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DETECTION OF TOMATO PLANT DISEASE BY LEVERAGING THE POWER OF DEEP LEARNING AND UAV IMAGERY

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Abstract: Precision agriculture is a farming system based on the combination of detailed observations, measuring and rapid response to optimize energetic input to maximize crop production. Precision Agriculture is one of the modern farming practices that make crop production more efficient. One of the major problems in agricultural domain is earlier detection of plant diseases. Currently, manual plant disease classification and counting are very time consuming with less accuracy. Detection of various diseases of plant is very essential to prevent the damage it can make to plant as well as to the farmers and whole Agriculture ecosystem. Regarding this practical issues, this project aimed to classify and detect plant diseases especially for tomato plant. Deep Convolutional Neural Network (CNN) based architecture is proposed for leaf disease detection and classification. The experimentation is carried out using Unmanned Aerial Vehicle (UAV) images. Plant village dataset, UAV images dataset, real-time images captured through UAV and some images downloaded from the internet are used. This system detects the diseases present in plant with more accuracy.

***Index Terms* – Precision agriculture, Deep Learning, Convolutional Neural Network (CNN), UAV images, Plant disease.**

I. INTRODUCTION

Precision agriculture seeks to use new technologies to increase crop yields and profitability while lowering the levels of traditional inputs needed to grow crops (land, water, fertilizer, herbicides and insecticides). In other words, farmers utilizing precision agriculture are using less to grow more. Plant disease detection plays an important role and challenging tasks in agricultural field. A wide number of techniques have been developed for plant disease classification has shown promising results in few selected diseases and crops [1]. In general, the plant disease classification methods are divided into three categories based on the features they use, namely handcraft feature learning method, unsupervised feature learning method and deep feature learning based method [2]. Earlier, plant leaf classification was based on the handcraft feature learning based method. This method [3] was mainly used for designing the engineering features, such as color, shape, texture, spatial and spectral information. The unsupervised feature learning method [4] is an alternative for the handcrafted features method and learning the unlabeled data for plant leaf classification.

The aim of unsupervised feature learning method is used to identify the low-dimensional features that capture some underlying high-dimensional input data. When the feature learning is performed in unsupervised way, it enables a form of semi-supervised learning where features learned from an unlabeled dataset are then employed to improve performance in a supervised setting with labeled data. There are several unsupervised feature learning methods available such as k -means clustering, principal component analysis (PCA), sparse coding and auto encoder. In real time applications, the unsupervised feature learning methods have achieved high performance for classification compared to handcrafted-feature learning methods [5]. However, the lack of semantic information provided by the category label cannot promise the best discrimination between the classes. So we need to improve the classification performance and to extract powerful discriminant features for improving classification performance.

The deep learning model is composed of multiple processing layers that can learn more powerful feature representations of data with multiple levels of abstraction [6]. The comparison with handcrafted feature learning and unsupervised feature learning, the deep learning method has been found to automatically learn from data using deep neural networks. In deep learning method there are several number of learning model available such as artificial neural network (ANN), convolutional neural network (CNN), deep neural network (DNN), stacked auto encoder (SAE), and so on. One of the challenging task is manual detection and classification of plant diseases.

This research paper has been organized as follows. Section II describes the review and related works for the plant leaf disease classification. Section III discusses the proposed works for tomato plant leaf recognition system. Section IV provides detail description about the benchmark dataset. Section V describes the experimental results and analysis. Finally, conclusions are shown in section VI.

II. Related Work

A lot of classification methods have been proposed to deal with the plant leaf disease recognition system. Machine learning models for the prediction of these plant leaf diseases were found to differ in accuracy. Various techniques are at present being used for the recognition of plant leaf diseases by the application of computer vision. The traditional classification based on either supervised or unsupervised learning methods. Some researchers have proposed plant leaf disease classification using supervised learning methods such as support vector machine, artificial neural networks, random forest, k-nearest neighbors, decision tree and sparse representation classifier [7]. The support vector machine is a supervised non-parametric learning technique, therefore no assumption made on data distribution. Zhang et. al. [8] have used the genetic algorithm support vector machines (SVMs) for the classification of Tomato leaf diseases. To recognize and classify tomato leaf diseases and healthy leaf. Alehegn [9] developed a technique based on color, texture and morphological features for classification of plant disease affected leaf and healthy leaf.

