Predicting Groundnut Disease usingCNN Models

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Abstract

Groundnut is one of the most important and popular oilseed foods in the agricultural field, and its botanical name is Arachis hypogaea L. Approximately, the pod of mature groundnut contains 1–5 seeds with 57% of oil and 25% of protein content. The groundnut cultivation is affected by different kinds of diseases such as fungi, viruses, and bacteria. Hence, these diseases affect the leaf, root and stem of the groundnut plant and it leads to heavy loss in yield. Moreover, the enlarger number of diseases affects the leaf and root-like Alternaria, Pestalotiopsis, Bud necrosis, tikka, Phyllosticta, Rust, Pepper spot, Choanephora, early and late leaf spot. To overcome these issues, we introduce an efficient method of convolutional neural network (CNN) because it automatically detects the important features without any human supervision. The proposed methodology can deeply detect plant disease by using a deep learning process. Ultimately, the groundnut disease classification with its overall performance of proposed methodology provides 96% accuracy.

Keywords: Plant diseases, CNN, AlexNet, SVM, Deep learning

1. Introduction

India is an agricultural country where in about seventy percentage of the population is dependent on productivity of agricultural crops/ plants. Today rural assets are getting the chance to be evidently scarcer and in this manner more beneficial. Groundnut is one of the most important oilseed crops cultivated across the world for the production of oil. Groundnut is the 6th most essential oilseed plantation on the planet. The global production volume of groundnut in 2018 is 37.64 million tonnes annually. Hence, Groundnut has become a standout amongst the most essential money plantation of India. It contains 48–50% of oil and 26–28% of protein, and is a rich source of dietary fiber, minerals, and vitamins while being a valuable source of all the nutrients it is a low priced commodity.The major diseases that can affect groundnut leaves are rust and early and late leaf spot disease as shown in the figure 1 and figure 2.

- Early and late leaf spot: Brown lesions (spots), usually surrounded by a yellow colour on the upper side of leaves, are the most common symptom of early leaf spot. Dark brown lesions (spots), usually on the underside of affected leaves, are the most common symptom of late leaf spot. It is very important to determine whether the crops are affected by late leaf spot since it will be difficult to control.
- Rust: Puccinia arachidis Pustules seem first on the lower surface and in exceptionally victimized cultivars the major pustules might be encompassed by colonies of auxiliary pustules which is secondary in nature. Pustules may likewise show up on the upper surface of the leaflets.

This project aimed solving the problem of disease classification for the groundnut plant using Deep learning. The models that were considered for the classification are AlexNet, ANN, KNN and SVM.

