Leaf Disease Detection Using Ecnnpld As An Augmentative Approach

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Abstract

One of the important sectors of Indian Economy is Agriculture. Employment to almost 70% of the countries workforce is provided by Indian agriculture sector. India is known to be the world's largest producer of pulses, rice, wheat, spices and spice products. Farmer's economic growth depends on the quality of the products that they produce, which relies on the plant's growth and the yield they get. Therefore, in field of agriculture, detection of disease in plants plays an instrumental role. Plants are highly prone to diseases that affect the growth of the plant which in turn affects the ecology of the farmer. In order to detect a plant disease at very initial stage, use of automatic disease detection technique is beneficial. The symptoms of plant diseases are conspicuous in different parts of a plant such as leaves, etc. Manual detection of plant disease using leaf images is a tedious job. Hence, it is required to develop computational methods which will make the process of disease detection and classification using leaf images automatic. The widespread development of deep learning has directed to the increasing research interest in image recognition technologies, which enables in the field of computerized image categorization and finding of plant diseases. Farmers are facing huge challenges in cultivation, such as illness. There are a number of leaf diseases that target the rate at which the crop grows. Appropriate measures on disease identification should be introduced to prevent the issues and minimise the losses. Regular monitoring and authentic disease identification in initial stages of plant growth can increase the quantity and quality of crop yield. Application of technical algorithm correlating the machine vision and mobile vision is actively explored for the sake of achieving the intelligence farming by early plant disease detection. A mobile application is obviously desirable to aid the farmers or garden enthusiasts in diagnosing the sorts of plant ailments. Although some similar applications exist, most of them achieve the function by submitting the image to a team of plant pathologists or expert garden advisors to get possible identification results and some advices. After improving the classification accuracy by using inverted residual block, android application based on image processing and remedy classification techniques used for the detection of plants by observing the symptoms on leaves is presented. The application named as ECNNPLD prediction app turns out to be user friendly to capture the leaf images from mobile camera to process the pre-processing stage, segmentation stage, feature extraction stage and classification stage to predict the diseases. Proposed research work also trained remedies for classified diseases. Application directly suggests curatives to the farmer for the purpose of crop protection. Further, it also focuses on enhanced convolutional neural network (ECNN) which is one among the CNN based powerful classification techniques.

Keywords: *Enhanced convolutional neural network, plant leaf diseases classification, android app.*

ISSN: 2233-7857 IJFGCN

1. INTRODUCTION

To enhance the food quality and productivity, research in agriculture increasingly gained attention recently. Accurate diagnosis of crop diseases and subsequent classification are the most complicated processes to perform as it can be influenced by different parameters such as climate, nutrition and environment. With the development of the science and technology, progressive scientific tools based on machine vision for achieving intelligent farming becomes active computing research areas. Besides crops production, garden enthusiasts often confuse about the symptom of their plants [1]. Students, researchers and farmers taking plant pathology as the core domain are often being asked by their friends or laboratory about the plants and measures to eliminate the diseases. Although curing the plant is too late at that time, it is still very useful to prevent the disease being spread to other plants in the future. Advantageous software is really desirable to help the plants enthusiasts in identification the disease as quickly as possible in the initial phase. A smart phone app is an apparently convenient approach for an untrained person to learn about what kinds of disease a plant suffers [2].

Although there have been some similar applications such as `Garden Compass Plant / Disease Identifier' (iTunes Store) for iPhone or`A&L Plant Disease Diagnosis'(Google Play) for Android app store, most of the farmers need to take a picture and submit it to a team of plant experts who will diagnose the symptom [4].However, the farmers have to wait long duration for the result and pay money for the application. The major drawback of the aforementioned applications is that the application is only meant for disease identification not for curative suggestion. The development of a machine learning based mobile application to satisfy the needs such as analyzing the picture, diagnosing the ailments, disease classification and recommendation of remedies which is free of charge and short result-waiting period is the longing requisite [3]. Moreover Access is hardware nonpartisan, needed to use a computer system, which can be inconvenient for the user. Thus, it can be seen that an implementation of a completely successful application for leaf disease detection and remedial suggestions is extremely useful for the garden enthusiasts for improved agricultural production.