A study in comparison of support vector machine (SVM) and ANN, was performed by Ren et. al. [10]. Algorithms for color extraction and texture features were developed, which were thus used to train SVM and ANN classifiers. The study presented a reduced feature set based approach for the recognition and classification of images of plant diseases. The results revealed that the SVM classifier was progressively reasonable for identification and classification of plant diseases. An SVM classifier was 92.17% than the ANN classifier that had an accuracy of 87.4%.

Sankaran et.al [1]., presented a review of the most distinguished conventional methods of plant disease detection techniques. These techniques include spectroscopic-based, imaging-based, and volatile profiling-based plant disease detection methods. The paper compares the benefits and restrictions of these approaches. In recent years, CNN has been used in various agricultural applications such as disease leaf object classification, leaf disease prediction and disease detection. However, in the literature, plant leaf disease identification using deep learning have not been handled so much. Therefore, novel approaches in this area are required. The authors in [10,11] presented deep CNNs for solving disease identification tasks using different datasets and different number of layers for various plant leaf diseases.

III. Proposed Work

3.1 Architecture

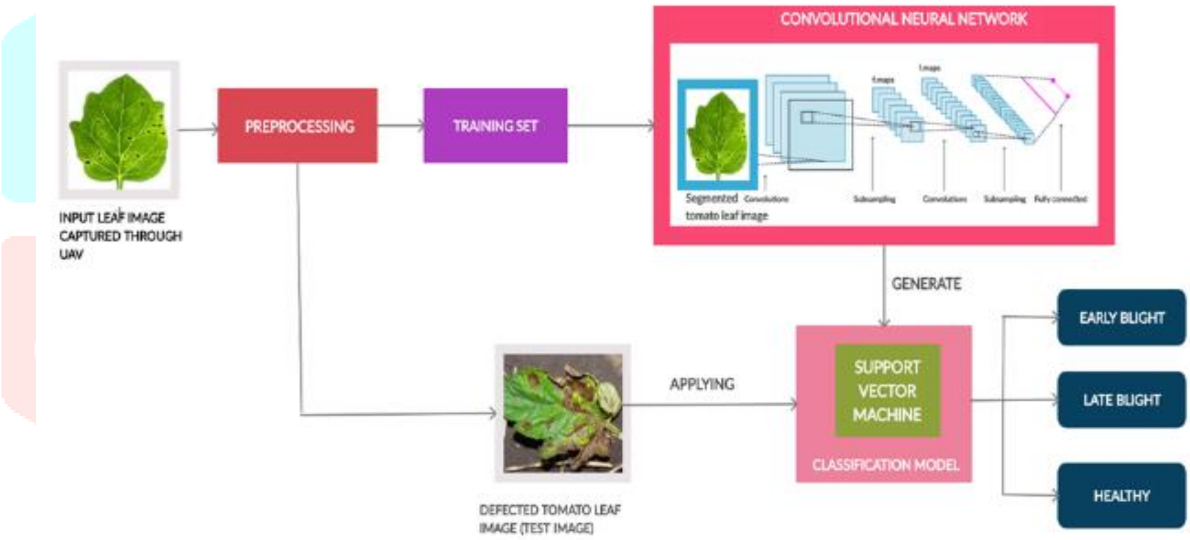

Fig. 1 Architecture of Tomato Plant Leaf Disease Classification Model

In fig.1, the tomato leaf is preprocessed and the features are extracted using CNN and a classification model is generated. A test image is given to the classification model and the output is predicted.

3.2 Preprocessing

This module collects the input data (here it is the image of the tomato leaf) and the data is pre-processed. Pre-processing involves reading the image, resizing the image, removing noise (De-noise) the image. In pre-processing, the background images are removed i.e., cropping the leaf images only. The dataset contains images with several diseases in tomato plants. The images are captured from the farm using Unmanned Aerial Vehicle (UAV). The image was collected at different time and orientation (e.g. illumination, different light intensity, placement, different rotation, scales). The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing.

