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Effective Groundnut Crop Management by Early Prediction of Leaf Diseases through Convolutional Neural Networks

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Abstract: Groundnut (*Arachis hypogaea L.*), is the sixth-most significant leguminous oilseed crop grown all over worldwide. Groundnut, due to its high content of various dietary fibers, is classified as a valuable cash, staple and a feed crop for millions of households around the world. However, due to varied environmental factors, the crop is quite prone to many kinds of diseases, identifiable through its leaves, for which Groundnut producers have to suffer major losses every year. An early detection of such diseases is essential in order to save this significant crop and avoid huge losses. This paper presents a novel Machine Learning based Deep Convolution Neural Network (CNN) model 'CNN8GN'. The model uses transfer learning technique for detection of such diseases in Groundnuts at an early stage of crop production. A Groundnut real image data set containing a total of 5322 real images for six different classes of Groundnut leaf diseases, captured in the fields of Gujarat state (India) during September 2022 to February 2023, is generated for training, testing and evaluation of the proposed model. The proposed deep learning model architecture is designed on eight different layers and can be used on varied sized images using simple ReLu and Softmax activation functions. The performance of the proposed CNN8GN model on Groundnut real image dataset is examined using a detailed experimental analysis with other six pre-trained models: VGG16, InceptionV3, Resnet50, ResNet152V2, VGG19, and MobileNetV2. CNN8GN results are also examined in detail using different sets of input parameters values. The proposed model has shown significant improvements for disease detection in comparative analysis with 99.11% training and 91.25% testing accuracy.

Keywords: CNN Classifier, Deep Neural Network, Image Classification, Machine Learning, Groundnut, Groundnut Diseases Detection.

1. Introduction

Groundnut is one of the most essential oilseed cash crops for millions of small farmers because of its economic and nutritional advantages. Grown over more than 100 countries, the oil seed is feed and fodder for millions of households around the world [1]. However, due to various biotic and abiotic factors the crop of groundnut is prone to varied diseases and damages. While damages based on environmental factors need assessment at policy making and socio-economic levels, the damages due to diseases need advanced tools and techniques during both pre and post production phases. Scientists have used crop simulation methods to assess the yields of Groundnut in 2050 and reported a decrease of nearly 25% as compared to 2010 [2]. The assessment of yields however has not considered technological advancements and its utilization impacts in farming sectors, which has a great potential for early detection of various loss enabling factors, thereby assisting decision making to avoid pre and post production issues at various levels of farming industry [3]. Use of technological and machine learning advancements [4-6] in farming sector has shown positive diversions in improving the yields as well as profits all over the world.

In India, groundnut is a significant oilseed crop that ranks first in terms of acreage and second in terms of production behind soybean [7]. India is the second largest producer of Groundnut in world. In 2020-21, groundnut, an important oilseed crop, contributed around 30% of the nation's total oilseed production [8]. The amount and value of India's exports of vegetable oil and groundnut oil meal from 2017 to 2020 [9] is shown in Figure 1 and 2 which shows state wise land usage for Groundnut production in India during years 2020 to 2022 [10].

The trend shown above in figures indicate that the quantities of groundnut exports have declined in consecutive years in recent times even though areas under the groundnut productions have not declined much. Biotic variables, in particular plant illnesses and diseases, are a significant contributor to reducing the groundnut output in Groundnut crop production in India and many other countries. Groundnut crop is susceptible to a variety of bacterial and fungal diseases like collar rot, rust, stem rot, rosette, bud necrosis, and leaf spot identifiable through its leaves [11]. Use of AI based IT technologies like drones, robots, weather forecasts etc. have been extensively in use in farming sector in recent times [12]. Machine Learning algorithmic techniques are the newest and most promising enabler among these. Harnessing Machine Learning to its fullest in farming sector for early prediction has varied dimensions which are under consideration now a days by policy makers as well as researchers [13]. Machines once trained in a regressive manner provides strong self-learning based algorithmic models for predicting trends with higher accuracy. The models have been utilized extensively in human medical sector, economic sectors and many more. In agriculture sector, however these algorithmic techniques are under research level.

In recent times, plant diseases identification using machine learning based image classification techniques has been evaluated by many researchers. Since the plant diseases are different in different categories of plants, focused datasets of specific plant images are needed with specific training and testing to develop machine learning prediction models. Primarily timely safe-guarding of economically beneficial plants are at higher priority, research have been motivated towards early disease detection in these plants. Some researchers have developed models in fruit-based plant diseases, while others have focused towards developing models for vegetable providing plants. Following Literature review shows presently developed SOTA (State of the Art) ML models in varied economically beneficial plants categories.

