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A Comparative CNN Based Deep Learning Model Investigation for Identifying and Classifying the Leaf Diseases of Arachis Hypogea (Groundnut Crop) Grown in The Semi-Arid Landscapes of Villupuram District of Tamil Nādu

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Abstract

Groundnuts are India's most important oil seed crop, and they serve a critical part in bridging the country's vegetable oil shortfall. Groundnut cultivation has been hampered by a variety of fungal, viral, and bacterial infections resulting in significant production loss. Adapting deep learning Investigations towards the identification and classification of various leaf diseases of groundnut may enroute a precisive model to combat such leaf diseases in its early stages itself. In this research article, we have considered the major leaf diseases which affects the groundnuts crops cultivated in the semi-arid geographical landscapes of Villupuram district in the state of Tamilnadu. We have made a comprehensive investigation based on the collected groundnut leaf images in a total of (1950) both diseased and healthy from the various groundnut fields of Villupuram, and trained a deep convolutional neural network based on VGG 16 Model neural network with the utilization of Adam optimizer to identify 5 major groundnut leaf disease classes along with the healthy leaf class. The trained model has achieved an overall accuracy of 99.82 %. This investigational model has been compared for its performance and error measures in par with the CNN based VGG16 model with RMSprop optimizer, Alexnet and Inception_V3 models and have proved to be outperforming all the compared baseline models in terms of performance metrics.

Keywords: Groundnut leaf disease · Deep learning, CNN, VGG16 Model.

1.INTRODUCTION

Groundnut crop (Arachis hypogea L.) is one of the important oilseed crop cultivated in India which stands first position in terms of cultivation area and second position in terms of the overall production. The major producer as well as consumer of peanut in the world is China with 171.50 lakh tones in 2017-18 followed by India (91.79 lakh tones), United States (32.81 lakh tones), Nigeria (24.20 lakh tones) and Sudan (16.41 lakh tones) [1]. Groundnut is the most important oil seed crop in India. which signifies around 50 percent of territory under oilseed crop and 45 percent of eatable oil creation. Almost 75 percent of the groundnut is being developed in a low to direct precipitation zone. In our country major Groundnut cultivation is carried out in five states viz., Gujarat (26.34 percent), Andhra Pradesh, Tamil Nadu, Karnataka and Maharashtra. On a whole these five states share 86 percent of the countries overall groundnut cultivation. The groundnut cultivation was 6.74 million hectares in 2004-05. It has shrunken to 3.78 million hectares by 2018-19. In the state of Tamil Nadu districts of Thiruvannamalai, Villupuram, Vellore, Namakkal, Salem, Erode and Cuddalore are the significant groundnut cultivating regions. The season Thaipattam (January) is the fundamental season for development. The cultivation territory of Groundnut shows a declining pattern throughout the years because of varied reasons. Groundnuts being the significant eatable oil seed crop in Tamil Nadu, organizers are worried about the declining zone [2]. Agriculture has been a key contributor to India's economic growth. The required crop is chosen by the farmer reliant on the soil type, condition of weather in the area, and economic scope. Agricultural sectors have begun to adapt technology in order to increase food

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production as a response of changing socioeconomic demands. This has provided an opportunity for researchers to work on more technically advanced, effective, and precise productive breakthroughs. Farmers can collect information and data using precision agriculture and information technology to make the best decisions for optimal prediction and production. Precision agriculture (PA) can be utilised for a variety of purposes, such as identification of plant pest, identification of weed, production of crop yield, and detection of diseases in plants. Roofing out the scope of bringing in the groundnut cultivation under precision farming, will surely lead to increased productivity by thus ensuring farmers economical sustainability. As groundnut stays to be the major oil seed crop in India, controlling its diseases and identifying it at the earlier stage may enhance the productivity of groundnut [3]. According to an Indian assessment, groundnut cultivation may experience 40–60 percent output reductions. Because of varying diseases in groundnuts based on leaf, root and stem, the ranges can sometimes reach 93 percent too. The sample set of groundnut leaf image dataset taken for the investigation is shown in the below figure 1. To improve the acknowledgement rate and precision of the findings, smart precision technologies like as ML and DL, as well as IoT, have been deployed. We conducted a complete analysis of Deep Learning Techniques (DL) Techniques in leaf disease diagnosis in this research, and based on the review, we intend to investigate a deep learning model based on the state of art of VGG16 Deep learning model with two types of optimizers (RMSprop and ADAM)for recognizing and classifying groundnut crop leaf diseases.A comparative performance analysis between the usage of these two varying type of optimizers has to be made along with the baseline comparative analysis with Alexnet and INCEPTION_V3 Deep Learning models.

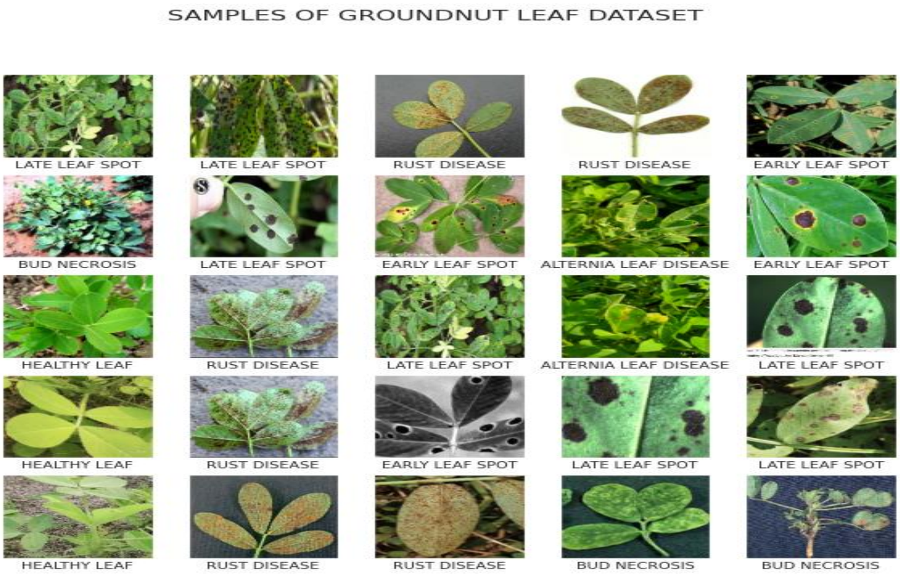

Figure :1(Sample set of groundnut crops healthy and diseased leaf images showing the presence of diseases such as "Early leaf spot, Late leaf spot, Alternia leaf, Rust Disease and Bud Necrosis")

2. RELATED WORK

Ganeshkumar P et al. [4] wrote a paper on how to classify peanut-hypogea disease using deep convolutional neural networks. This article describes how to train Deep CNN using stochastic gradient descent. Researchers in this group achieved a 95.28 percent accuracy rate in diagnosing peanut pituitary disease.