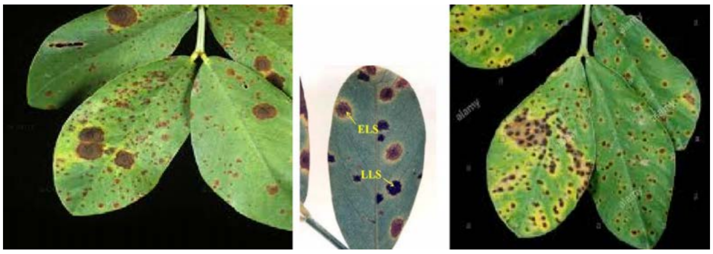

Fig 1: Early and late leaf spot disease

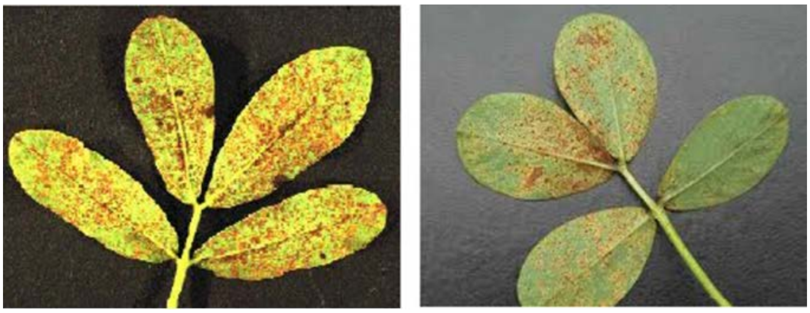

Fig 2: Rust

2. Related Work

Deep learning constitutes a recent, modern technique for image processing and data analysis, with promising results and large potential. As deep learning has been successfully applied in various domains, it has recently entered also the domain of agriculture. To examine the particular agricultural problems and study, the specific models and frameworks employed, the sources, nature and pre-processing of data used, and the overall performance achieved according to the metrics used at each work under study. Moreover, to study comparisons of deep learning with other existing popular techniques, in respect to differences in classification or regression performance. Findings indicate that deep learning provides high accuracy, outperforming existing commonly used image processing techniques. Convolutional Neural Networks (CNN) constitute a class of deep, feed-forward ANN.

India is an agricultural country and groundnut is one of the most important oilseed crops cultivated across the world for the production of oil. An image-processing based approach for detection and classification of groundnut leaf disease is proposed. This approach has been tested on six classes that includes all five major groundnut leaf diseases and one healthy leaf they are: Early leaf spot, Rust, Bud Necrosis, Blight, Late leaf spot. The proposed work concentrates majorly on Feature detection, feature extraction and classification [2][3].

The dataset used here consists of several varieties of plants of both affected and healthy, and all these images are collected from various freely available sources and manually[4]. Then some machine learning classification techniques such as KNN and SVM are used for classification and a comparison is made among their performances[14][16]. The purpose of the proposed system is to identify the leaf spot using image processing techniques. In this research the disease detection is done in four stages, image acquisition, image segmentation, feature extraction and classification. For image segmentation is done with K-means clustering method and features are computed from disease affected cluster[11].

The Residual Network model (ResNet) can accurately detect and classify disease from images of leaves. An average weighted precision and an accuracy was achieved by ResNet model. These two performance metrics for the ResNet model are also compared with that of four other techniques- SVM, K-NN, Decision Tree and Logistic Regression. The proposed model is found to have higher accuracy and precision values compared to the other four models[5]. An efficient method using convolutional neural network (CNN) for the detection and classification of groundnut diseases. The deep learning process is intensely used to detect the leaf disease and the CNN classification is utilized to categorize the diseases.The best accuracy results was obtained for CNN AlexNet [1][12]. A solution for the leaf disease detection using simplest method while keeping minimum computational complexity and minimal resource to gain fast and accurate result as convolutional neural network (CNN) automatically extracts features for classification of input image into various classes. The experimental results obtained by the developed model was 95.93%[6]. CNN architectures may also use different learning rates and optimizers for experimenting the performance and accuracy of the model. With the achieved accuracy of 96.5%, the proposed model can assist farmers to detect and recognize plant diseases[10].

3. Proposed Methodology

The design methodology followed for the groundnut disease classification using DL is as shown in the figure 3. It consists of three stages namely, data pre-processing, feature extraction and classification. In the pre-processing stage, the image is resized according to the model, a feature vector is then derived with the respective DL models and the classification is performed using ML algorithms. Algorithm 1 shows the steps followed for the spatial exploitation in image forgery detection. The details each stage is explained as follows.

Algorithm1 :Groundnut_disease_classification()
Input: A set of input images <I_1, I_2, I_3, …, I_n> divided into training and testing
Output: Forged/Non-forged
Begin <Trainset, Testset><- load_dataset() <featuresTrain, featuresTest><- load_neural_networks(AlexNet, ResNet, KNN, SVM) <$classifer_1$, $classifer_2$, …, $classifer_n$,><- load_classificationAlexNet, ResNet, KNN, SVM) <$pred_1$, $pred_2$, …, $pred_n$,><- get_predictions($classifer_1$, $classifer_2$, …, $classifer_n$) <acc_1, acc_2, …, acc_n><- get_accuracy($classifer_1$, $classifer_2$, …, $classifer_n$) End