3.3 Convolution layer (Feature Extraction)

Convolution has a set of learnable filters which are a matrix (W x H x D). The input image is considered as a matrix and the filter is imagined sliding through the input image matrix in order to get the convoluted image which is the filtered image of the actual input image. If a filter is applied on the input image, the result would be an output matrix smaller than the original image. Padding plays an important role if we need to get the same size outputted as the input size. The purpose of convolution in image data is to extract features from the input image. Convolution will produce linear transformations of input data according to spatial information on the data. The weight on that layer specifies which convolution kernel is used, so that convolution kernels can be trained based on input on CNN.

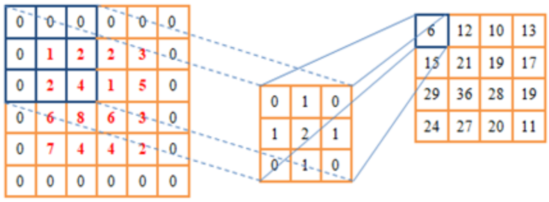

Fig. 2 Convolution Process

3.4 Activation function

The activation function used is the Rectified Linear Unit (ReLu). The size of the kernel or filter used for each convolution layer is 3 × 3 with the aim of speeding up the training process and increasing the accuracy of identification. In practice, ReLU converges six times faster than tanh and sigmoid activation functions. The ReLU activation function is defined as:

$$b_{i,j,k} = \max(a_{i,j,k}, 0) \quad (1)$$

where, ai,j,k is the input of the activation function at location (i, j) on the k-th channel. In this layer we remove every negative values from the filtered images and replaces it with zeros. The Figure 4 elaborates the process of activation function. Figure 3 illustrates the graph of Rectified Linear Unit (ReLU).

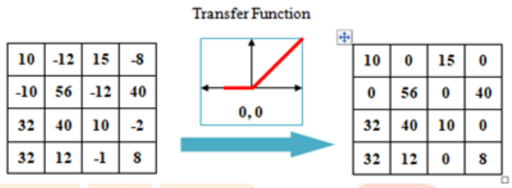

Fig.3 Pictorial representation of activation function

3.5 Pooling or Sub-sampling layer

Pooling is another important concept of CNN. The function of the pooling layer is to gradually reduce the spatial size of the representation. This reduces the amount of parameters and computation in the network, and hence, it controls overfitting. The pooling layer operates independently on every layer of the input and resizes it spatially, using the pooling operation. The most common form of a pooling layer is with filter of size 2 × 2 applied with a stride of 2 down-samples every depth slice in the input by 2 along both width and height, discarding 75% of the activations.
Spatial pooling can be of different types: max, min, average, sum, etc. For spatial pooling, spatial neighborhood of 2 × 2 window is defined and largest element from the feature map is taken within that window if it is max pooling as depicted in Figure 4.

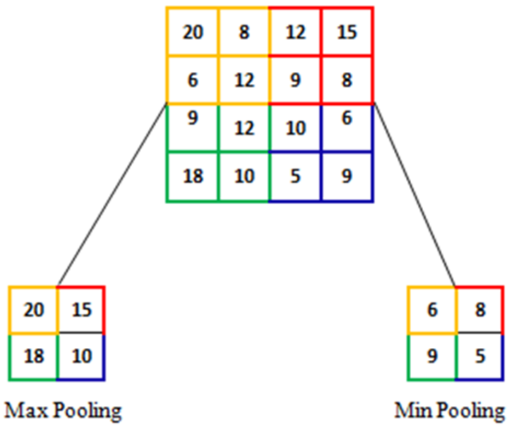

Fig.4 Max, Min and Average Pooling Layer

3.6 Flatten layer or Fully connected layer

After the pooling stage is complete, the flattening stage will be carried out or level the results from pooling into the fully connected layer. The purpose of flattening is converting all the resultant two dimensional arrays into a single long continuous linear vector. The working principles of flatten layer as shown in Figure 5.

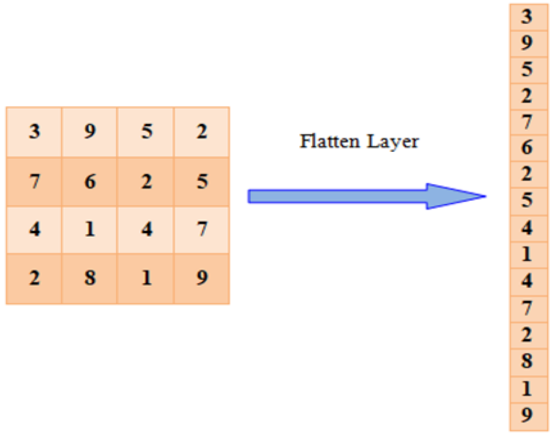

Fig. 5 working process of Flatten layer

Classification can be either binary class classifier or multi class classifier. For binary class classification, the activation function sigmoid is used where as for multi-class classification soft-max function is used as a classifier.