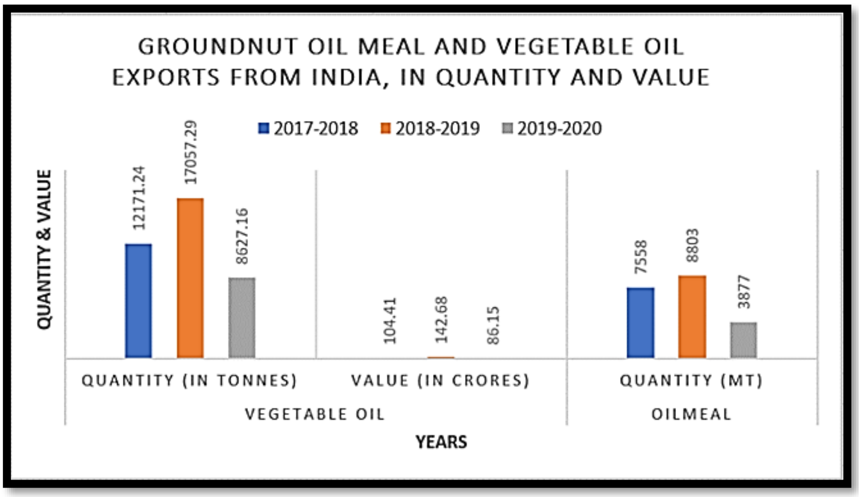

Figure1. Groundnut Oil and Vegetable Oil export from India

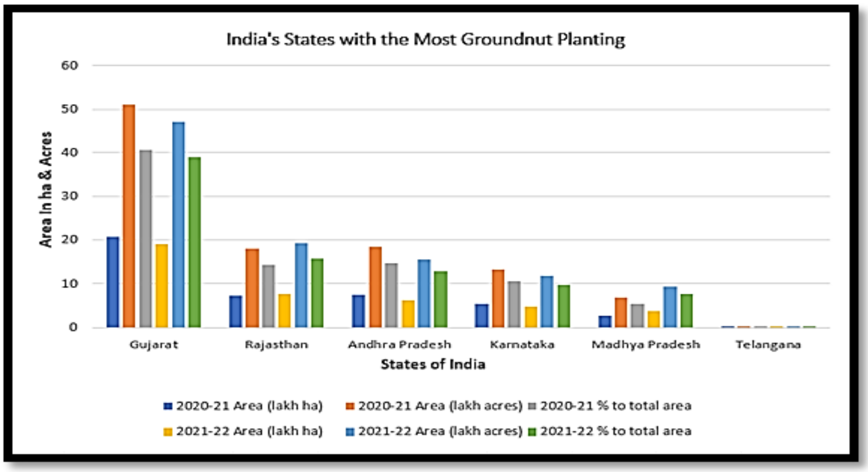

Figure 2. Indian State-specific planting of Groundnuts

Fruit and Vegetable producing plants disease classification models: A CNN model was developed to classify diseases that affect *mango* leaves [14]. Real-time datasets for multilayer convolutional neural networks are offered by the author in this research. 1070 photos in all were utilized in this paper. The proposed work's higher performance is supported by its accuracy of 97.13 percent. There are total of four classes in this article: healthy mango leaves, unhealthy mango leaves, healthy other plant leaves, and other plant leaves (with disease). The use of *sea cucumber* for behavior trajectory analysis and detection is discussed by Li et.al. [15]. Faster R-CNN algorithms are employed in this paper for analysis and detection. 3810 total real-world field pictures were used in this work. Processing was done for this paper using MATLAB and the TensorFlow framework. Faster R-CNN provided an accuracy of 93.88% in this article. Ai, Y. *et. al.* [16] proposed a solution for detecting crop diseases for apple, cherry, tomato, and corn leaves. The author used a total of 47363 images for this paper. Inception and the ResnetV2 algorithm were used in this study. This algorithm had an accuracy rate of 86.1%. Jiang, D *et. al.* proposed leaf disease classification model for *tomatoes*. In this paper, Resnet50 algorithm was used. In this paper total of 6749 images were collected from AI challenger [17].

The proposed research paper used Tensorflow to build the model for disease classification. The proposed model provided an accuracy of 98.03%. Other researchers, Meeradevi et al. applied Deep convolutional neural networks to identify leaf diseases in tomatoes [18]. Militante, S. V *et al.* [19] applied deep learning for identification of *sugarcane* diseases. The comparative evaluation of deep learning to find diseases on potato leaves was covered in the proposed research article by researchers as mentioned in the report by North Eastern Hill University. Department of Biomedical Engineering *et al.,* n.d. [20]. In this paper self-Build, CNN, and MobileNet algorithms were used. For this algorithm total of 2152 images were collected the from plant village dataset. self-Build CNN and MobileNet algorithm used TensorFlow, Keras, and Python library. The self-Build CNN and MobileNet algorithms provided an accuracy of 99.71% and 98.75%. In another paper, a transfer learning system was used to detect plant diseases [21]. A total of 70295 images of various crops, including apple, tomato, soybean, corn, grape, cherry, orange, and potato, were used for this study. The images come from a GitHub source. The experiment was done using VGG16, VGG19, AlexNet, ResNet50, and CNN. Various parameters, including batch size, steps per epoch, total number of epochs, validation steps, optimizer, learning rate, and momentum, were used to create the model in this study. In some other, researchers have applied CNN on various leaves data set such as citrus leaves, apple leaves, and cotton leaves for varied disease identifications studies [22-24]. A tomato leaf disease detection was discussed using transfer learning-based system in the research conducted by Bir, Kumar, & Singh [25]. A total of 18160 images from the plant village collection were used in this article. For this paper diseases detection of tomato leaves using different algorithms like CNN, MobileNetV2, EfficientNet, and VGG19. For this paper, TensorFlow and Keras frameworks were used for the proposed model and provided an accuracy of 83.46%. Oraño, J. F. V [26], used convolutional neural networks to classify jackfruit damage. In this paper for the classification of jackfruit leaves diseases, a total of 2409 images were collected from real fields. In this paper CNN algorithms were used and provided an accuracy of 97.93% using TensorFlow and Keras framework. The overall data in this study were separated into five categories, including "healthy," "fruit borer," "fruit fly," "Rhizopus fruit rot," and "sclerotium fruit rot".

Tea Leaves Diseases Classification models: Latha *et al.* [27] used convolutional neural networks to detect diseases in *tea leaves*. In this paper, total of 2341 images were used from different data sources like ImageNet, Plant Village CIFAR-I, and Real Field. For this paper, the CNN algorithm was used with TensorFlow and Keras and an accuracy of 95.93% was reported. Other researchers [28], also tested CNN on tea leaves and reported good prediction accuracies.

Grain Plants Diseases Classification Models: In the research work conducted by Haider *et al*. [29], wheat leaves were used to identify diseases using a deep learning model. 2100 images in total were used in this paper and came from online sources. For this paper, CNN was used with python, HTML, CSS, NoSQL for database, anaconda, and TensorFlow.

Below Table 1 showing the accuracy of different algorithm for above mentioned research work.

The above presented literature review suggests application of deep learning for detection of diseases on some of the plants where image data set was either available or specially generated using image capturing soft wares or techniques. Since groundnut being an important food and feeder crop, and grown in more than 100 countries, its disease classification using ML techniques needs to be assessed. With no dataset availability, till now this has not been scrutinized using deep learning. This paper therefore presents a complete framework of deep based learning model for groundnut leaves diseases classification by creating a dataset of over 5000 images of groundnut leaves from the real fields. The model presented is executed with comparatively a smaller number of layers and simpler activation function as compared to already applied CNN neural network learning on farming-based data set. The model also is adaptable to different sizes of images making it flexible and robust. Next section presents the details of developed and tested model.

Table 1. Summary of Significant prior research in Plant Disease prediction with reported prediction accuracies for various crops

Citation of Paper	Crop Name	No of Images	Algorithms used	Accuracy
Li *et al.* [15]	Sea Cucumbers	3810	Faster R-CNN	93.88%
Ai *et al.* [16]	Potato, Apple, Puccinia Polysra, Cherry, Tomato, Corn	47363	Inception-ResnetV2	86.1%
Jiang, D *et al*. [17]	Tomato	6794	ResNet50	98.03%
Meeradevi *et al*.[18]	Tomato	6341	VGG16	95.90%
Militante, S. V *et al.* [19]	Sugarcane	13842	CNN	95%
North Eastern Hill University. Department of Biomedical Engineering *et al*., n.d.[20]	Potato	2152	Self-Build CNN and MobileNet	99.71%, 98.75%
Khulna University of Engineering & Technology et al., n.d. [21]	Apple, Cherry, Corn, Grape, Orange, Potato, Soyabean, Tomato	70295	CNN, VGG16, VGG19, AlexNet, Resnet50	99.80%
Bir, Kumar & Singh [25]	Tomato	18160	CNN, MobilenetV2, EfficientNet, VGG19	83.46%
Oraño,J.F.V [26]	Jackfruit	2409	CNN	97.93%
Bhowmik *et al.* [28]	Tea Leaves	2341	CNN	95.93%
Haider *et al.* [29]	Wheat	2100	CNN	98%