This paper is organized as follows. Section II briefly summarizes the proposed system related work. Section III provides the detailed description of the proposed enhanced Artificial Neural Network based leaf disease remedies classification System. Section IV presents the Experimental results and analysis. Conclusions and future work are given in Section V.

2. RELATED WORKS

This section discusses about some of the existing work which gives the leaf disease detection using neural networks and by using the same developed an application. Ali, H et al (2017) detected the infections on cotton leaf utilizing Principle Component Analysis (PCA), Nearest Neighborhood Classifier (KNN). Various types of image features are extracted for various diseases affecting the cotton leaf, generally the leaf of infected image has elliptical in shape, major and minor axis calculation is the major challenge in this work. Since fuzzy logic is more effective to handle the vague image data as author claims, the author discusses several aspects and techniques of precision agriculture which employ Fuzzy logic [5].

M. Akila, et al (2018) presents a machine learning approach for recognition of the visual symptoms of plant diseases in the color images. Segmentation is processed initially to separate diseased regions of cotton crops, further group of features extracted from segmented image. RGB

ISSN: 2233-7857 IJFGCN

encoding technique used in this work to separate the red, green and blue component images were separated, the patterns formed and images of various healthy betel leaves collected and stored in the system. The network connectivity is measured to compose the feature vectors which discriminates these damages. The results of automatic classification using LDA and SVM are reviewed after obtaining the characteristics. [6].

Detection in grape leaf is done by Padol et al (2016) via Support Vector Machine (SVM) classifier. Digital clicks of leaves are taken as input and fed into training and testing phases. Further image quality is enhanced. Resizing the image to size 300x300 is performed and components of green color are attained by means of thresholding. Gaussian filtering eliminates the noise. K-means clustering identifies the segmented region of diseased and extraction of features of color and texture are done. Hence, the sort of leaf infection is detected via Linear Support Vector Machine (LSVM) classification technique and achieved high accuracy of 88.89% [7].This Image processing automated systems serve the community of farmers by providing solutions based on image processing; the images of crop leaf, fruit, flower and Stalk samples are processed to know the inherent features of visual symptoms and classifying the disease outbreaks. The solutions include type and quantity of pesticide sprayings, healthy cultivation methods and weather impacts etc.

The diagnosis and classification of leaf and stem diseases are performed by an approach developed by Bashish et al (2010). Initially in image-processing-based process, K-Means approach performs the segmentation [8] and transmitted to a pre-trained neural network. Al-Ghor area in Jordan is taken as input data in a test bed. High accuracy is achieved here significantly and detects leaf diseases automatically. Accuracy and automated detection are achieved by the experimental results. Statistical classification-based approach of the developed Neural Network classifier attained 93% precision in detection and classification [9].

Current CNNs, as defined Inception (Simonyan and Zisserman, 2016), ResNet (He et al., 2016), and DenseNet (Huang et al., 2017), both abandon the full connection layer, adopt Global Average Pooling layer (Lin et al., 2013). The advantage of Global Average Pooling layer is not only to solve the problem of a large number of parameters in the full connection layer, but also to realize image input of different size. References (Zheng et al., 2016) shows that appropriate increase of image size can improve classification accuracy, However, as the size of the input image increases, the amount of computation required increases by square, whi, A. Lavin and S. Gray (2016) proposed technique was found to outperform both other deep CNN based and neural based clustering scheme in all the cases during entire research [10].

However, H. G. Chenet al (2016) proposed a combination of further normalizing the extracted Eigen values and using eigenvectors of part of the samples for training the CNN and ASP sensor [11] which have been used in recognition of Alternaria Alternata, Cercospora Leaf Spot, Bacterial Blight, Anthracnose and wheat leaf rust. This problem is addressed here using color, shape and texture features of the diseased images. The idea is based on the first layer of CNNs to lead to significant feature extraction. Y. W. Q. H. Jiaxiang Wu et al (2015) introduced QCNN for Mobile apps is a framework of deep convolutional neural network (CNNs), that achieves 4:02x speed-up against the existing apps [12] [14].