For diagnosing Oryza sativa diseases, K.Suganya Devi et al.[5] prepared a research article based on Deep Convolutional Neural Networks. These researchers developed EAFSO, a method that combines Deep Convolutional Neural Networks with LSTM to identify Oryza sativa diseases with a 97.5 percent accuracy rate, which is higher than DCNN-SVM and DCNN-ANN approaches.

Deep learning would soon become the standard approach for identifying images, according to Barbedo et al. [6]. On average, our method's accuracy was 12% higher than that of experts who used the actual image. Despite this, even when more than ten diseases had been considered, each plant had a precision of less than 75%. Although the study does not cover all possible circumstances, the results confirms that deep learning approaches can be used to detect and identify plant diseases provided there is enough data.

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Song et al. [7] predicted masking of damaged shallow wells in volcanic basins using long-short-term memory (LSTM) neural networks, covering the limitations of previous approaches and detailed prototyping requirements. We used particle swarm optimization (PSO) techniques to optimize key developments in LSTMs. The results show that exceptionally designed LSTMs are superior to other methods.

According to Iqbal et al.[8], citrus leaf diseases are a problem. As a result, they investigate feature extraction, preprocessing, segmentation, selection features, and classification algorithms for unique photographs. Discuss the importance of feature retrieval methods and deep learning techniques, in fact as a result of the study's findings, automated techniques for diagnosing and classifying citrus plant ailments are still in the early phases of development and certification.

Jayamala et al. [9] intended to demonstrate a image retrieval (CBIR) system based on content for recovering leaf's of sick soyabean. It makes use of leaf colour, figure, and quality. To improve presentation, colour, shape, and quality factors are also used. Mosaic virus, Septoria brown spot, and pod mottle disease each have a recovery ability of about 96%, 68%, and 76% for soybean leaves, respectively.

In 2011, Shen et al. [10] used the Radial Baseline Neural Function Network (RBFNN) to train the data and predict the stock indices of the Shanghai Stock Exchange. They help AFSA improve its RBF. To validate the utility of our technique, they compared the prediction errors of RBFs enhanced by AFSA, Genetic Algorithms (GA) and Swarm Optimization (PSO)[11], as well as predicting failure of ARIMA, BP and Support Vector Machine (SMV). Their investigation showed that AFSA-enhanced RBF was a simple process with high accuracy.

In accumulation to this study, we reviewed multiple image processing approaches and machine learning classifiers that can be used for peanut disease detection. Image acquisition, image pre-processing, image enhancement, image segmentation, feature extraction, and image classification are the six main research phases. According to a review of the literature, all work provided is primarily focused on the identification of foliar diseases of peanuts, with accuracy achieved only through the application of automatic weight distribution. with the DL architecture platform.

Implementation flow diagram for DL: The dataset is first collected [12], after which it is divided into two halves, with eighty percent for the training set and twenty percent for the validation set. Then, either from scratch or via the transfer learning technique, Deep Learning models are trained and their T/V plots are derived to determine the models relevance. Then, for picture classification (kind of specific plant disease), performance measures are applied, and ultimately, visualisation methods/maps [13] where used for the detection or classification of the images.

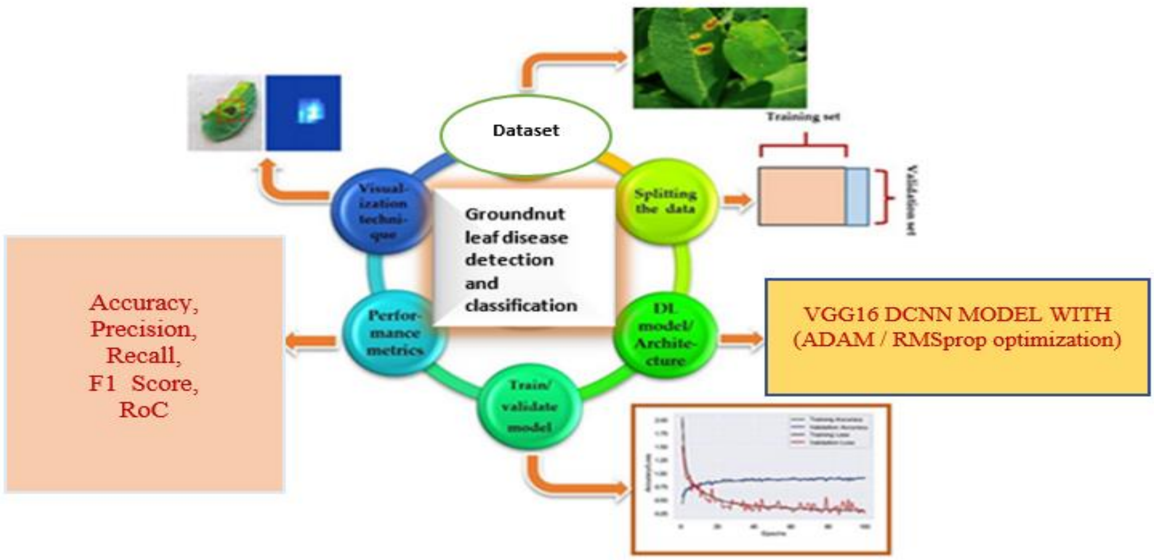

Figure 2: Proposed DL implementation flow for Groundnut leaf diseases identification and classification

2.1. Implementation of various plant disease identification using Deep Learning Models

2.1.1. Deep Learning Model without any usage of visualization approach.

In [18], CNN model adapted for the diseases patterns classification in maize plants in which histogram method is used to exhibit the worth of the model. In [19], various Convolutional NN architectures namely AlexNet, GoogLeNet and ResNet are used towards the identification of tomato leaf diseases. ResNet turns to be the best among the all of them based on the Training/validation accuracy. The diseases in Plantain leaf is detected using architecture LeNet which has been instigated using Classification Accuracy and F1-score to evaluate the model based on Color and Grayscale modes [28]. Nearly among the Five CNN architectures used in [20], In [21], Nearly 8 different plant diseases can be predicted using DL models such as "GoogLeNet, ResNet50, ResNet101, Inceptionv3, InceptionResNetv2 and SqueezeNet" also "Support Vector Machine (SVM), Extreme Machine Learning (ELM)) and KNearest Neighbor (KNN)". Based on performance metrics and F1 scores, ResNet50 with the SVM classifier produced optimal results**.** The cassava disease detection model Inception-v3 was employed in [22]. As a result of utilising two CNN basic versions to classify cucumber plant illnesses in [23], the most accurate classification rate was 0.823. A Super-Resolution Convolutional Neural Network replaces the old disease diagnosis method (SRCNN)is used. In article [24]. tomato plant disease classification was done by Alex Net and SqueezeNet v1.1 out of which Alex Net was found to have produced a better accuracy rate [25]. In [26] to select the optimal architecture in DL for detection of plant diseases A comparative analysis was defined. In [27], DL architectures Alex Net & VGG-16 were used in the classification of six tomato plant diseases with a detailed comparison and a classification accuracy. In all the above articles discussed there is no any usage of visualization technique in order to identify the plant disease.