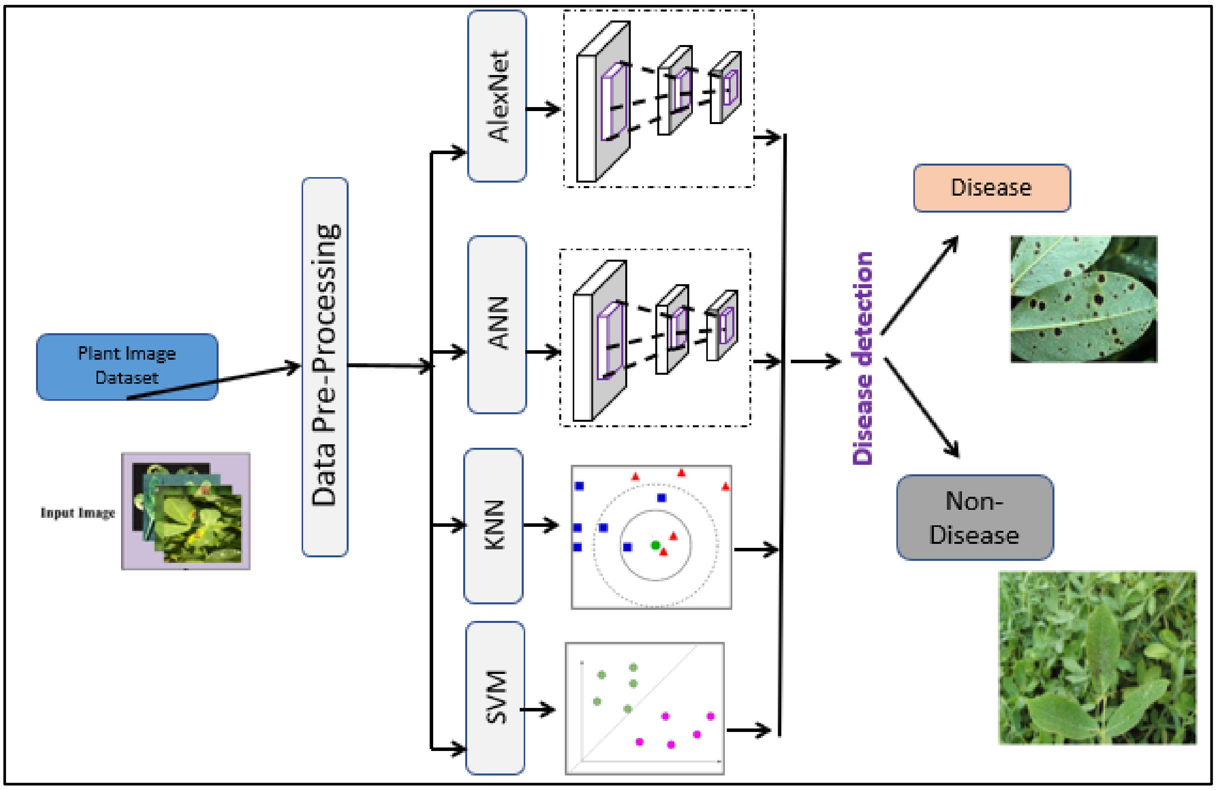

Figure 3. System Architecture for Groundnut disease classification

3.1. Data Pre-Processing

In this stage, the input image is resized according the model for feature extraction and classification. The dimensions of the input image required for AlexNet is 227x227, ANN is 222x222 and VGG16 is 227x228. In this phase, the input image is pre-processed and provides a feature vector that is required for the classification. The feature extraction stage and classification is explained in the next section.

3.2. Feature Extraction

A set of input images $<I_1, I_2, I_3, \ldots, I_n>$ from the dataset is divided into the training and testing set initially. The training images are then fed into the models AlexNet, ANN, KNN and SVM. The pre-trained weights are used for the extraction of the feature vector of the images by removing the last fully connected (FC) layer in the neural networks. These networks provide the feature vector for each image in the dataset. The feature vectors are then used for the classification of the diseased or non-diseased images.

3.3. Classification

The trained feature vectors obtained by the models are then provided for the classification. The predictions are then estimated on different classifiers using the test images. The accuracy of the classification is then estimated using the difference between the actual and predicted images.