DATASET DESCRIPTION

Diseases are the most destructive symptoms for the growth of any crop which causes significant loss in agriculture production. Therefore, timely action is required to detect and prevent disease occurrence is of imperative requisite to improve yield of crop. Plant village data

ISSN: 2233-7857 IJFGCN

sets and tea leaves are collected from benchmark. From the site we collected 1200 image datasets for both training and testing. After collecting the samples the plant pathologists diagnosed the leaves and capturing the images by using smart phone. The cultivation of crops is facing devastating degradation due to unpredictable disease occurrences and such issues are needed to be addressed. Information technology is leaving its mark in agriculture by developing Disease diagnose Systems for solving variety of issues including weed discrimination, plant recognition, crop disease identification and classification, soil profile discrimination and disease forecasting. Various method-analysis and prediction mobile apps and other application for diseases prediction are existing but the farmers are unable to distinguish which disease is affecting their crops and what control measure has to be taken. The Agriculture scientists are unable to visit the farms because of lack of convenience to reach places.

3. PROPOSED METHODOLOGY

This research uses two consecutive mapping i.e. deep convolutional networks which is a scheme in order to preserve the mapping in concert with an adaptive vector quantization; and spectral clustering which is an assorted learning based on Eigen composition along with the local density oriented similarity. CNNs are the most important parts of deep learning and extensively used in computer vision. CNN's recognizing visual patterns with pre-processing straight from pixel images. The advanced rise in popularity of CNN is helping to its immense effectiveness. One of the most common architecture is Mobile Net used here for the prediction and remedial solution of mobile app. In a feed-forward manner Mobile Net connects each layer with every other layer .The feature-maps all the previous layers are used as inputs for each layer, and their feature-maps are used in all subsequent layers as inputs. Mobile Nets solves the problem of vanishing gradient, strengthen feature extraction propagation, encourages reuse of features, and reduces the number of parameters. Each *i*th layer has *I* inputs, composed of the feature maps of all preceding convolutional blocks. It passes its feature-maps to all A-i subsequent layers. This introduced A (A + 1)/2 connections in an A-layer network. This architecture has a dense connectivity pattern, therefore called a Convolutional neural network.

It performs a depth wise convolution in the first layer followed by a 1x1 point wise convolution layer. The point wise Convolution layer combines the output of a single filter of each channel of the image .In this paper, we trained the plant village leaf images and tea leaves with the MobileNet CNN architecture. The transfer learning model associated tensor flow Hub. It is derived and implemented in the GoggleCollab GPU environment by using Keras, and in the back end tensor flow is implemented. The activation function of the MobileNet is Relu. In addition to the MobileNet architecture, we have added another twolayers with two dropouts in the model. Initially, a dropout with a dropout rate of 0.2and a hidden layer with 516 hidden neurons were applied in the model with the Relu activation function. In the next level, another dropout with a dropout rate of 0.4 added to the architecture. Before final layer hidden layer with 64 hidden neurons with a regularization rate of 0.02 added in the model to reduce the overfitting of the model. Finally, the output layer with 3 hidden neurons introduced in the model to classify the leafdiseases from healthy with a softmax activation function.

ISSN: 2233-7857 IJFGCN

International Journal of Future Generation Communication and Networking
Vol. 13, No. 4, (2020), pp. 4124–4135