2.2.2. Visualization approach adapted DL Models

Here is an outlook over the various DL based architectures which have dealt the plant disease identification problem using the vizualization approach, In [29] the authors have demonstrated saliency map towards visualizing the plant disease symptoms, In [30] thirteen diverse types of plant ailments have been identified by the aid of an architecture called CaffeNet CNN and they achieved Classification Accuracy equals 96.30%, which seems to be better than the earlier approaches . Along with this, several filters have been used to mark out the disease spots. to state, In [31] architectures such as AlexNet and GoogLeNet have been used with the publicly available datasets from Plant Village. As part of the performance evaluation, overall accuracy, Precision ,recall and F1score were taken into account.

As a result of the inclusion of three scenarios, including colour, grayscale and segmentation for the evaluation of its performance indicators & for the comparison, this paper is a first in its field. This article concludes proving that GoogLeNet has been outperforming AlexNet. Evidently, the disease spots are depicted by the process of activation of visualisation in the first levels. To detect plant disease in olive trees, a modified version of the model LeNet has been employed [32]. For spotting the diseases in the plants, segmentation and edge maps techniques has been used . For Detecting 4 cucumber plant diseases in article [33] accuracy rate has been compared with the following models RF, SVM, and AlexNet , along with that, the image segmentation technique has been adapted to detect the diseases symptoms in the plants In article [34] DL Model defined as teacher/student network has come out with a proposal of introducing a novel method for visualizing and identifying the diseased spots in plants. Deep Learning models implemented with some detectors was presented in the article [35], in which plant diseases are marked together with its percentage of prediction ,3 detectors, namely FasterRCNN, RFCN & SSD, have been used alongside with the architectures such as "AlexNet, GoogLeNet, VGG, ZFNet, ResNet-50, ResNet-101 and ResNetXt-101" for a comprehensive comparison which showcases the best of all the architectures tested. As a part of the conclusion "ResNet-50 with the detector R-FCN" produced the most optimal result. A type of bounding box has been drawn to find the identity of particular types of disease in the plants.

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3. Deep-Convolutional Neural Network

Deep learning is one among the most prominent neural network ideas. Here the metadata is the input source, the data operations are carried out utilising a variety of non-linear conversion layers, by which the classification output is calculated. As a result, the following section outlines the various operations of the deep learning process.

3.1. Traditional pattern recognition

Previously, the feature extraction method has been implemented by a programmer or an expert. The features are then inputted into a standard neural network, which categorises the input data. Fixed and handcrafted characteristics are present in the traditional pattern. The handcrafted feature extraction technique becomes more complicated, and the torturous steps are eliminated. Figure 1 depicts the recognition of conventional patterns.

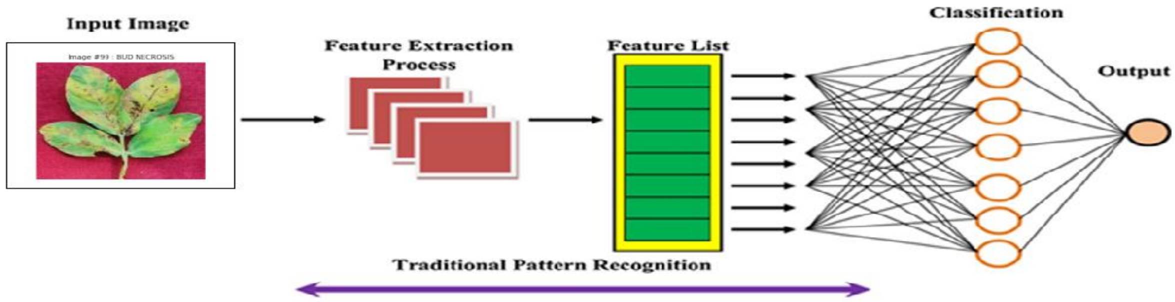

Figure.3

3.2. A layered approach: DL

An important part of deep learning is automatic feature extraction. Fixed or custom features aren't necessary because the problem-solving components are automatically selected for us. Selecting the explicit features is done, and the number of specialised activities is cut back (i.e. traditional pattern recognition). A variety of supervised, semi-supervised, and unsupervised challenges were therefore found. However, a minimum of three concealed layers is required. Nonlinear feature transformation is presented by deep learning [14]. Significatively, the properties of each buried layer are learned using a group of neurons, and the previous layer's output is taken into account when training. The number of hidden layers, as well as the generalisation and complexity of the data, grows as the data becomes more complicated. The trainable classifier with a hidden layer extracted low-, mid-, and high-level features [14]. As shown in Fig. 2, the architecture of deep learning consists of several different aspects.

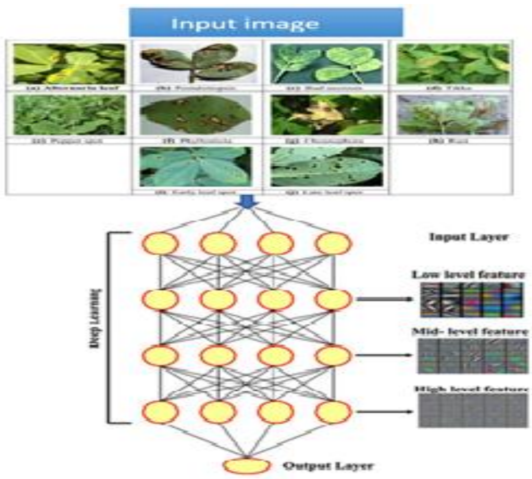

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Figure 4

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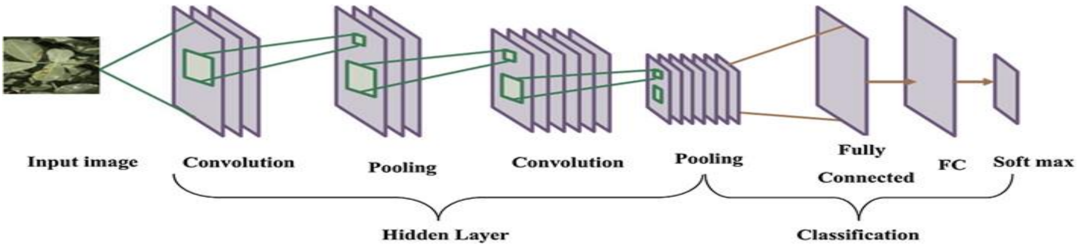
3.3. The DCNN outlook

In common deep learning is categorised into four categories: Boltzmann machines, autosparse, Convolutional neural networks, and Autoencoders [15]. DCNN is used to perform the proposed Groundnut disease classification (DCNN) task. The convolutional neural network performs better in terms of training and testing. The representation is shown in Figure 3 as an architecture.

The training step, which consists of multiple layers, is critical to DCNN's structural design. The network training procedure's forward and backward phases are frequently used. The fundamental Figure 3



purpose of the forward phase is to display the input image of each layer of current factors, such as weight and bias. The low-level features of lines, corners, and edges are extracted using the first layer.

The remaining layers are utilised to detect mid- and high-level features in shapes and objects [14]. The ground truth labels are derived from the prediction output's cost loss, and the chain rules for each parametric gradient are derived from the cost loss with a backward phase. Every parameter is phases of a network learning process were then closed in multiple cycles after that.

