since it gauges one's capacity to record all pertinent occurrences of the positive class.

## 6. Conclusion

The VGG 16 exhibits superior accuracy in this proposed study when compared to the other two CNN models, MobileNet and EfficientNet. The method that compares well for assessing the leaf detecting process is CNN. In order to determine the leaf identification procedure, the CNN approach was tested with MobileNet, EfficientNet, and VGG 16. In order to determine which model would work best for identifying or detecting the diseased leaf, which is briefly detailed in the results section, the accuracy, precision, and recall of the dataset are evaluated.

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