Neural networks in machine learning are robust algorithms that uses human brain-based learning techniques for predictions, with deep neural networks provide architectural support to handle highly complex problem domain learning and solution evolution. Deep neural networks such as Convolution Neural Network (CNN) are highly efficient to handling training and solutions predictions based on visual images. Deep CNN however always struggle with availability of image data sets, training and testing and hence are not been harnessed to their full level in many areas including Groundnut farming. This paper is a proposes a novel deep convolution neural network-based model 'CNN8GN' for Groundnut leaves disease identification at an early stage of farming and reduce losses to farmers. The model is trained on real life Groundnut leaves dataset that is created using real life images to train the model. The dataset was created by capturing real life images of groundnut leaves from the field of Gujrat during late 2022 and early 2023 with due permissions from the local farmers. The dataset contains 5322 real life images for six different classes of Groundnut Leaves belonging to healthy as well as diseased categories. The visible groundnut leaves diseases belong to five main categories; hence the dataset's images were captured with a focus on these five categories of diseases only. The images are captured in Gujarat state of India from September 2022 to February 2023. Gujarat is a pioneer state in India to cultivate Groundnut.

The main contributions of the paper are as follows:

- A novel Deep Convolution Neural Network based Predictive machine learning classification model 'CNN8GN' for prediction of groundnut leaves diseases.
- A real life novel classified data set of 5322 images of real Groundnut Leaves classified into 6 different classes including healthy as well as diseased leaves classes.
- Detailed experimental analysis for different parameter settings of learning rate, epochs as well as with the results of other CNN models.

2. Materials and Method

2.1 Collection and Creation of Datasets

For conducting the research, a dataset of 5322

Images consisting of healthy groundnut leaves images as well as images of 5 different groundnut leaf diseases. This dataset was created by capturing real field images using a smartphone (Mi 6A with a 5.0-megapixel camera) during September 2022 to February 2023 at Shelavadar, Gujarat (India) with due permissions from the field owners and farmers. As the visible leaf diseases in Groundnut during the time of capturing images in Gujrat fall primarily in five categories named Alternaria leaves diseases, Early Leaf spot diseases, Late Leaf spot, Rust leaves and Late Rust leaves [30], therefore our focus was to capture images in these five diseased categories. All of the images were taken in different weather situations in agricultural fields. The dataset images collected were primarily segregated into 6 classes named Groundnut_Healthy_Leaf, Groundnut_Alternaria_Leaf, Groundnut_Early_leaf_Spot, Groundnut_late_leaf_spot, Groundnut_rust_and_late_leaf_spot, and Groundnut_rust_leaf_spot. Sample images for all the six classes are shown in Figure. 3.

Table 2 shows the number of images captured for each class.

2.2. Description of Groundnut Diseases Classes used in Dataset

The dataset consists of images of healthy leaves as well as images belonging to five diseased classes. The five diseased classes are quite commonly observed in Gujrat area, hence we focused on collecting images of these five diseased leaves. Healthy Groundnut leaves are spotless and shiny bright. Five diseased classes and their identification criteria [30] are described as below.

1) Early leaf spot: The early leaf spot disease is seen to arise after around a month of sowing. Initially tiny near to circular chlorotic marks develop on upper surface of leaf. The spots are seen to develop brownish color with a yellow boarder around. Sternly infected leaves are likely to shed prematurely. Lesions may also develop which may extend to the stem and branches.

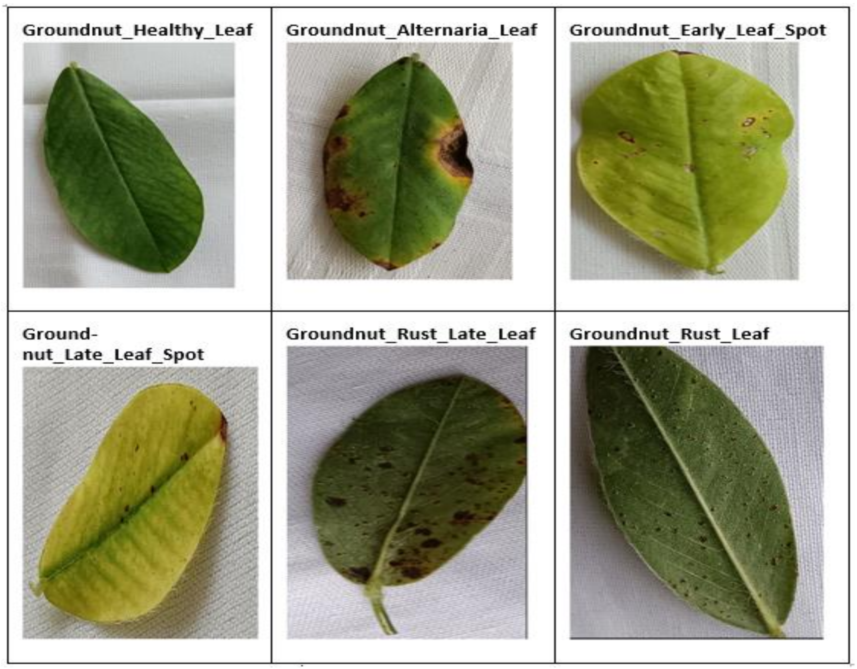

Figure 3. Six Classes of Ground Image Data set

Table 2. Groundnut dataset classes with image counts in each class

Class	Total Sample
Groundnut_Healthy_Leaf	1600
Groundnut_Alternaria_Leaf	870
Groundnut_Early_Leaf_Spot	632
Groundnut_Late_Leaf_Spot	670
Groundnut_Rust_Late_Leaf	565
Groundnut_Rust_Leaf	985
Total Number of Images	5322

2) Late leaf spot: Late Leaf spot disease signs are normally observed around two months later than the sowing period and remain till the time of harvesting. The lesions appear to be around 1-6mm in diameter, approximately circular dark brownish shade on the lower surface of leaves. It is also observed that the lesions may extend up to stem and branches and make leaves drop off prematurely.
3) Rust and Late Rust: Rust disease may be early or may be late. It is observed to have chlorotic spots in the starting phases which arise on the upper surface of the leaf. The lower surfaces of the infected leaves also show orange colored eruptions. The eruptions generally have diameter sizes in the range 0.5 to 1.4 mm. severely infected leaves in late rust wither or dehydrate while remaining attached to the main plant. The fruit and seeds formed in the infected plants are mostly dried and small in sizes.
4) Alternaria: The disease can be identified by having disfiguring of the apical portions of leaflets, somewhat light to dark brown in color. In the later stages of alternaria, disfigured leaves tend to curl inward and become hard. Close lesions generally tend to coalesce and make leaves appear as shabby and destroyed. Primarily the disease is observed to develop quite fast on the upper portion of the canopy as compared to on the lower portion. It appears that leaves have wounds which are water soaked, enlarged and irregular with center portion as pale and dry.