3.4. Conceptions from CNN

CNNs have their own vocabulary and concepts, which distinguishes them from other neural network architectures.[16] The following are the most important ones to understand:

3.4.1. Volumes of Input/Exit

With CNNs, image data is frequently utilised. Every image is built on the foundation of a pixel value matrix. The bit size of each pixel dictates the range of values that can be prearranged in it. The most common pixels are eight bit or one byte pixels. As a result, one pixel can signify any number between 0 and 255. The addition of several color channels (3 in the case of RGB photographs) adds a third dimension to the data, making it three-dimensional. As a result, each RGB image of dimension 255x255 (Width x Height) pixels will contain three matrices, one for each color channel. Accordingly, the complete image is a three-dimensional structure known as the input volume (255x255x3).[16]

Figure 5 shows the cross-section of a 4 x 4 x 3 input volume. It is made up of the input image's three colour channel matrices.

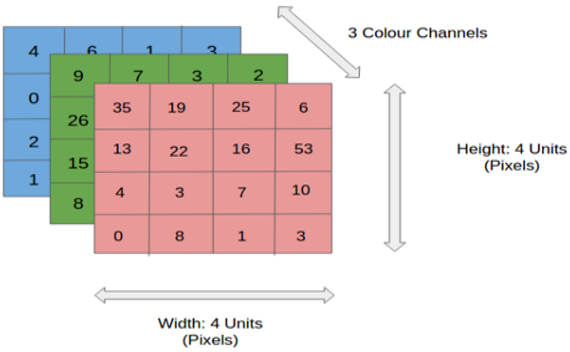


Figure:5

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3.4.2. Features

An observation or pattern that contributes in the desired picture analysis is referred to as a feature, as its literal meaning suggests. CNN learns these properties from the input photos. They normally appear in the data a few times before garnering a lot of traction in the media. To detect leaf disease, the system will look for a detectable variation in the layer of each damaged leaf. This feature can then be processed by the system and detected by the distinct layers. In general object categorization, the edge contours of the objects are employed as characteristics.

3.4.3. Filters (Convolution Kernels)

As part of the layered design, a filter (also known as a kernel) plays a key role. On the whole, it refers to an image-altering algorithm that modifies information represented in pixels. An image kernel in reality, on the other hand, is an array of real-valued components in a smaller matrix relative to the picture's input dimensions

As a result, "activation maps" are created by combining the kernels with the input volume. In other words, activation maps highlight where kernel-specific features detected in the input data. The actual values of the kernel matrix change with each training iteration in the training set, indicating that the network is learning which regions are needed to extract features from the input. [16]

3.4.5. The Receptive Field

In order to bind all neurons to all possible input volume regions, it is impossible. As a result, there would be a large number of weights to train and a high amount of computational complexity involved. It is not necessary to connect each neuron to every potential pixel. Instead, we construct a two-dimensional region dubbed the "receptive field," which extends to all depths of the input (5x5x3 for a three-color channel input) (5x5x3 for a three-color channel input). Network layer cross-sections (each consisting of numerous neurons (called "depth columns")) function and build the activation map over these small regions. [16]

3.4.6. Concept of Zero-Padding

Zero padding refers to the process of evenly padding the input matrix with 0's. You can vary the size of the input to suit your needs with this basic modification. Sometimes it's necessary to keep the input volume's dimension in the output volume when designing CNN layers. [16]. A zero-padded 4 x 4 matrix becomes a 6 x 6 matrix, is shown in the above figure.6

Figure: 6

0	0	0	0	0	0
0	35	19	25	6	0
0	13	22	16	53	0
0	4	3	7	10	0
0	9	8	1	3	0
0	0	0	0	0	0

3.5. Basic composition of CNN Architecture

A CNN's architecture is divided into two parts:

Features are extracted from an image using a convolutional algorithm. Convolution output is used to predict image class based on characteristics obtained in earlier steps. [17].

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The below figure depicts the layers.

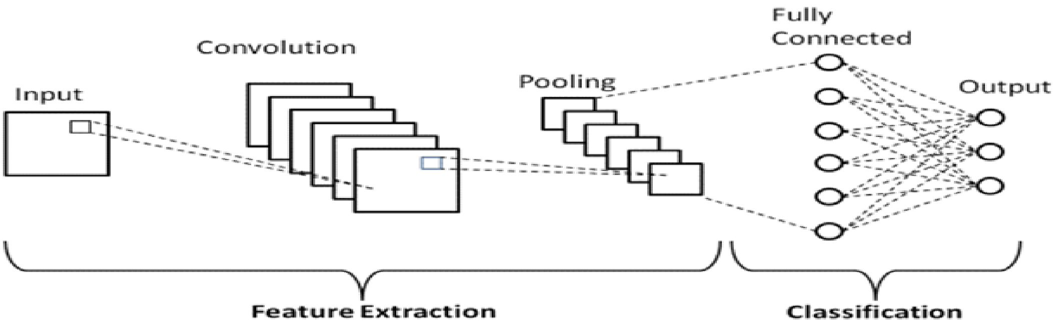

Figure: 7

3.5.1. Concept of Convolution and its Layers

These three categories of layers - convolutional, pooling, and fully connected (FC) - make up the CNN. After stacking these layers, you'll have a CNN architecture in place. In addition to these three classes, there are two other important factors that are dropout class and activation function. [17]

3.5.1.1. The Convolutional Layer

When a picture is scanned, it is the level1 layer which extracts the individual features. A MxM filter of a certain size is used in this layer to perform the mathematical convolution. Dragging a filter over the input image creates a dot product between the filter and its parts corresponding to the size of the filter. (MxM). [17]

An image's corners and edges are recorded in a feature map. As a result of this feature map, other layers can then learn a range of other features from the input image.

3.5.1.2. The Pooling Layer

Next to Convolutional Layer, a Pooling Layer is normally added. In order to reduce computational costs, the primary purpose of this layer is to minimize the size of the convoluted feature map. In order to achieve this, layers are separated and each feature map is operated individually. Pooling processes can in a variety of forms, reliant on the mechanism used.

The largest element in Max Pooling is obtained from the feature map. Average Pooling is used to calculate the average of the elements in a predefined sized Image segment. When using a predetermined segment, Sum Pooling calculates the total sum of the components in that part. This layer acts as a link between the Convolutional Layer and FC layer[17].

3.5.1.3. FC Layer

A fully connected (FC) layer is made up of neurons, as well as weights and biases, and is used to connect neurons between layers. A CNN Architecture's last layers are usually placed before the output layer.

A flattened version of each layer's input image is then sent to the FC layer. then, the flattened vector is passed to a few extra FC layers, for the mathematical functional operations. [17]

3.5.1.4. The Dropout

Overfitting can occur when all attributes are coupled to a single FC layer. Models that perform so well on training data that they have a negative influence on new data suffer from overfitting.