4. Experiments and Results

4.1. Dataset and Disease classification

The models that were considered for the classification are AlexNet, ANN, KNN and SVM. The dataset that was considered for the disease classification is MABC [21]. It includes the research work carried out in evaluating marker assisted backcross (MABC) lines for rust and late leaf spot (LLS) resistance in five locations during 2015 rainy season. The evaluation were carried out at Aliyarnagar, Tamil Nadu; Directorate of Groundnut Research (DGR) Junagadh, Gujarat; Dharwad, Karnataka; ICRISAT, Patancheru and KasbeDigraj, Maharashtra. It consists of the attributes:late leaf spot (LLS), SHP- Shape feature, HSW (100 seed weight) pod yield hectare (kg/ha) (PYH).

4.2. Results of Classification using AlexNet

The table 1 gives the confusion matrix for the AlexNet Model. The optimizers SGDM, Adam and RMSprop were implemented for the classification. It was found that the SGDM optimizer was efficient with the correct classification of diseased (81.56%) and non-diseased (15.26%). The optimizer Adam provided the classification of diseased (50%) and non-diseased (35%). Similarly the optimizer RMSprop provided the classification of diseased (50%) and non-diseased (35.91%). Hence, it was found the SGDM optimizer was better with the AlexNet Model with ROC curve as shown in the figure 4.

Table 1. Confusion matrix of AlexNet

Fine-tuned DL Model	**Optimizers**		**Disease predicted**	**Non-disease predicted**
AlexNet	**SGDM**	Disease	81.56%	0%
		Non-Disease	3.18%	15.26%
	Adam	Disease	50%	0%
		Non-Disease	15%	35%
	RMSprop	Disease	50%	0%
		Non-Disease	14.09%	35.91%

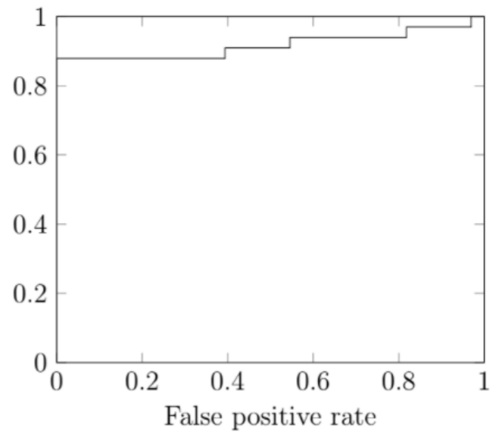

Figure 4. ROC Curve for AlexNet

4.3. Results of Classification using ANN

The table 2 gives the confusion matrix for the ANN Model. The optimizers SGDM, Adam and RMSprop were implemented for the classification. It was found that the SGDM optimizer was efficient with the correct classification of diseased (79.82%) and non-diseased (18%). The optimizer Adam provided the classification of diseased (52%) and non-diseased (33%). Similarly the optimizer RMSprop provided the classification of diseased (49%) and non-diseased (36.91%). Hence, it was found the SGDM optimizer was better with the ANN Model with ROC curve as shown in the figure 5.

Table 2. Confusion matrix of ANN

Fine-tuned DL Model	Optimizers		Disease predicted	Non-disease predicted
ANN	**SGDM**	Disease	79.82%	0%
		Non-Disease	2.18%	18%
	Adam	Disease	52%	0%
		Non-Disease	15%	33%
	RMSprop	Disease	49%	0%
		Non-Disease	14.09%	36.91%

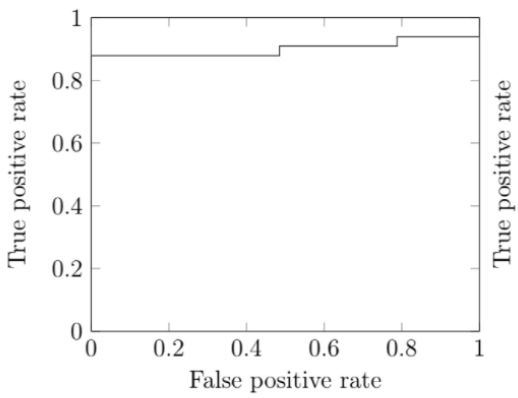

Figure 5. ROC Curve for ANN

4.4. Results of Classification using KNN

The table 3 gives the confusion matrix for the KNN Model. The optimizers SGDM, Adam and RMSprop were implemented for the classification. It was found that the SGDM optimizer was efficient with the correct classification of diseased (75.82%) and non-diseased (21.02%). The optimizer Adam provided the classification of diseased (49%) and non-diseased (36%). Similarly the optimizer RMSprop provided the classification of diseased (51%) and non-diseased (32.91%). Hence, it was found the SGDM optimizer was better with the KNN Model with ROC curve as shown in the figure 6.