2.2 Deep CNN Models for Comparison

In this work, the VGG16, InceptionV3, VGG19, ResNet50, MobilenetV2, and ResNet152V2 pre-trained deep CNN models were examined and a detailed comparative analysis with proposed model is performed. Convolutional neural networks are a type of deep learning approach used for difficult pattern recognition and classification issues with large databases. The four primary layers of the model are convolution, max pooling, fully connected, and output, and they are constructed one on top of the other. Additional CNN models are available in addition to GoogleNet, VGG, AlexNet, and ResNet. These models range in depth, nonlinear function setup, and unit count. In complex processing, to address classification and pattern recognition challenges, two variables that can be modified are the dropout rate and learning rate. The design of above-mentioned Deep CNN models used for comparative analysis is discussed below.

2.2.1. VGG16

VGG16 is a 16 layers CNN including convolutional and fully linked layers. The key feature of VGG16 is its uniformity in design, with small 3x3 convolutional filters and max pooling layers used throughout the network. In VGG16, each convolutional layer uses a 3x3 filter with a stride of 1 and a padding of 1 to preserve spatial dimensions. A deeper architecture can be achieved while retaining a tolerable number of parameters by using smaller filters. The 2x2 window and a stride of 2 in the max pooling layers help to reduce spatial dimensions and capture invariant characteristics in this model.

2.2.2. VGG19

VGG19 was developed by the Visual Geometry Group at the University of Oxford. VGG19 is a CNN with 19 layers, an expansion of the VGG16 architecture. It starts with a set of convolutional layers, then moves on to layers with maximum pooling for down sampling, and finally layers with fully linked layers for classification. VGG19 has a fixed-size input of 224x224 RGB images.

2.2.3. MobilenetV2

MobileNetV2 is a convolutional neural network (CNN) architecture designed for efficient and lightweight image recognition on mobile and embedded devices. It is an evolution of the original MobileNet architecture, aiming to improve model accuracy while maintaining computational efficiency and small model size. MobileNetV2 utilizes depthwise separable convolutions as its fundamental building block. MobileNetV2 models are often used for transfer learning, where the model is fine-tuned on specific tasks with limited training data.

2.2.4. InceptionV3

InceptionV3 is a convolutional neural network (CNN) architecture that was developed by Google. One key feature of InceptionV3 is the use of "Inception modules" that employ multiple filter sizes (1x1, 3x3, 5x5) within the same layer. This allows the network to capture information at different levels of abstraction and spatial resolutions.

2.2.5. ResNet50

ResNet50 refers to a variant of the ResNet (Residual Network) architecture that consists of 50 layers. Unlike earlier network architectures that struggled with the vanishing gradient problem when increasing depth, ResNet introduces residual connections or skip connections.

2.2.6. ResNet152V2

ResNet152V2 refers to a specific variant of the ResNet (Residual Network) architecture that utilizes 152 layers. These models typically aim to enhance the model's performance, training efficiency, and generalization capabilities as compared to earlier RestNet CNN models. Below Table 3 summarizes the mentioned CNN model parameters with input shapes of images.

2.3 Proposed CNN Model Architecture – CNN8GN

CNN models are machine learning models that are based on neural network training and testing phases. Since CNN dataset are images of large sizes, various intermediary layers are included to extract significant information and reduce the sizes of input images in a defined manner. Some filters related to resizing and reshaping along with feature extraction are important steps in any CNN model. However, the number of layers and activation functions along with learning rates may vary. Following Figure. 4 depicts a block diagram for the functionality of our proposed model called CNN8GN model for Groundnut disease classification.

During the training phase the image preprocessing is executed using initial Layers of our CNN and reduced data sets features are extracted for learning models' parameters to classify images into 6 classes. 80% of data set images are used in training phase, once the parameters are learned and model function is generated, testing and validation phases with remaining 20% images are done to assess the validity of learned variables of CNN8GN model. The proposed Deep CNN model's architecture as CNN8GN model is primarily 8 layers based. The block diagram showing all layers of CNN8GN is sown in Figure 5 below.

Table 3. Information About the Parameters of the existing CNN Model

Architecture	Input Shape	Parameters		
		Trainable	Non-trainable	Total
VGG16	224×224×3	150,534	14,714,688	14,865,222
VGG19	224×224×3	150,534	20,024,384	20,174,918
MobileNetV2	224×224×3	376,326	2,257,984	2,634,310
InceptionV3	224×224×3	307,206	21,802,784	22,109,990
ResNet50	224×224×3	602,118	23,587,712	24,189,830
ResNet152_v2	224×224×3	602,118	58,331,648	58,933,766