With the dropout layer as a solution, a few neurons are deleted from the neural network while it's being trained. This leads to an even smaller neural network model. 30% of nodes in the neural network are dropped at random after passing a dropout of 0.3. [17]

3.5.1.5. AF and its need

In the CNN paradigm, the activation function is critical. When learning or estimating any continuous or complicated link between variables in a network, they're used. Generally, it determines which model information should be sent forward and which should not at the network's end.

The network becomes non-linear as a result of this. Most commonly used activation functions include "ReLU, Softmax, TanH, and Sigmoid". There is a distinct use for each of these functions Binomial and multi-class CNN models frequently use sigmoid and SoftMax functions. [17]

4. EXPERIMENT METHODOLOGY

Visual Geometry Group (VGG), is a multi-layered deep Convolutional Neural Network (CNN) architecture. The VGG model, also known as VGGNet, supports 16 layers, the optimality of the model can be utilized for the purpose of Groundnut crop leaf disease identification and classification. The robustness of this pretrained Deep Learning model serves well towards the need.The architecture of the Deep CNN_VGG16 is discussed below.

4.1. Architecture of the CNN_VGG16:

The input to the network is a dimensional image (224, 224, 3). The first two layers have 64 channels with the same padding as the 3 * 3 filter size. Next, two layers with a 256 filter size and a filter size (3, 3) convolution layer, after the maximum pool layer for stride (2, 2). This is followed by the same maximum pooling step layer (2, 2) as the previous layer. Then there are two convolution layers with filter sizes (3, 3) and 256 filters. Then there are two sets of three convolutional layers and a maximum pool layer. Each has a 512 size (3, 3) filter with the same padding. This image is then passed to a two-layer convolution stack. For these convolution layers and maximum pooling layers, the filter size used is 3 * 3. Passing out from convolution and maxpooling layers, there is a feature map (7, 7, 512). Flattening this output into a feature vector (1,25088). followed by three fully connected layers. The classification vector is passed to the softmax layer for normalization. After the classification vector is output, the top 6 categories are evaluated. ReLU acts as an activation function for all hidden layers. ReLU is computationally efficient because it speeds up learning and reduces the likelihood of vanishing gradient problems. Figure 8 below shows the general architecture of VGG_16 proposed in this study.

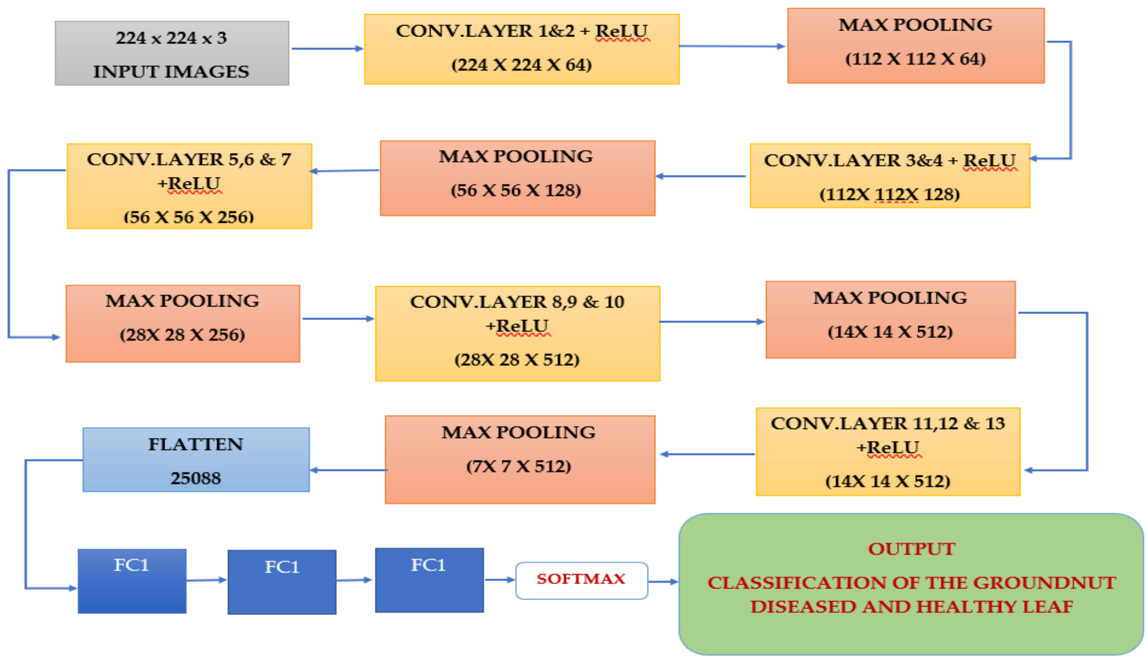

Figure 8: Proposed Architecture of VGG16 for the identification and classification of groundnut leaf diseases

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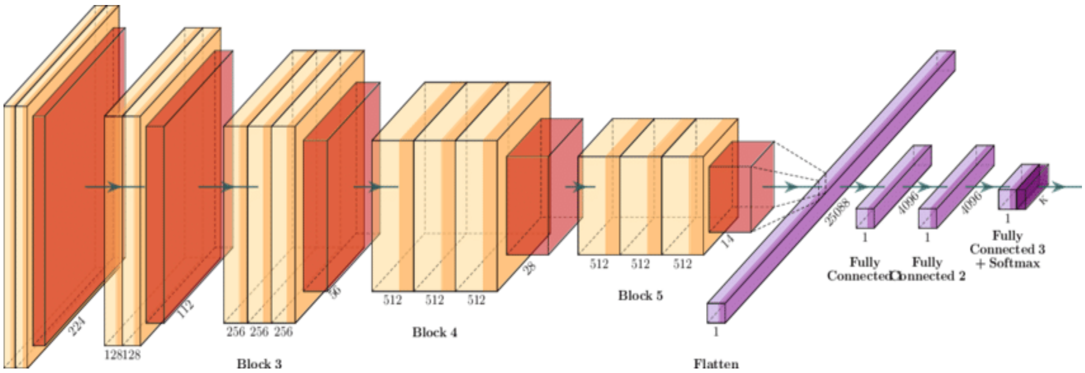


Figure 9:Layered Architecture of the CNN VGG16 Deep Learning Model

The presence of 16 in the name VGG implies to the fact that it is a neural network with 16 layers (VGGNet). This means that VGG16 is a large network with approximately 138 million parameters. Even by modern standards, it is a massive network. The simplicity of the VGGNet16 architecture, on the other hand, is what makes the network appealing. Its architecture, by itself, suggests that it is quite uniform. Following a few convolution layers, there is a pooling layer that reduces the height and width. When it comes to the number of filters that can be used, there are approximately 64 available, which can be doubled to approximately 128 and then to 256 filters. In the final layers, 512 layers are used.

4.1.2.Fine Tuning the Model using Optimizers

While training the deep learning model, we need to change the weight of each epoch to minimize the loss function. An optimizer is a function or algorithm that modifies neural network attributes such as weights and learning rates. As a result, it helps reduce overall loss and improve accuracy. Since deep learning models usually have millions of parameters, choosing the right weights for the model can be a daunting task. It emphasizes the importance of choosing the right optimization algorithm for your application. Therefore, the understanding of these algorithms is necessary before deepening to the field.