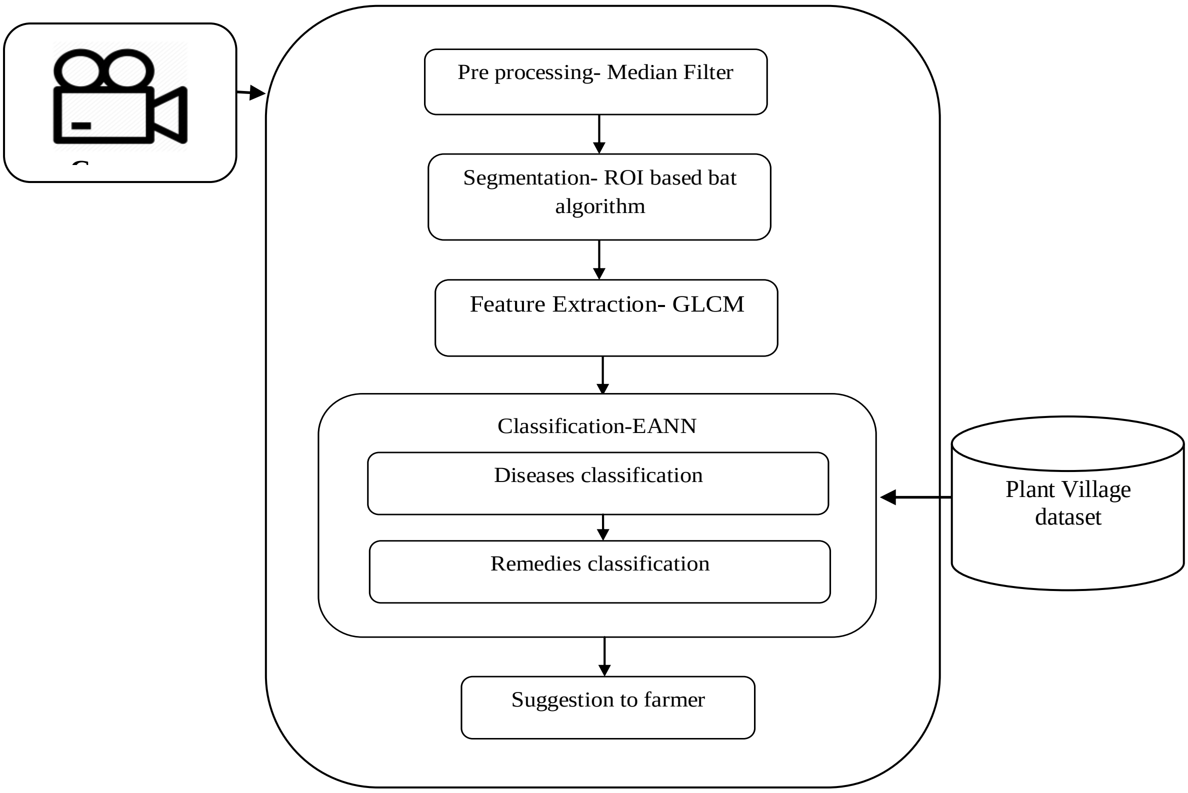

Fig 1. Architecture diagram for proposed EANNPLD prediction app

Proposed mobile application carried and continues ofK.Subhadra and Dr.N.Kavitha (2020) windows application of plant disease classification application. Pre-processing stage used in median filter, segmentation of image used to ROI based Bat algorithm approach, feature extraction GLCM method applied to predict finally classification ECNN approach used to diagnosis the diseases [15]. Plant village Datasets are used for leaf diseases diagnosis, previous windows application predicts only the leaf diseases not the suggestions regarding remedies as windows application is not suitable for providing suggestion. This drawback is being rectified by the proposed mobile based approach and previous window application methods are more suitable for proposed mobile based application and extended to remedies suggestion. Figure 1 describes the proposed ECNNPLD prediction architecture modal.

1) ECNNPLD prediction app: Google analysist [13] applied and implemented proficient method for CNN MobileNets for embedded based apps. ECNNPLD prediction model is modified version for MobileNet model. The proposed ECNNPLD disease-diagnose system involving the most effective methods are to be implemented for effective and efficient for less convolution identification of diseases in fruit crops. There is an urgent need for undertaking detailed studies in the development of aetiology, epidemiology and management of controlling the various diseases affecting fruits and thereby minimizing the loss of fruits in the field, in transit and in storage.Figure 2 illustrates proposed architecture model.

b) Brief description of adapted model

ECNNPLD prediction modeldepends on both methods profundity wise distinguishable filters and factoring to minimize the total computation in the initial layers. To minimize the

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computation, the convolution is factoring into depthwise that coverup with each noise removal to entire channel and pointwise which applies a 1×1 convolution to combine the profundity wise. In addition to both the operations, ECNNPLD prediction uses CNNReLU activation function for all layers. Here we differentiate the cost of computation between the use of convolution and profundity wise approach. The ECNNPLD prediction model applies 3×3 profundity wise distinguishable convolutions, minimizing the computation to 9 times lesser. Consider that W - size of input image with M - input channels, $F(Dk \times D_k)$ - kernel convolution (generally are 3×3 or $1 \times 1)$, N- expected output convolutions, architecture of deep convolutional neural networks model inspired by successful model in mobile and embedded systems that is ECNNPLD model architecture.