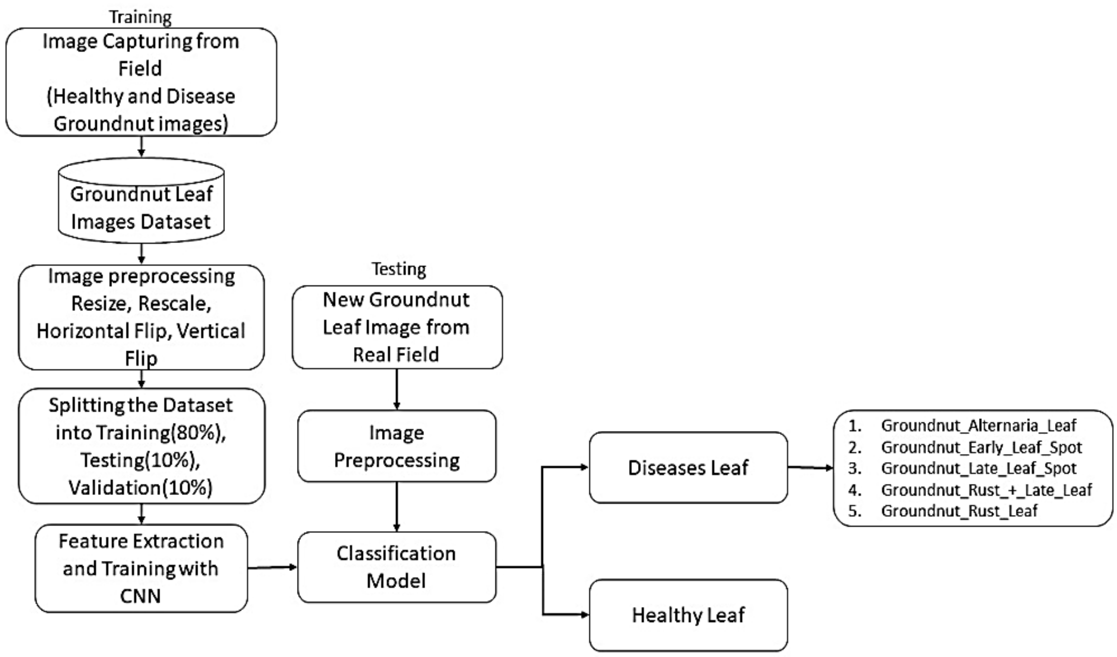

Figure 4. Block diagram for Groundnut leaf disease classification using CNN8GN

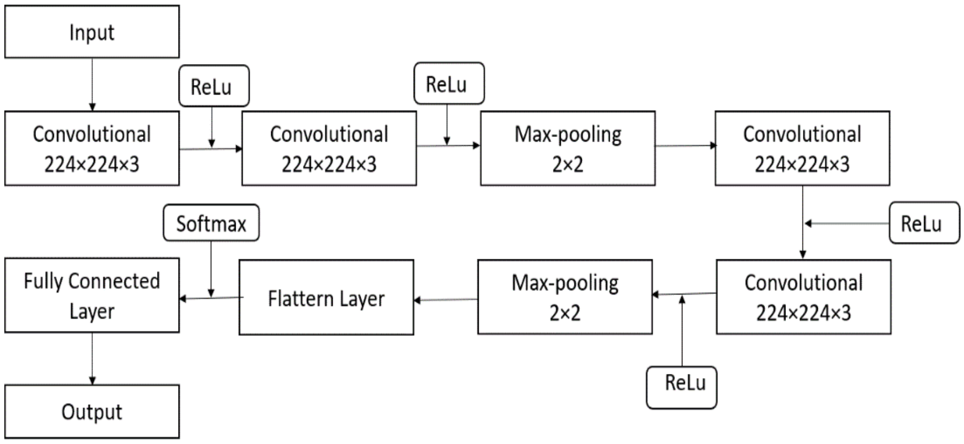

Figure 5. Details of all Layers in CNN8GN's Architecture

Table 4. The suggested CNN's various settings and configuration information is provided

Parameter Name	Value
Optimization	Adam, Adamax, AdaDelta, RMSprop, SGD, AdaGrad, Nadam
Epochs	10,15,20,25
Batch Size	10,16
Learning Rate	0.01, 0.001
Execution Environment	GPU Google Collaboratory
Verbose	2
Activation Function	SoftMax
Image size	150×150×3, 195×195×3, 224×224×3, 255×255×3

The model includes following layers: A final output layer with a SoftMax activation function; Two max-pooling layers; Four convolutional layers; Two dense or completely linked layers. Following each of these layers is a corrected liner unit (ReLu). To increase speed and facilitate data management, the images are flattened into a one-dimensional array using a hidden layer. Each convolutional layer is 3 by 3 in size, and each max-pooling layer is 2 by 2 in size. Configuration information used for execution of CNN8GN is provided in Table 4.

3. Results and Discussion

3.1 Experimental Environment

This paper compares six existing CNN modelss with the proposed CNN model CNN8GN using the Keras and Tensor Flow frameworks. Table lists the hardware setup and related operating environment used for implementation and comparative analysis.

Table 5. Hardware set up used for the CNN8GN model Building

Hardware Configuration	Type
CPU	Intel Core i3 7^{th} generation
RAM	4.00 GB
GPU	NVIDIA-SMI 460.32.03
Tensor Flow Version	2.9.2
Operating System Version	Windows 64-bit operating system

3.2 Result obtained

The complete dataset of Groundnut images is initially divided into a training dataset and a testing dataset with about 80% of the images are in the training set, while only 20% are in the testing set. The training and testing sets are randomly selected from the dataset to achieve this. Applications of neural networks frequently use this ratio distribution. To train the CNN, a total of 4257 images were used, and 1065 images were retained to assess the model's performance. Table 6 shows the distribution of various classes of images in training and testing sets. The distribution is as such that the testing set contains representative images from all classes.

A CNN is trained by making a prediction and assessing the results or errors while delivering training samples from the input layer to hidden layers and the output layer. Then, a proposed classification model based on many layers of convolutional neural networks is constructed to recognize and categorize groundnut leaves. Each image from the normalized training dataset is fed into the multilayer convolutional neural network model to retrieve the features. For each training image, this model forecasts the class label. Below Table 7 comparing the accuracy and loss of existing models on our Groundnut dataset.

Figure. 6-11 show the obtained accuracy and loss results in graphs Table 6 for VGG16, Table 7 for VGG19, Table 8 for MobilenetV2, Table 9 for InceptionV3, Table 10 for Resnet50 and Table 11 Resnet152v2 demonstrates the accuracies and loss obtained on existing Deep CNN for Groundnut dataset.

Table 6. Class wise images used for training and testing of CNN8GN model

Different Disease Class	Number of Images		Total
	Training	Testing	
Gorundnut_Healthy_Leaf	1280	320	1600
Groundnut_Alternaria_Leaf	696	174	870
Groundnut_Early_Leaf_Spot	505	127	632
Groundnut_Late_Leaf_Spot	536	134	670
Groundnut_Rust_Late_Leaf	452	113	565
Groundnut_Rust_Leaf	788	197	985
Total Numbers of Images	4257	1065	5322

Table 7. Deep CNN pre-trained models result on Groundnut Dataset

Model	Epochs	Training		Testing	
		Accuracy	Loss	Accuracy	Loss
VGG16	20	0.91	0.21	0.49	2.10
VGG19	20	0.89	0.26	0.42	2.35
MobileNetV2	20	0.87	1.99	0.49	15.52
InceptionV3	20	0.55	1.03	0.17	35.61
ResNet50	20	0.50	1.76	0.52	3.78
ResNet152_v2	20	0.52	1.37	0.08	53.18