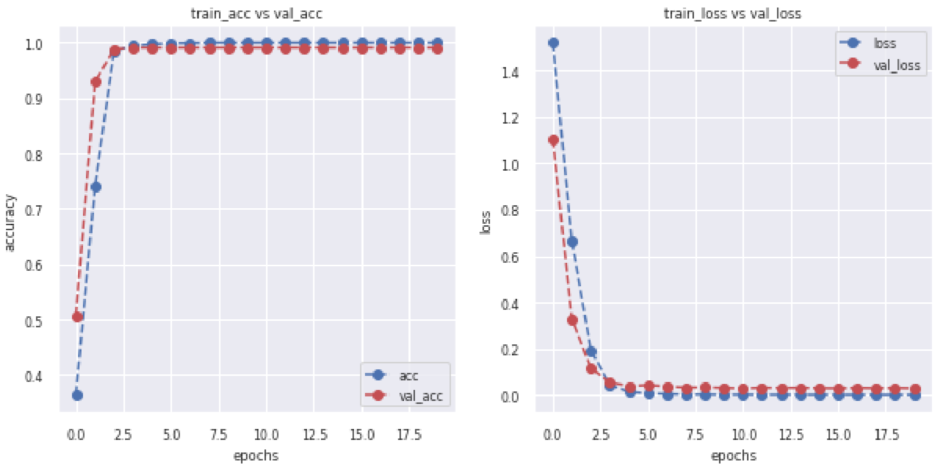
Various optimizers can be used to make changes in the weights and learning rate. However, choosing the best optimizer depends upon the application. The list of optimizers is shown in the below table 1.

SL.NO	**OPTIMIZERS**
i.	“Gradient Descent”-GD
ii.	“Stochastic Gradient Descent”-SGD
iii.	“Stochastic Gradient descent with momentum”-SGDM
iv.	“Mini-Batch Gradient Descent”-MBGD
v.	“Adagrad”-AG
vi.	“RMSProp”-RP
vii.	“AdaDelta”-AD
viii.	“Adam”

TABLE 1

Based on the level of Optimization rendered, we have used two optimizers, i) Adam and ii) RMSprop, towards this investigation and found that the performance optimality of the Adam based model optimization has resulted in reducing the overall loss rate and has produced an improved accuracy rate, when compared with the RMSprop optimization, the below shown figure 10,which depicts the effectiveness of the Adam optimizer.

CNN VGG16_ADAM



CNN_VGG16_RMSPROP

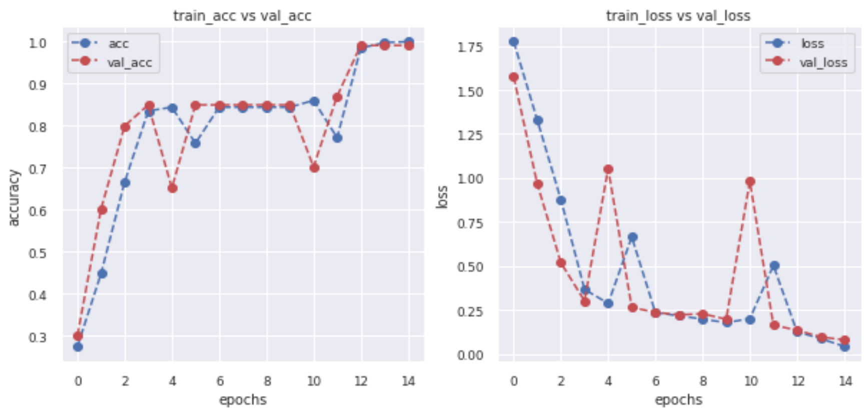


Figure 10: Comparing the performance (Accuracy and Loss) of CNN VGG16_ADAM with CNN_VGG16_RMSPROP

Adaptive moment estimation is the terminology from which "Adam" has been derived from. Further Adam optimization scheme derives to be an extension from SGD "Stochastic gradient descent", which updates weights of the network during the process of training, Rather observing a single learning rate via training in stochastic gradient descent, Adam optimization algorithm performs updation of learning rates for each network and its corresponding weight exclusively.

Adam optimizer Inherits the functionality of "Adagrad and RMSprop" algorithms. Rather adjusting the learning rate based on the first moment (mean) as in the RMSprop, Adam also uses the second moment of the gradient which is adapted as a standard for deep learning papers and recommended as a default optimization scheme. The Adam optimization algorithm implies a upfront approach towards implementation, it delivers faster run time, takes less requirements in terms of memory, and entails less tuning compared with other optimization schemes.

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta w_t}\right]^2 \rightarrow(1)$$

In The above given formula (1) working of Adam optimizer has been depicted, where B1 and B2 are used to signify the deterioration rate of the average of the gradients.

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5. Experiment Results and Discussion

The evaluation of the proposed model adapting CNN_VGG16 using Adam optimization scheme has produced an overall testing accuracy of 99.82%. The groundnut crop leaf image datasets constituting both (diseased and Healthy leaf) are taken from the farmlands of Villupuram districts in the state of Tamilnadu and are used for the process of evaluation, considering the amount of RAM speed required for the deep learning process, we have choosen the open source Google colab platform for the execution of the model for that the code and image datasets are mounted on Google Drive, and the model is evaluated on the Google Colab platform. Turning onto the GPU mode during the execution has lead to the faster training time in terms of execution. In this process of investigation, we have collected and utilized nearly 1945 image dataset which includes various diseased and healthy leaf images. We have used Realme5 AI Quad Camera with Ultra Wide-angle Macro Lens 12MP camera along with Raspberry Pi 4 Model-B camera module for the collection of various groundnut leaf images. The distribution of various diseased and healthy leaf set is shown in the below figure 11.

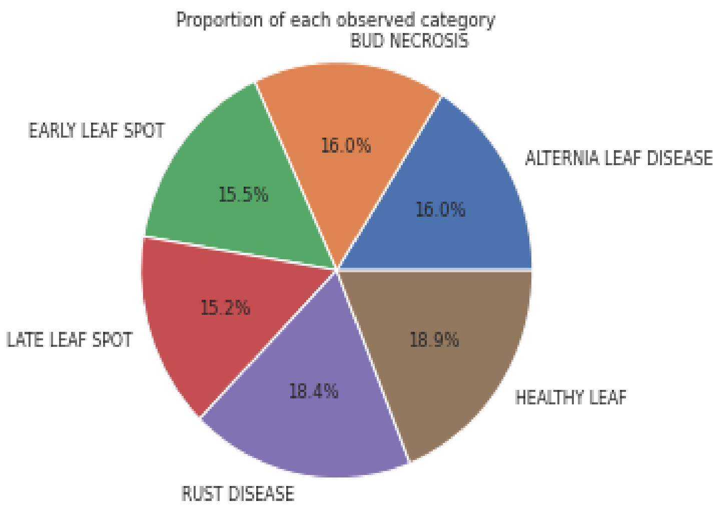

Figure 11: Distribution of the Groundnut Leaf Datasets

Since the distribution of leaf images based on the various diseases obtained varied in the count, we have splitted the image dataset based the distribution of the proportion, as shown in the below figure 12.In general the overall train and test split ratio is 80% and 20% respectively.