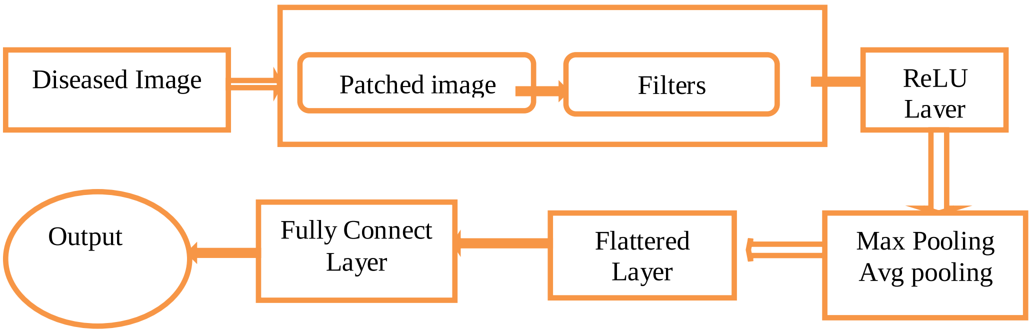

Figure 2. Layers of CNN

Fig 3. Pseudo codes for ECNNPLD model

Input: Video Sequence
Output: Visual output, remedies classification
Steps
1. Initialize the camera sequence
2. Capture leaf frames i.e Frame 'i' and frame 'i+1'. (The time interval between these two frames is limited by the delay for moving object detection)
3. Convert each of these leaf image to grey scale.
4. Subtract images 'I' from 'I+1' to generate different types of depth images CNN parameter.
5. Filtering images to remove noise and to detect the edges of the images
6. If the diseased leaf is the task and if the distance between the marked areas is larger, then repeat the process (vice-versa).
7. Calculate the difference between the images measured in terms of pixel. Extract the feature compare to the train model.
8. Perform evaluation of the output extracted with respect to trained modal predict the diseases and suggest remedies.

Figure 3 illustrates the details of ECNNPLD based pseudocode for leaf diseases detection. The model accepts an input color image of size 224×224. It consists on a series of profundity wise distinguishable convolutions with profundity wise and pointwise layers followed by batchnorm(BN) and CNNReLU. One layer corresponds to 3×3 profundity wise Conv, BN, 1×1 Convolution, BN and CNNReLU activation function. To get classification of diseases, the model is ended by average Pooling of pooling layers, full connected and the Softmax function with 7 classes.

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4. RESULTS AND DISCUSSION

Proposed ECNNPLD applicationeffectively deals with plant village and tea leaves, in the tool of matlab2013 and classified results are discussed in this section. Accuracy values are estimated based on the 120 types of plant leaves used as trained pattern. Table 1 shows, different diseases and number of images used to mobile application trained pattern from 120 images. Proposed dataset comprises of a total 1200 images out of which 200sample images are of Alternaria Alternata, 250 images are of bacterial blight and Cercospora Leaf Spot each, 150 images depict Anthracnose disease. 400 images contain leaf rust disease as the deformity. Remaining 200 images are from healthy leaf category. Figure 5 displays user home screen considered as cloud-based user registration. Each data is being stored and validation of the user is performed. The main application page is displayed where the user can select a stored photograph of the plantpart to be tested.