Table 3. Confusion matrix of KNN

Fine-tuned Model	Optimizers		Disease predicted	Non-disease predicted
KNN	**SGDM**	Disease	75.82%	0%
		Non-Disease	3.16%	21.02%
	Adam	Disease	49%	0%

		Non-Disease	15%	36%
	RMSprop	Disease	51%	0%
		Non-Disease	16.09%	32.91%

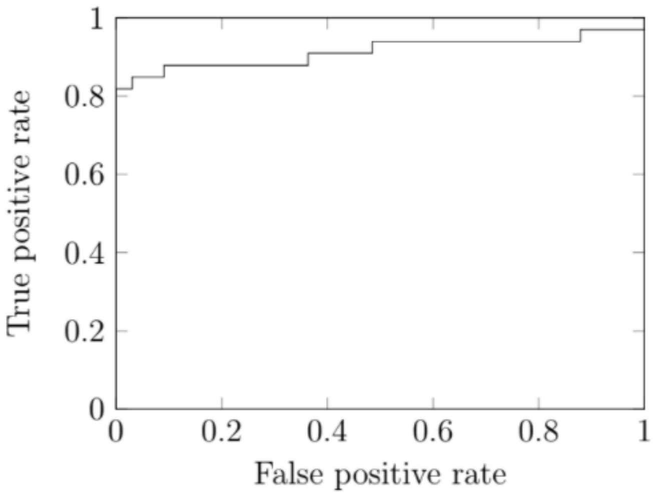

Figure 6. ROC Curve for KNN

4.5. Results of Classification using SVM

The table 4 gives the confusion matrix for the SVM Model. The optimizers SGDM, Adam and RMSprop were implemented for the classification. It was found that the SGDM optimizer was efficient with the correct classification of diseased (75.82%) and non-diseased (21.02%). The optimizer Adam provided the classification of diseased (49%) and non-diseased (36%). Similarly the optimizer RMSprop provided the classification of diseased (51%) and non-diseased (32.91%). Hence, it was found the SGDM optimizer was better with the SVM Model with ROC curve as shown in the figure 7.

Table 4. Confusion matrix of SVM

Fine-tuned Model	**Optimizers**		**Disease predicted**	**Non-disease predicted**
SVM	**SGDM**	Disease	71.85%	0%
		Non-Disease	4.18%	23.97%
	Adam	Disease	45%	0%
		Non-Disease	12%	43%
	RMSprop	Disease	49%	0%
		Non-Disease	14.09%	36.91%