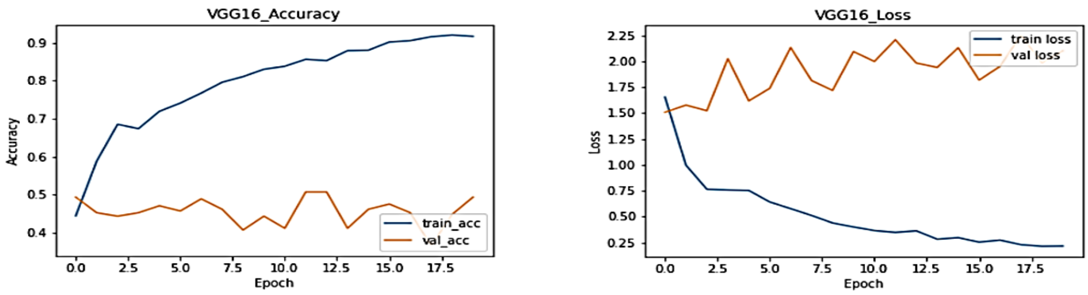

Figure 6. Accuracy and Loss of VGG16 Model

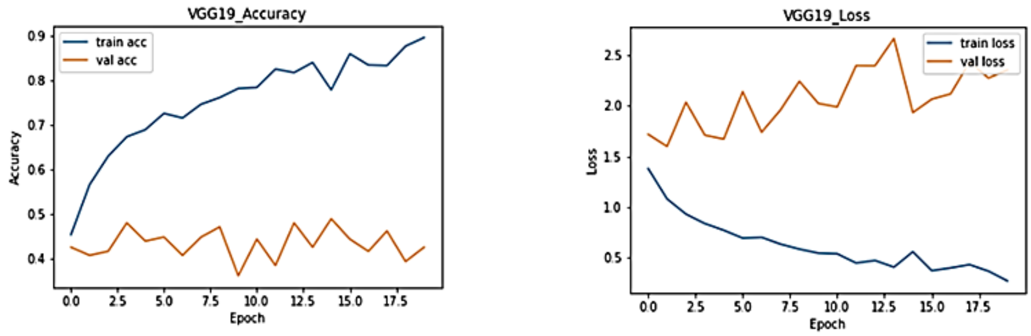

Figure 7. Accuracy and Loss of VGG19 Model

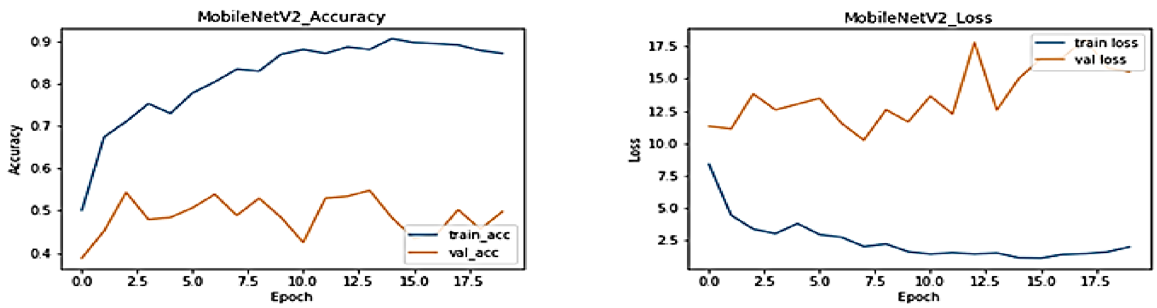

Figure 8. Accuracy and Loss of MobilenetV2 Model

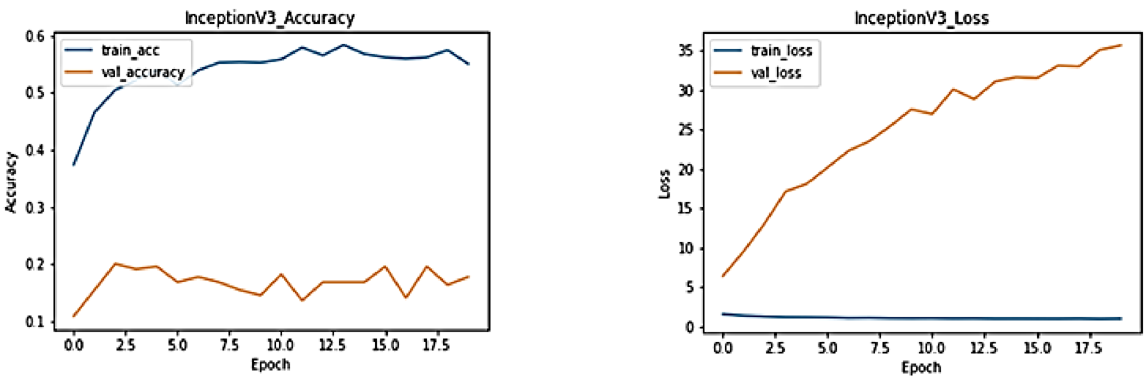

Figure 9. Accuracy and Loss of Inception V3 Model

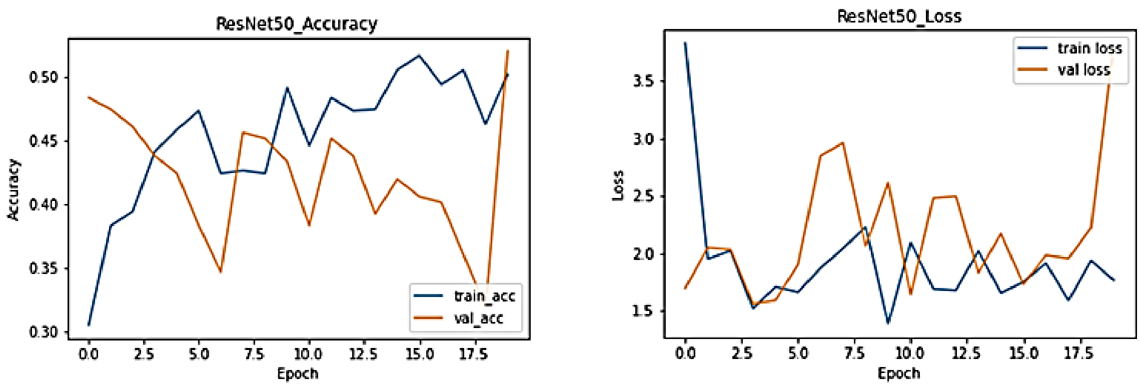

Figure 10. Accuracy and Loss for ResNet50 Model

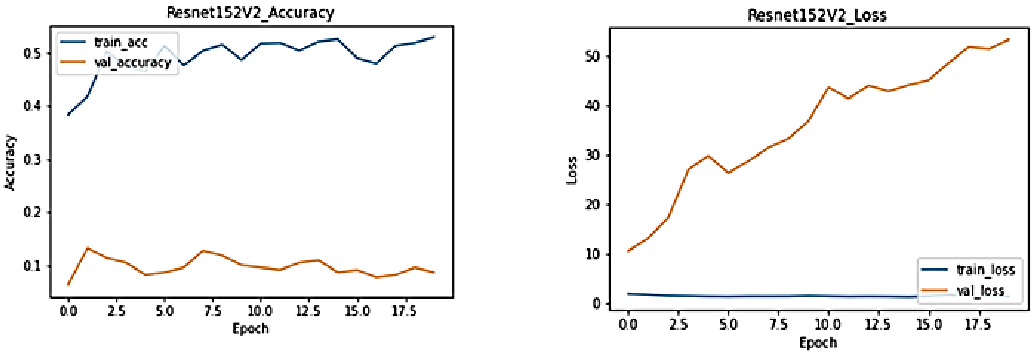

Figure 11. Accuracy and Loss for ResNet152V2 Model

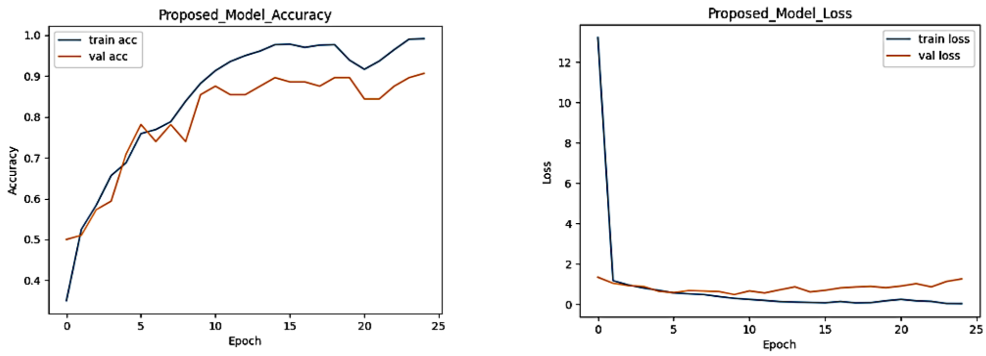

Figure 12. Accuracy and Loss for CNN8GN Model

Table 8. CNN8GN model's accuracy and losses with the change in Image sizes

Image Size	**Epochs**	**Training**		**Validation**	
		Accuracy	**Loss**	**Accuracy**	**Loss**
150×150	20	0.98	0.07	0.91	0.47
195×195	20	0.91	0.30	0.80	1.03
224×224	20	0.99	0.03	0.91	0.98
255×255	20	1.00	1.74	0.92	0.60

Table 9. Hyperparameter tuning on CNN8GN Model's Performance

Epochs	Batch Size	**Learning Rate**	**Accuracy**	**Loss**
10	10	0.001	0.8455	0.6311
15	10	0.001	0.9890	0.1241
20	10	0.001	0.9581	0.0449
25	**10**	**0.001**	**0.9989**	**0.0088**
10	16	0.01	0.3627	1.6655
15	16	0.01	0.3627	1.6655
20	16	0.01	0.3627	1.6655
25	16	0.01	0.3627	1.6655
10	32	0.001	0.6641	0.7486
15	32	0.001	0.6708	0.7947
20	32	0.001	0.9062	0.2608
25	**32**	**0.001**	**0.9911**	**0.0302**

Table 10. Analysis of Training, Validation and Testing Performance CNN8GN Model using best tuned hy-perparameters

	Parameters	**Suggested CNN Model**
Training	Accuracy	0.9911
	Loss	0.0302
Validation	Accuracy	0.9062
	Loss	1.2552
Testing	Accuracy	0.9125
	Loss	0.9855
	Training_Time	7s 135ms/step
	Testing_Time	57s 42ms/step

The proposed CNN8GN model using the Python programming language and the Tensor Flow open-source software framework, a training, testing, and validation procedure was created. The figure depicts the proposed model CNN8GN accuracy and loss of results. **Error! Reference source not found.** displays the proposed model's CNN8GN accuracy and loss. The model efficacy is better than existing models' performances as shown in above figures.

Efficacy of proposed CNN8GN model is also evaluated using different image sizes. Table 8 further lists experiment result of proposed CNN8GN model with various image sizes using 20 epochs in the proposed model.

150×150 image size is useful for some jobs when fine-grained details are not essential or when memory or processing resources are limited. It is comparatively modest. 195×195 image size is little bit larger than the previous size, this image dimension offers a little bit more detail and can be suitable for applications that call for a moderate amount of visual information. 224×224, is frequently employed in deep learning frameworks, including the well-known convolutional neural network (CNN) models VGG16 and ResNet. It finds a balance between computing effectiveness and getting all the necessary visual elements. When working with certain datasets that require greater image resolutions or when finer details are necessary, this size might be employed.

Table 9 shows the experimental results of accuracy and loss for our proposed model CNN8GN with different parameters values such as epochs, batch size, learning rate. It is evident that CNN8GN performance was efficient with 0.001 learning rate with epochs 25 size for both batch sizes 10 and 32. These are therefore suggested parameter settings for proposed CNN8GN model.