3.7 Classification & Prediction

Classification is an important module in plant disease detection systems. This manuscript considers systems that detect plant diseases using an image, thus classification here is defined as a process of categorizing plant leaf images based on three stages of diseases i.e., Early blight, Late blight, Healthy. Researchers have developed several modeling techniques using Support Vector Machines (SVM), to validate the test data set. Hence SVM is used to classify the plant diseases.

IV. IMPLEMENTATION

Software and hardware details

In this experiment, the proposed CNN model was trained and tested using tensor flow in Core i7 CPU 2.6GHz, 1 TB of Hard Disk and 8 GB of RAM.

5. RESULTS AND DISCUSSION

Dataset description

The Plant Village dataset is a large scale high-resolution image that has been captured from UAV Aerial vehicle. The dataset contains 3,300 images which consist of 3 classes. Each class contains 1100 images of size 256x256 pixels.

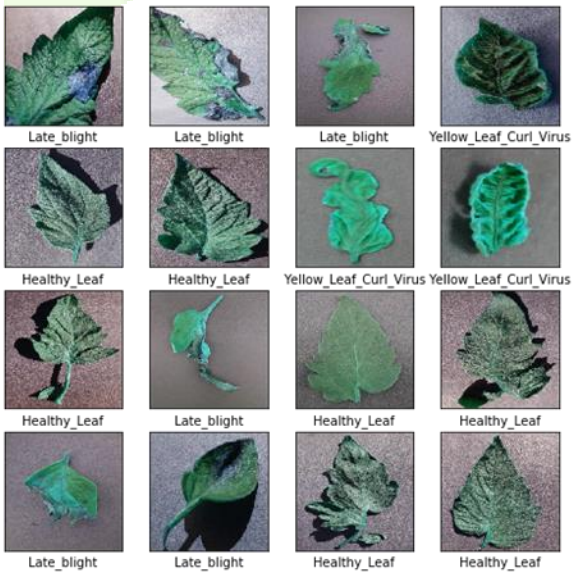

Fig. 6 Dataset description of Plant Village

In proposed CNN model, the dataset has been split into training, validation and testing datasets separately. The training, validation and testing dataset description are shown in Table-1. In each image, three spectral bands were used including red, green and blue.

Performance Evaluation Metrics

The evaluation metrics plays an important role for accessing the classification performance and improving model selection. We have used confusion matrices, accuracy, precision, recall and F1-score for evaluating the effectiveness of the proposed approach. Fig. shows a confusion matrix for a Tomato leaf disease classification problem having true positive (TP), false positive (FP), true negative (TN) and false negative (FN) class values. If the classifier predicts correct response of class at each instance and it is counted as "success", if not, it is an "error". The overall performance of the classifier is obtained by error rate, which is a proportion of the errors made over the whole set of instances.

		Actual Value	
		Positive	Negative
Predicted Value	Positive	TP	FP
	Negative	FN	TN

Fig. 7 Confusion Matrix for Tomato leaf disease classification

From the confusion matrix, it is possible to extract a statistical metrics (Precision, Recall and F-measure) for measuring the performance of classification systems and is defined as follows: Precision (P) or detection rate is a ratio between correctly labelled instances and total labelled instances. It is a percentage of positive predictions in specific class that are correct. It is defined by:

$$\text{Precision (P)} = \frac{TP}{TP+FP} \quad (2)$$

where, TP is the number of true positive and FN is the number of false negative predictions for the particular class. The total number of test samples of the particular class is TP + FP. Recall (R) or Sensitivity is a ratio between correctly labelled instances and total instances in the class. It has an ability to measure the prediction model and is also called as true positive rate. It is defined by:

$$\text{Recall (R)} = \frac{TP}{TP+FN} \quad (3)$$

where, TP is the number of true positive and FN is the number of false negative predictions for the particular class. The total number of test samples of the particular class is TP + FP. The F1-measure is the harmonic mean of precision and recall and it attempts to give a single measure of performance. A good classifier can provide both recall and precision values high. The F1-measure is defined as:

$$F1 = 2.\frac{P.R}{P+R} \quad (4)$$

The Accuracy can be defined as follow:

$$\text{Accuracy} = \frac{\text{Total No.of Correct Prediction}}{\text{No.of Input Samples}} \quad (5)$$