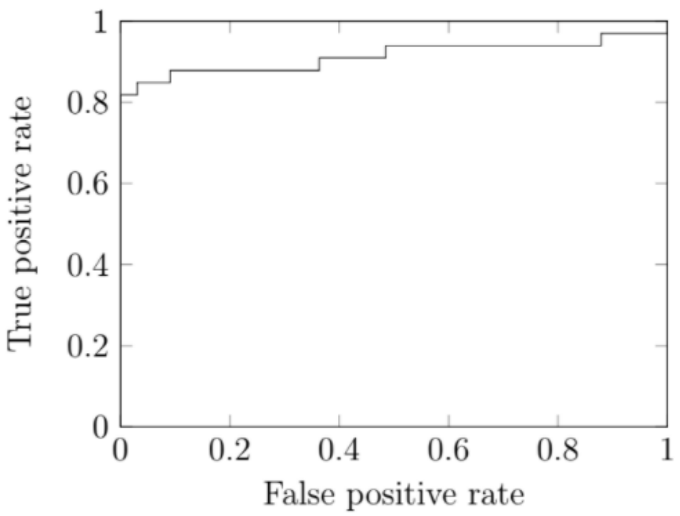

Figure 7. ROC Curve for SVM

4.6. Performance Comparison

In this section, we discuss the performance comparison of the models AlexNet, ANN, SVM and KNN using the metrics accuracy, precision, recall and F1-Score. The table 5 gives the performance comparison of the accuracy of the models AlexNet, ANN, KNN and SVM. It can be observed that the accuracy of the AlexNet model achieves higher accuracy (95.95%) as compared to the others namely ANN(93.85%), KNN (88.32%) and SVM (82.65%). The table 6 gives the performance comparison of metrics precision, recall and F1-score for the models. It can be observed that the precision of the AlexNet (97.82%) is higher as compared to the others namely ANN(93.85%), KNN (94.23%) and SVM (84.95%). Similarly, it can be observed that the recall of the AlexNet (98.54%) is higher as compared to the others namely ANN(91.85%), KNN (92.9%) and SVM (85.45%). Hence, it is concluded that the accuracy of the AlexNet model achieves more accuracy and precision as compared to the other models as shown in the figure 8..

Table 5. Performance Accuracy of models for disease classification

Models	**Accuracy**
Alexnet	95.95
ANN	93.85
KNN	88.32
SVM	82.65

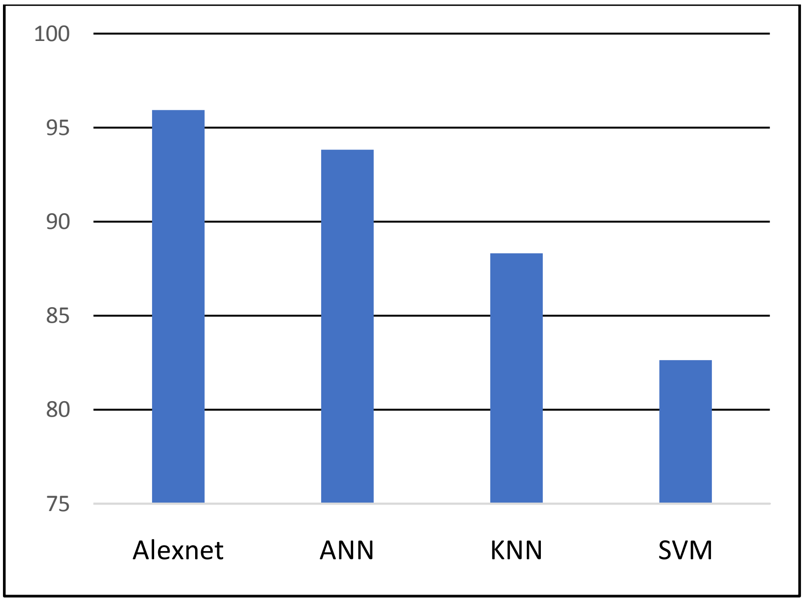

Figure 8. Accuracy comparison of classification

Table 6. Performance Comparison of models for disease classification

Models	Precision	Recall	F1-Measure
Alexnet	97.82	98.54	97.65
ANN	93.85	91.85	90.87
KNN	94.23	92.9	93.1
SVM	89.45	87.54	85.45

5. Conclusion

This project aimed solving the problem of disease classification for the groundnut plantusing Deep learning. The models that were considered for the classification are AlexNet,ANN, KNN and SVM. The dataset that was considered for the disease classification isMABC [ref]. The experiments were conducted on the dataset that consisted of 105 imagesin total. It was found that AlexNet model with the SGDM optimizer was efficient with thecorrect classification of diseased (81.56%) and non-diseased (15.26%). It was also foundthat ANN model with the SGDM optimizer was efficient with the correctclassificationof diseased (79.82%) and non-diseased (18%). On similar lines, the KNN model with theSGDM optimizer was efficient with the correct classification of diseased (75.82%) andnon-diseased (21.02%). The SVM model with SGDM optimizer was efficient with thecorrect classification of diseased (75.82%) and non-diseased (21.02%).

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