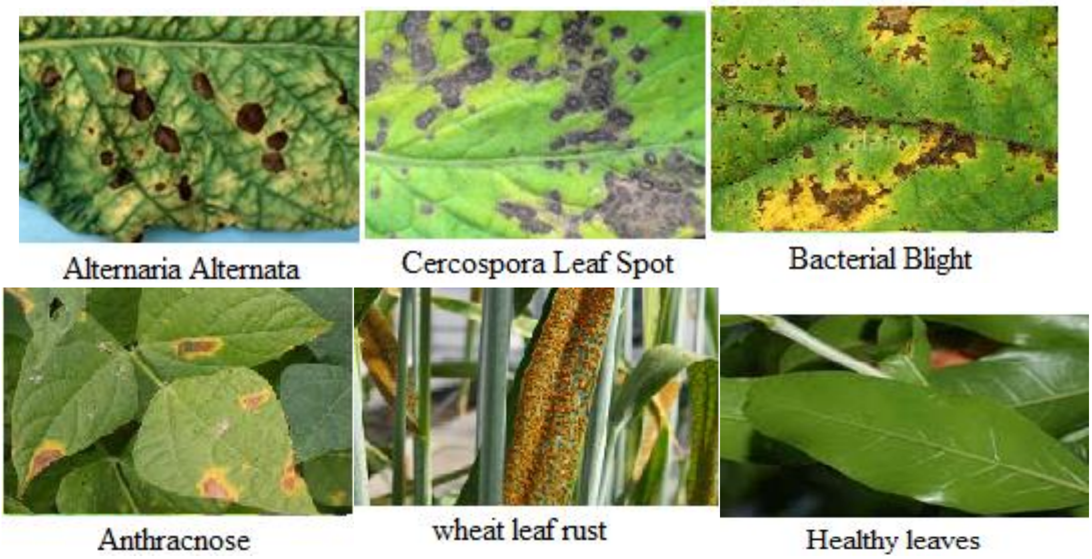


Fig 4. Tomato leaves with diseases

Table 1. Images Number of Each Class

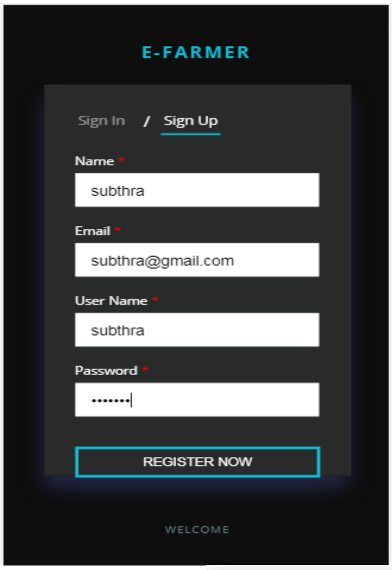
Class(disease type)	Number of images
Alternaria Alternata	200
Cercospora Leaf Spot	250
Bacterial Blight	250
Anthracnose	150
wheat leaf rust	400
Healthy Leaves	200

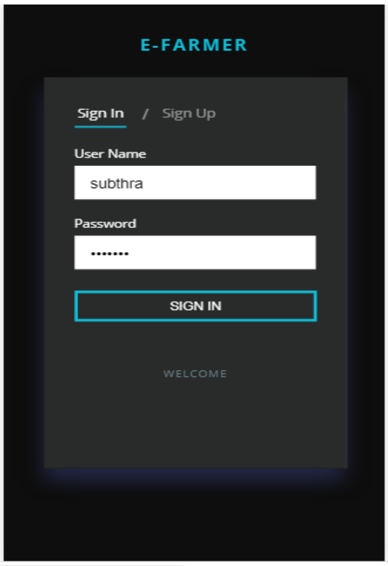
The image analysis takes place and an image with four levels of gray appearsshowing the background in white, the normal leaf (or plant part in general) in gray and the spotsin black color (Figure 6a).Figure 6 b)represents the proposed segmentation results of the Agricultural leaf input

ISSN: 2233-7857 IJFGCN

image. The images are of Multiplanar Reconstruction (MPR) type. The affected and unaffected diseases regionsare categorized as a part of segmentation technique.Demarcation between affected region and unaffected portions is available in the result of Figure 6 b).

Features are extracted from segmented diseased regions and corresponding values are listed to figure 6(c) different types of are analysed to identify the impact of high grade upon the leaves.11 different types of features are taken into account for classification and curative suggestion purpose. The extracted features of a testphotograph are compared against the disease signatures in order to select the most likely disease.These enhancements to feature extraction techniques are applied based on the paper by K. Subhadra and Dr.N. Kavitha (2020) Multi Label Leaf Disease Classification Using Enhanced Deep Convolutional Neural Network (15). Figure 6 shows the effectiveness of the proposed methodology in resolving agricultural image datasets and extract the features. Finally EANN technique is used to carry out the computer aided diagnosis of leaves which is extensively preferred and remedies are being suggested.