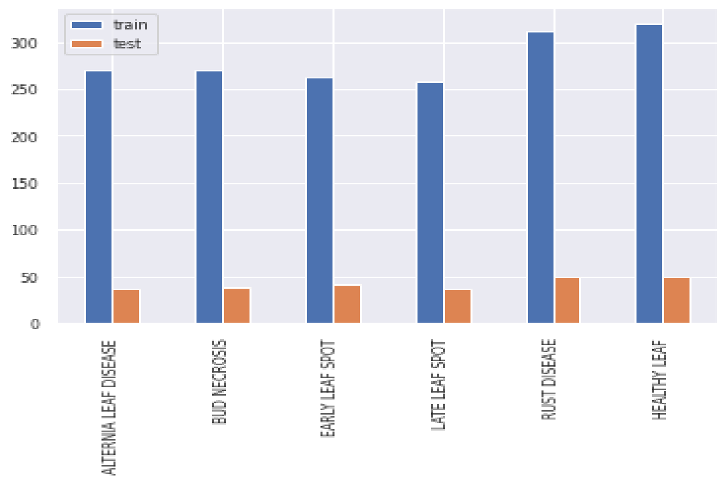

Figure 12: Training and Testing distribution of the Groundnut leaf Datasets

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5.1. Consideration of Performance Measures

The overall performance measure of the proposed CNN_VGG16 Model with Adam optimization in terms of Accuracy, precision, Recall, F1-score, Kappa Score is formulated as shown in Table 2.

Performance Metrics	Description	Investigated CNN_VGG16 Model with Adam optimization value
ACCURACY	$ACCURACY = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$	0.99822
PRECISION	$PRECISION = \frac{T_P}{T_P + F_p}$	0.99811
RECALL	$\mathrm{RECALL} = \frac{\mathrm{TP}}{TP + FN}$	0.99809
F1-SCORE	$1 = 2 * \frac{PRECISION * RECALL}{PRECISION + RECALL}$	0.99816
ROC	ROC (receiver operating characteristic) Curve this curve define the true positive rate vs. false positive rate at different classification thresholds.	0.99786

Table 2

Comparison of the Investigated CNN_VGG16 Model with Adam optimization with Baseline CNN Models (AlexNet, Inception_V3.CNN_VGG16_RMSprop) based on Performance measures, is depicted in the below table 3, the below figure 13 depicts the optimality of the proposed model over other compared CNN models.

	ALEXNET	INCEPTION_V3	CNN_VGG16_RMS PROP	CNN_VGG16_ADAM
ACCURACY	0.94371	0.96721	0.97213	**0.99823**
PRECISION	0.94302	0.96652	0.97072	**0.99814**
F1_SCORE	0.94123	0.96124	0.97349	**0.99812**
RECALL	0.94021	0.96042	0.97154	**0.99809**
ROC	0.93223	0.95321	0.96642	**0.99786**

Table 32

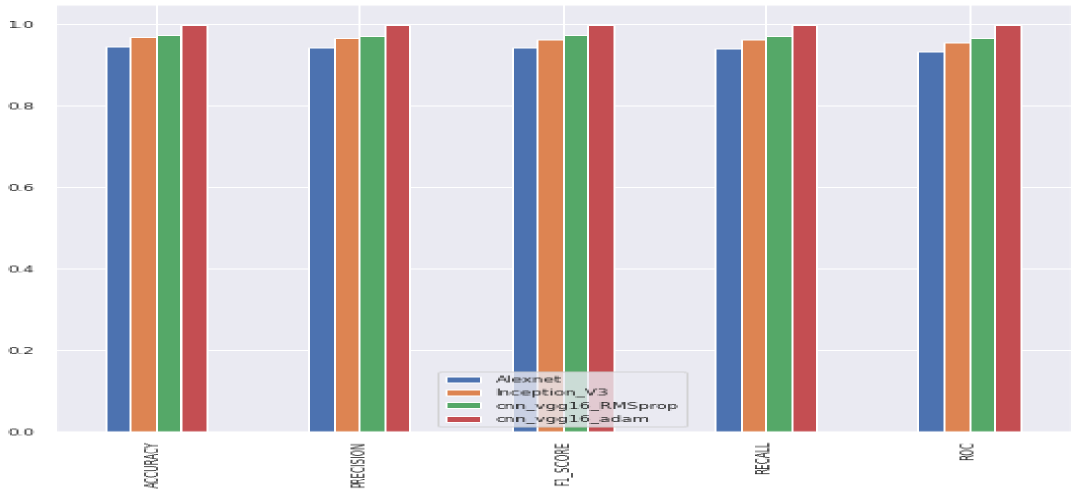

Figure 13

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5.1. Consideration of Corelation and Error Measures

The overall Corelation and Error Measures of the proposed CNN_VGG16 Model with Adam optimization in terms of MSE, RMSE,MAE,KAPPA_SCORE and R² is formulated as shown in the table 4.

Corelation and Error Measures	Description	Investigated CNN_VGG16 Model with Adam optimization value
MSE	$\frac{1}{n}\sum_{k=1}^{n} \lvert y_i - x_i \rvert^2$	0.0010
RMSE	$\sqrt{\frac{1}{n}\sum_{k=1}^{n} \lvert y_i - x_i \rvert^2}$	0.03162
MAE	$\frac{1}{n}\sum_{k=1}^{n} \lvert y_i - x_i \rvert$	0.0326
KAPPA_SCORE	$k = (p_o - p_e) / (1 - p_e)$	0.9786
R^2	$1 - \frac{\sum(yi \cdot \hat{y})^2}{\sum(yi \cdot \widehat{yr})^2}$	0.9828

Table 4

The below shown table 5 depicts the calculated error metrics in comparison with all the three different CNN based Deep learning Models baseline models (AlexNet, Inception_V3.CNN_VGG16_RMSprop) with the CNN_VGG16_Adam optimizer model and the corresponding graphical representation as shown in Figure:14 that depicts the performance of the CNN_VGG16_Adam with a minimal loss in the process of prediction and hence optimality in terms of achieving low error metrics. The calculated Coefficient of Determination (R^2) Value and the Kappa score of the Investigated Model stands way ahead in terms of evaluation with all the baseline models, and thus denotes how well the coefficient fits with the values in the training dataset.