Table 10 summarizes the best accuracy and loss metric values of CNN8GN on training, testing and validation data using best suggested parameters of Table 9 above, which show visible improvement as compared to existing CNN models.

4. Conclusion

The research proposed an image-based classification model using Deep CNN called CNN8GN for classifying Groundnut leaf disease using transfer learning. A dataset of 5322 real groundnut images were generated for the purposes. For this work different convolutional neural network models like MobileNetV2, VGG16, ResNet152V2, ResNet50 and InceptionV3 are also evaluated for comparative analysis. The proposed model is 8 layers based which makes it simple and faster as compared to existing models. A detailed experimental analysis establishes the efficacy of the proposed model. Our findings demonstrate that the proposed CNN8GN model has comparatively higher level of training accuracy, validation accuracy, and testing accuracy with respective values of 99.11%, 90.62%, and 91.25% in comparison to various other CNN based models. The model is also tested using different size of images and effective results were generated. The categorization of groundnut leaf disease will require further work on data augmentation techniques to produce big datasets and train the deep CNN model from scratch. The proposed CNN8GN model's performance can be improved by using a different function in place of the SoftMax activation function, making it suitable for identifying a variety of diseases to create a web or internet-enabled (IoT) real-time illness monitoring system.

References

[1] C. Pazderka, A. Emmott, Chatham House Procurement for Development Forum:

Groundnuts Case Study. Chatham house, 10. (2010).

[2] P. Singh, S. Nedumaran, B.R. Ntare, K.J. Boote, N.P. Singh, K. Srinivas, M.C.S. Banti-lan, Potential benefits of drought and heat tolerance in groundnut for adaptation to climate change in India and West Africa. Mitigation and adaptation strategies for global change, 19, (2014). 509-529. https://doi.org/10.1007/s11027-012-9446-7

[3] M.D.M. Kadiyala, S. Nedumaran, J. Padmanabhan, M.K. Gumma, S. Gummadi, S.R. Srigiri, R. Robertson, A. Whitbread, Modeling the potential impacts of climate change and adaptation strategies on groundnut production in India. Science of the Total Environment, 776 (2021), 145996. https://doi.org/10.1016/j.scitotenv.2021.145996

[4] A. Hafeez, M.A. Husain, S.P. Singh, A. Chauhan, M.T. Khan, N. Kumar, A. Chauhan, S.K. Soni, Implementation of drone technology for farm monitoring & pesticide spraying: A review. Information processing in Agriculture, 10, (2022) 192-203. https://doi.org/10.1016/j.inpa.2022.02.002

[5] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, R. Kaliaperumal, Smart farming: Internet of Things (IoT)-based sustainable agriculture. Agriculture, 12(10), (2022), 1745. https://doi.org/10.3390/agriculture12101745

[6] A. Gabriel, M. Gandorfer, Adoption of digital technologies in agriculture-an inventory in a european small-scale farming region. Precision Agriculture, 24(1), (2023), 68-91. https://doi.org/10.1007/s11119-022-09931-1

[7] J.C. Saha, A study on oilseed economy of India. Indian Journal of Agricultural Marketing, 37(1), (2023), 74-94.