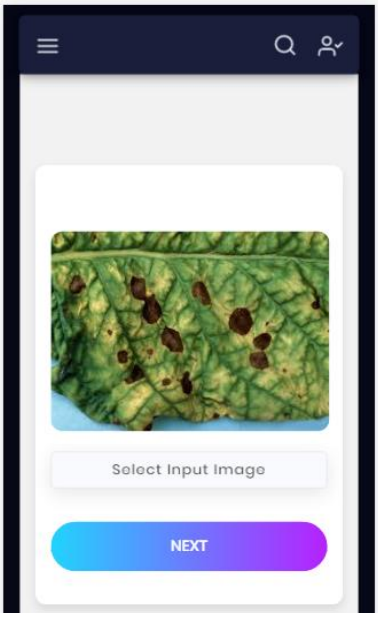


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Fig 5. Proposed system home screen

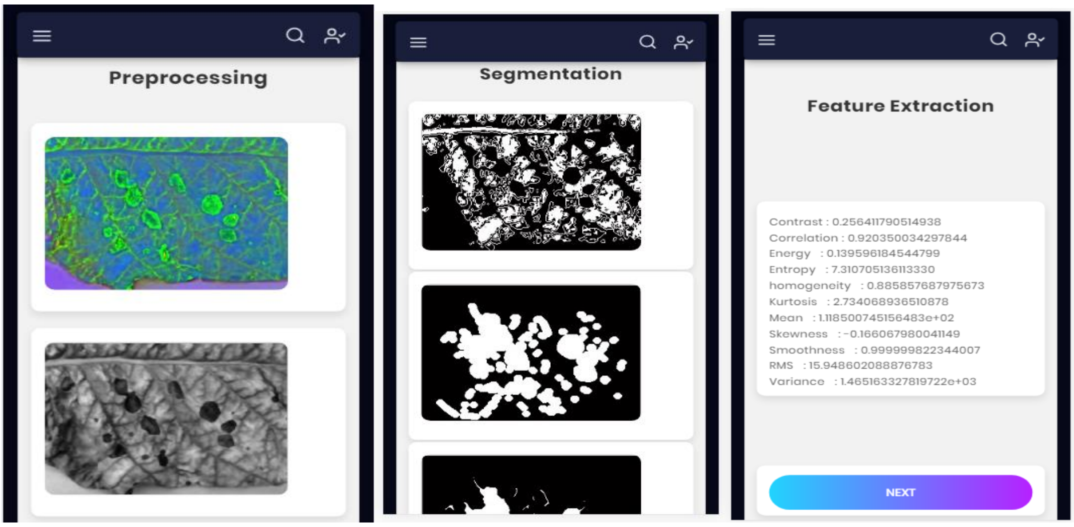

Fig 6. a) pre-processing image b) segmentation images c) feature extraction

Tested ECNNPLD application on some test images example listed figure 6, and obtained the results as tabulated in the below table (II). Proposed results of recognition of the obtained results of diseases are attained with significant gaps compared to others diseases. For example, proposed result of Alternaria Alternata with 0.93640% compared to others diseases as shown in the table(II). The reason behind the larger gap, maybe due to the big difference of appearance between diseases.

Figure 6 represents the designed ECNNPLD application which achieves higher true positive rate for existing prediction. From the figure 7 proposed system result shows classification result of Alternaria Alternata diseases and additionally the result are enhanced to suggest the fungicide solution to control Alternaria Alternata diseases along with the mulch and crop rotation method to prevent Alternaria diseases. The accuracy was experimentally measured between 90% and 98%. An acceptable accuracy higher than 90% can be achieved in most of the cases since the lesion spots can recognized interactively with high precision.