	ALEXNET	INCEPTION_V3	CNN_VGG16_RMSPROP	CNN_VGG16_ADAM
MSE	0.005212	0.002621	0.001953	**0.0010**
RMSE	0.07219	0.05119	0.04419	**0.03162**
MAE	0.0722	0.0512	0.0442	**0.0326**
KAPPA_SCORE	0.8821	0.9227	0.9445	**0.9786**
R^2	0.8921	0.9215	0.9448	**0.9828**

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Table 5

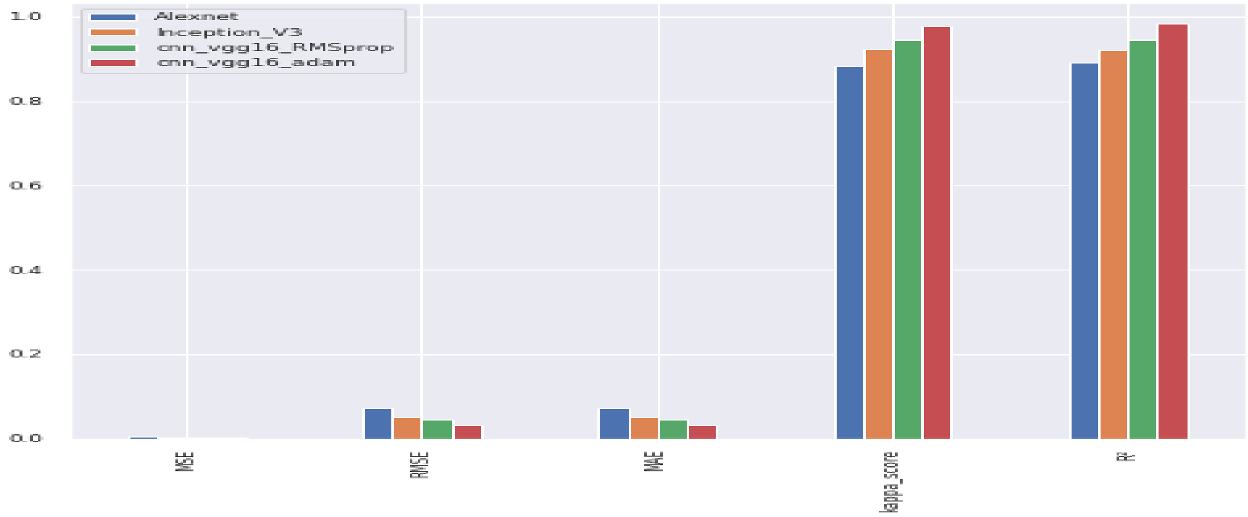
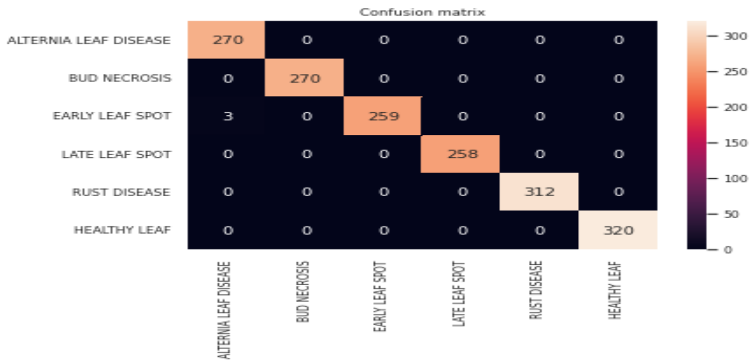
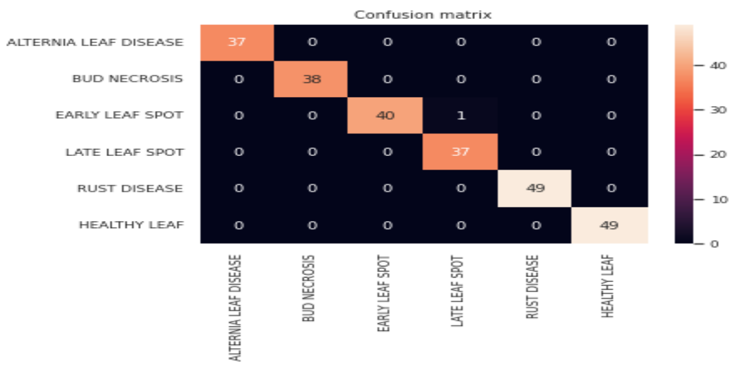


Figure 14

The proposed investigated CNN model VGG16 using Adam optimizer schemes prediction efficiency is tested using the five different groundnut leaf diseases datasets along with a collection of healthy leaf dataset by deriving the confusion matrix figure 15. The computed confusion matrix for the proposed model, has shown evident prediction results by producing most optimal prediction accuracy rates for classifying the five different sets of groundnut leafs ,which includes (Early leaf spot, Late leaf spot, Alternia leaf, Rust Disease and Bud Necrosis) as well as the healthy leaf datasets for both the Training and Testing process.



(a)



(b)

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Figure 15: (a).Derived Confusion Matrix for the Groundnut leaf dataset Trained,(b)Derived Confusion Matric for the Groundnut leaf dataset tested .

6.Conclusions and Future Directions

In this research article a comprehensive investigation on CNN based deep learning approaches towards the identification and classification of the various groundnut crop leaf diseases prevailing in the state of Tamilnadu has been made. Inferring from the related article reviews made from many types of visualization techniques/mappings which have been summarized to recognize various set of plant diseases, we draft to a conclusion that a significant progress was observed during the last half a decade pertaining to disease identification and classification in crops. CNN based deep learning models have been showing significant amount of improvement in terms of the classification and identification of the plant leaf diseases. In this research article we have made a detailed investigation in terms of analysing the performance optimality of the CNN _VGG16 model with the fine tuning of two different optimisers (Adam and RMSprop).The investigation of the proposed CNN_VGG16 model has been carried out separately with the involvement of the two different optimizers(Adam,RMSprop).The result of the investigation made has clearly shown that Adam optimization scheme has shown a more accurate classification output with respect to the trained and tested Groundnut leaf images by producing an overall accuracy rate of 99.8% comparing to the RMSprop optimization fine tuning which resulted only 97.21%.

Apart from optimiser-based investigation, we have also made a comparative analysis of the our proposed investigational CNN based VGG16 + Adam optimization with the few proven optimal CNN models such as AlexNet and Inception_V3 models based on the performance metrics, correlation and Error metrics. The comparative analysis as shown in the tables 2 and 4 also confirmed that overall accuracy rates of the CNN based VGG16 + Adam optimization has shown a clear out peak in terms of all the performance comparison and ensures very less error rates in comparison with all the baseline models.

In this research work, instead of using plant image datasets from Plant Village Dataset, we have collected Groundnut leaf image datasets direct from the farms of Villupuram district (Gingee and Vanur). This investigation of CNN models has lead to a more efficient way of identifying the top five Leaf Diseases which affect the groundnut crops which are being cultivated in the state of Tamilnadu with utmost accuracy rates.

Adapting the prototype of research work that we have carried out towards aiding towards the sustainable cultivation and growth of groundnut crops, similar strategies can also be investigated for various other crops in their earlier identification and classification of diseases. Smart Hand held device based applications aiding for the purpose will better serve the farmers in identifying the crop diseases in its initial stage of its occurrence and to combat it in a more effective manner.

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