[8] Annual report 2020-21, Department of Agriculture, cooperation and farmers welfare, Ministry of Agriculture and Farmers welfare, Government of India. https://agricoop.nic.in/Documents/annual-report-2020-21.pdf

[9] Groundnut Crop Survey Reports APEDA, Government of India. 2017-2020, https://apeda.gov.in/apedawebsite/GroundNut/GroundNut.htm

[10] V.J. Naik, C. Umesha, Effect of organic manures and bio-fertilizers on growth and yield of Groundnut (Arachis hypogaea L.), The Pharma Innovation Journal, 11(5), (2022), 1249-1251.

[11] S.K. Bera, K. Rani, J.H. Kamdar, M.K. Pandey, H. Desmae, C.C. Holbrook, M.D. Burow, N. Manivannan, R.S. Bhat, M.D. Jasani, S.S. Bera, A.M. Badigannavar, G. Sunkad, G.C. Wright, P. Janila, R.K. Varshney, (2022). Genomic Designing for Biotic Stress Resistant Peanut. In Genomic Designing for Biotic Stress Resistant Oilseed Crops, Cham: Springer. 137-214. https://doi.org/10.1007/978-3-030-91035-8_4

[12] S. Young, The Future of Farming: Artificial Intelligence and Agriculture. Harvard International Review, 41(1), (2020), 45-47.

[13] E.A. Abioye, O. Hensel, T.J. Esau, O. Elijah, M.S.Z. Abidin, A.S. Ayobami, O. Yerima, A. Nasirahmadi, Precision irrigation management using machine learning and digital farm-ing solutions. AgriEngineering, 4(1), (2022), 70-103. https://doi.org/10.3390/agriengineering4010006

[14] U.P. Singh, S.S. Chouhan, S. Jain, S. Jain, Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease. IEEE Access, 7, (2019), 43721-43729. https://doi.org/10.1109/ACCESS.2019.2907383

[15] J. Li, C. Xu, L. Jiang, Y. Xiao, L. Deng, Z. Han, Detection and Analysis of Behavior Trajectory for Sea Cucumbers Based on Deep Learning. IEEE Access, 8, (2020), 18832–18840. https://doi.org/10.1109/ACCESS.2019.2962823

[16] Y. Ai, C. Sun, J. Tie, X. Cai, Research on recognition model of crop diseases and insect pests based on deep learning in harsh environments. IEEE Access, 8, (2020), 171686–171693. https://doi.org/10.1109/ACCESS.2020.3025325

[17] D. Jiang, F. Li, Y. Yang, S. Yu, (2020) A tomato leaf diseases classification method based on deep learning. In 2020 chinese control and decision conference (CCDC) IEEE. China. https://doi.org/10.1109/CCDC49329.2020.9164457

[18] R.V. Meeradevi, M.R. Mundada, S.P. Sawkar, R.S. Bellad, P.S. Keerthi, Design and Development of Efficient Techniques for Leaf Disease Detection using Deep Convolutional Neural Networks. 2020 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics, IEEE, India. https://doi.org/10.1109/DISCOVER50404.2020.9278067

[19] S.V. Militante, B.D. Gerardo, R.P. Medina, Sugarcane disease recognition using deep learning. In 2019 IEEE Eurasia conference on IOT, communication and engineering (ECICE), IEEE, Taiwan. https://doi.org/10.1109/ECICE47484.2019.8942690

[20] U. Barman, D. Sahu, G.G. Barman, J. Das, Comparative assessment of deep learning to detect the leaf diseases of potato based on data augmentation. *In 2020 International Conference on Computational Performance Evaluation (ComPE)*, 682-687. IEEE https://doi.org/10.1109/ComPE49325.2020.9200015

[21] I.Z. Mukti, D. Biswas, (2019). Transfer learning based plant diseases detection using ResNet50. *In 2019 4th International conference on electrical information and communication technology (EICT)* 1-6. IEEE. https://doi.org/10.1109/EICT48899.2019.9068805

[22] U. Barman, R.D. Choudhury, D. Sahu, G.G. Barman, (2020) Comparison of convo-lution neural networks for smartphone image based real time classification of citrus leaf disease. Computers and Electronics in Agriculture, 177, (2020), 105661. https://doi.org/10.1016/j.compag.2020.105661

[23] H. Sun, H. Xu, B. Liu, D. He, J. He, H. Zhang, N. Geng, (2021) MEAN-SSD: A novel real-time detector for apple leaf diseases using improved light-weight convolutional neural networks. Computers and Electronics in Agriculture, 189, (2021), 106379. https://doi.org/10.1016/j.compag.2021.106379

[24] H. Kukadiya, D. Meva, (2022) Automatic Cotton Leaf Disease Classification and Detection by Convolutional Neural Network. In International Conference on Advancements in Smart Computing and Information Security, Springer, Cham. https://doi.org/10.1007/978-3-031-23092-9_20

[25] P. Bir, R. Kumar, G. Singh, Transfer learning-based tomato leaf disease detection for mobile applications. 2020 IEEE International Conference on Computing, Power and Communication Technologies, GUCON. IEEE, India. https://doi.org/10.1109/GUCON48875.2020.9231174

[26] J.F.V. Oraño, E.A. Maravillas, C.J.G. Aliac, Jackfruit Fruit Damage Classification using Convolutional Neural Network. In 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), IEEE, Philippines. https://doi.org/10.1109/HNICEM48295.2019.9073341

[27] R.S. Latha, G.R. Sreekanth, R.C. Suganthe, R. Rajadevi, S. Karthikeyan, S. Kanivel, B. Inbaraj, Automatic detection of tea leaf diseases using deep convolution neural net-work. In 2021 International Conference on Computer Communication and Informatics (ICCCI), IEEE, India. https://doi.org/10.1109/ICCCI50826.2021.9402225

[28] S. Bhowmik, A.K. Talukdar, K. Kumar Sarma, Detection of Disease in Tea Leaves Using Convolution Neural Network. International Conference on Advanced Communication Technologies and Signal Processing, IEEE, India. https://doi.org/10.1109/ACTS49415.2020.9350413

[29] W. Haider, A. Ur Rehman, A. Maqsood, S.Z. Javed, Crop Disease Diagnosis using Deep Learning Models. 2020 Global Conference on Wireless and Optical Technologies, GCWOT, IEEE, Spain. https://doi.org/10.1109/GCWOT49901.2020.9391605

[30] V. Kumar, P.P. Thirumalaisamy, (2016). Diseases of groundnut. Disease of field crops and their management. Indian Phytopathological Society, Today and Tomorrow's Printers and Publishers, New Delhi, 459-487.

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Author contribution statement

Hirenkumar Kukadiya: Conceptualization: Investigation: Methodology, Data collection, Writing original draft; **Divykant Meva:** Conceptualization, Supervision, Validation, Review and Editing; **Nidhi Arora:** Supervision and Validation, Review and Editing; **Shilpa Srivastava:** Conceptualization, Data Analysis, Review and Editing. All the authors read and approved the final version of the manuscript.

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Availability of Data and Materials

Upon request, the Groundnut Image Dataset will be made available.

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