V. RESULT

In this experiment, the proposed CNN model was trained and tested using tensor flow in Core i7 CPU 2.6GHz, 1 TB of Hard Disk and 8 GB of RAM. The training process is a process to make the system learn the features that exist in the image and classify these features. In this study, Tomato plant disease images with 3,300 images with different types of Tomato plant leafs, namely Healthy Leaf, Late Blight, and Early Blight. In figure 8, Shows the results of accuracy on the CNN model used, with accuracy results of 98.18% accuracy and loss of 0.06%.

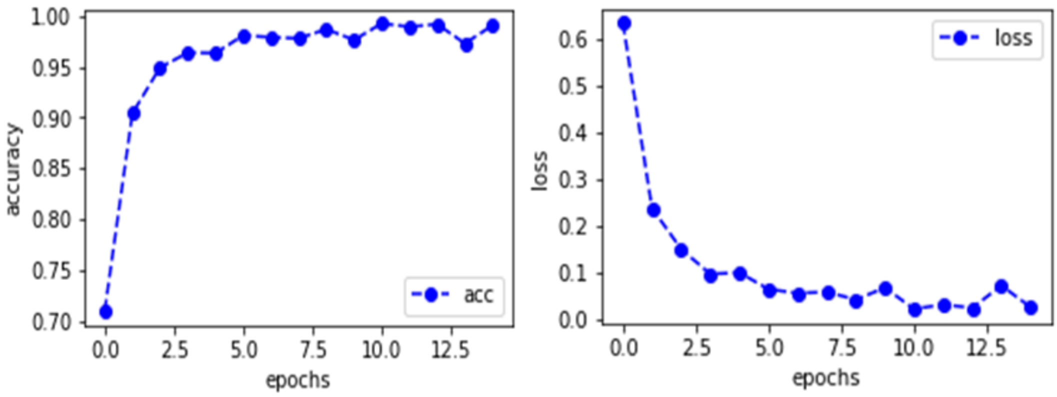

Fig. 8 Accuracy and Loss of Proposed System

Figure 9 shows a Performance of proposed plant leaf disease recognition system. The correctly classified data items are placed in diagonal of matrix, remaining miss predicted data items are placed above and below the diagonal of matrix. We found that the error occurs when 'late blight' classified as 'Healthy leaf' and 'Yellow curl virus'. The confusion matrix for object classification is shown in Figure 10.

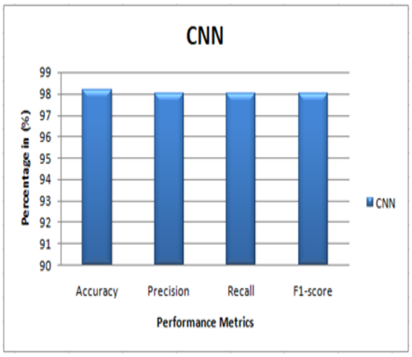

Fig. 9 Performance of Proposed System

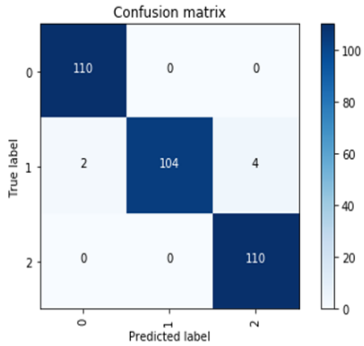

Fig. 10 Confusion matrix of Plant leaf recognition system

VI. CONCLUSION

In this paper, we have proposed an approach for Tomato leaf disease classification and prediction model using Convolutional Neural Networks. The CNN model act as a feature extractor and classifier for the given training images as well as validation images. The use of CNN outperforms other traditional method and allowed us to achieve 98.18% of accuracy. In future, we have planned to develop a real-time leaf disease detection and classification and it can be expanded to all types of plants.

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