Table 2. Sample Test Image with Predicted and Expected Results

Image example	**Obtained result**	**Expected results**
	Alternaria Alternata - 0.96630	Alternaria Alternata
	Anthracnose - 5.420e-20	
	wheat leaf rust – 9.4526e-15	
	Healthy Leaves -7.693e-22	

ISSN: 2233-7857 IJFGCN

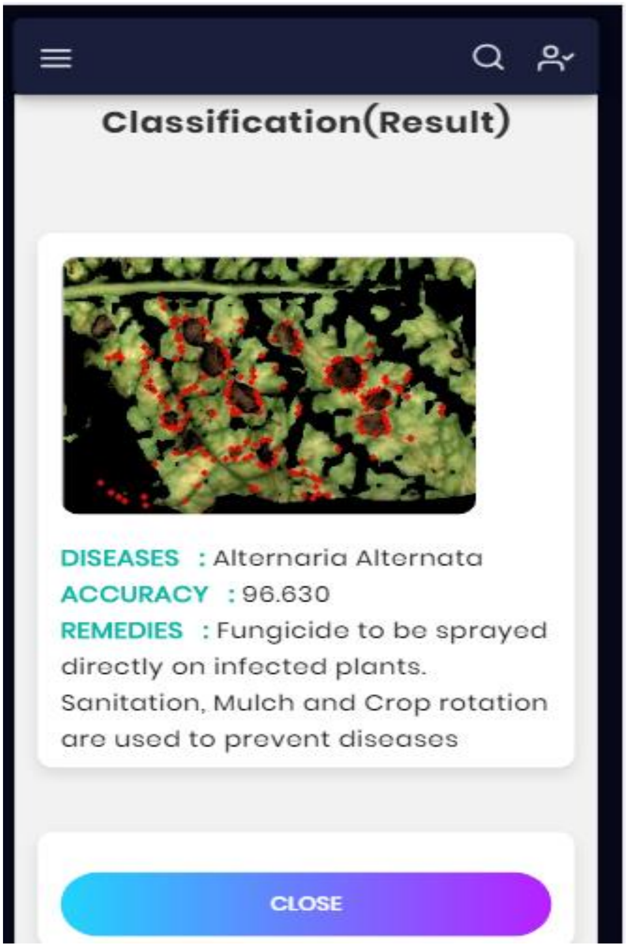

Fig 7. Remedies classification

c

Table 3 proposed system Remedies classification

Diseases	Remedies	Prevention
Alternaria Alternata	Fungicide to be sprayed directly on infected plants.	Sanitation, Mulch and Crop rotation are used to prevent diseases
Cercospora Leaf Spot	Sulphur sprays, copper-based fungicides,	Seed treatments, Baking soda and neem oil.
Bacterial Blight	Spray Streptomycin sulphate + 300gram Tetracycline and 1250-gram Copper oxychloride.	seed treatments,
Anthracnose	multipurpose insecticide destroys larvae and eggs of insects.	Neem oil spray and seed treatments
wheat leaf rust	triazole fungicides	seed treatments, Foliar fungicides are used to

ISSN: 2233-7857 IJFGCN

		control

The developed application has selected the most likely disease after performing the appropriate analysis. In case of leaves, it had to select between six alternatives while it had to choose the most likely disease between four alternatives in the case of plant leaves. As a conclusion from the discussion above we can state that the proposed plant disease diagnosis method has achieved very good accuracy compared to standard classification methods and the referenced approaches. It is obvious that higher accuracy can be achieved by a larger training set. The disease signatures defined here, were based on a small number of representative training photographs allowing the extension of the supported set of diseases by an end user that does not have access to the application source code. Future study can be based on the disease severity to suggest the remedies to farmer which in turn reduces the cost and time to prevent the diseases.

5 CONCLUSIONS

The cultivation of plants faces threat of various diseases caused by pest, microorganisms, weather conditions, soil profile and deficiency of nutrition etc., which leads to significant reduction in crop yield and hence, disease diagnosis is very essential to enhance crop production and to improve the economic growth. Our contribution and results while using a mobile device by farmers to recognize the plants diseases based on deep convolutional neural networks, compared to the previously published, is still preliminary, and deriving from a rather straightforward adaptation of ECNNPLD prediction Model. The proposed ECNNPLD model can effectively classify 5 common diseases through image recognition and corresponding suggestion. To improve plant diseases identification accuracy, we still need to provide thousands of high-quality plant diseases images samples by means of eliminating these qualities that are now redundant, their performance in classification is enhanced with a huge reduction in the cost of classification. The simple use of ECNNPLD prediction Model in computer vision and its applications, especially smart mobile plant diseases recognition is useful in early detection of the diseases and suggestions of remedies are provided to the farmer to increase production

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ISSN: 2233-7857 IJFGCN