

Smart Farming: An Approach for Disease Detection Implementing IoT and Image Processing

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ABSTRACT

With the increasing demand on smart agriculture, the effective growth of a plant and increase its productivity are essential. To increase the yield and productivity, monitoring of a plant during its growth till its harvesting is a foremost requirement. In this article, an image processing-based algorithm is developed for the detection and monitoring of diseases in fruits from plantation to harvesting. The concept of artificial neural network is employed to achieve this task. Four diseases of tomato crop have been selected for the study. The proposed system uses two image databases. The first database is used for training of already infected images and second for the implementation of other query images. The weight adjustment for the training database is carried out by concept of back propagation. The experimental results present the classification and mapping of images to their respective categories. The images are categorized as color, texture, and morphology. The morphology gives 93% correct results which is more than the other two features. The designed algorithm is very effective in detecting the spread of disease. The practical implementation of the algorithm has been done using MATLAB.

KEYWORDS

Back Propagation, Color, Image Processing, Neural Network, Segmentation, Texture

1. INTRODUCTION

The advancement in Sensor nodes and evolution of 5G technologies has gained recent attention and the objective of this article is focused on considering the use of Internet of Things and smart sensor for the application of agriculture (Lin et al., 2018). The evolution of sensor networks and IoT has gained attention in agriculture domain and the deployment of sensor node in real time environment collects the field data at any time and collected data is analysed in real time basis through IoT analytics platform. The cloud platform provides the real time analysis of data for the detection of adversaries in data. The IoT is termed as the network of objects or smart devices, smart vehicles, smart home, buildings and each item which is embedded with electronics, smart sensors, network connection and software's as these advancement in technologies enables these smart devices to collect and exchange data among each other. The Internet of Things is addressed as the global organization towards information society and provides advanced solutions and services through connecting physical and virtual smart devices (things) on the basis of their evolution and existence of communication approaches. The objective of this article is then collaborated with the image processing for the confirmation and detection of

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diseases in crops along with the concept of cloud computing for meeting the requirement analysis of obtained data in real time. Majority of the smart farming application has adopted Internet of Things and presents the benefits of using the advanced sensing and analysis for crop production (Gayatri et al., 2015). The adaptability of IoT in majority of applications has proved the potential of the technology for various areas that includes tracking of assets, industrial management, security aspects, energy utility and monitoring based on conditions. IoT serves variety of other applications such as smart transportation, smart homes, lifestyle, smart building, smart agriculture, healthcare and environment monitoring. IoT is often named as thing of things or network of networks and because of this, IoT technology can perform different tasks at the same time with more accuracy and much efficiently. Image processing is the process in which the images are processed by implementing some mathematical expressions. Image processing uses signal processing at which the input is any image or multiple images or videos whereas the output of an image processing can either be any image or the extracted characteristics which are related to that image or series of images and output image is often termed as digital image (Sharma et al., 2017). Digital image processing requires various algorithms for the operation of performing image processing at digital images (Dogra et al., 2020). The prime operation of digital image processing involves classification (identification of the class at which the new extracted observation belongs), pattern recognition (recognition of known and discovering unknown patterns), feature extraction (derivations which are made using initial information), signal analysis (processing of signals) and at last projection (formation of planar surface by conversion of three dimensional object).

India is a country where most of its population for their living depends upon the agriculture. In India farmers can choose various different crops depending upon the productivity and selects particular pesticides as per the requirement. The economy of India is significantly relied upon farming. The improvement in this field will exceptionally add to the economic government assistance. Innovation is playing an important role in bringing the change and progress in numerous areas. The study of crop and plant diseases referred to as the study of visually analyzing the patterns of particular crop. Monitoring the growth of plant, crop, and fruit is critically important for sustainable agriculture (Rao and Sridhar, 2018). The early detection of plant disease can stop the cause or reduce it through proper management strategies and leads to the overall increase in productivity. The disease in crop affects the crop in terms of its quality degradation and quantity reduction. Image processing provides the capability of studying the visible observation patterns to study the plant diseases. The regular monitoring of particular crop results in analysing the health of plant and plays a significant role for the cultivation of crop. Initially, the operation of plant health monitoring and analysing the diseases is carried out manually by the experts. The disadvantage of manual prediction is that it consumes lot of time and there exist many wrong predictions. Moreover, manual prediction requires ample amount of efforts along with the intensive processing time. The detection of diseases in plants through image processing is an effective solution for early and accurate detection.

The symptoms of disease in most of the cases are observed on stems, fruits and on leaves. The detection of disease from the leaf of plant is considered as the symptoms of plant disease. Some of the common diseases in tomato are early blight, buck eye rot and late blight. These some of the diseases in tomato crop are the most common that can occur at any stage of plant and fruit growth (Mekala and Viswanathan, 2019). The disease of early blight is observed on tomato which appeared as a small black lesion. On the other hand the buck eye rot type of disease appears green in color and occurs mostly when the fruit touches the ground. The late blight is one of another kind of plant disease which happens because of high humid conditions. The overall purpose of this article is to monitor the plant disease specifically on the tomato leaves and to find the solution to reduce the cause in order to increase the health of plant and overall productivity. This process is achieved by adapting image processing and concept of neural network for the detection and analysis of diseases in plant. The database for the purpose of training is created for the diseased images. The features of each image are extracted by implementing morphology and texture analysis.

The incorporation of IoT along with image processing provides various advantages in agriculture domain (Amit Sharma et al., 2019). The routing protocols in sensor networks plays a significant role in energy efficiency of the network (Sharma et al., 2019). The integration of IoT and image processing providing high quality crop products and reducing failures in crops. The aim of this article is to reduce the failure in crop and providing the information of environmental condition on regular basis which ultimately helps farmers to know which crop is suitable at particular environment. The task of continuous monitoring of agriculture field and environment using IoT based smart devices increases the overall crop productivity. The rest of the paper is arranged in four section. Section 2 deals the literature review of the most recent trends in IoT, image processing and their adaptability in the application of smart agriculture. The proposed methodology is represented in Section 3. The results and discussion is presented in Section 4 and at last the conclusion is presented in Section 5.

2. RELATED WORK

This section presents the discussion of various approaches of image processing for the detection of plant diseases. (Sharma and Kumar, 2016) have compared the performance of various routing protocols in ad-hoc sensor networks. The indirect monitoring of diseases in plants can be achieved from the computation of vegetation indices through hyper spectral data, but these approaches are not capable in distinguishing different crop diseases. (Martinelli et al., 2015) have introduced a new approach of spectral indices for the identification of wheat diseases during winters. In their work they have considered three different types of pest names as powdery mildew, aphids and yellow rust that causes wheat crop to get diseased during winters. The Relief-F algorithms is discussed and presented to be the least and most related wavelength for various wheat crop diseases. The experimental results presents the classification accuracy of their discussed approach with new indices for detecting the healthy and infected leafs for powdery mildew, aphids and yellow rust and the observed accuracies were 88.7%, 89.4%, 90.5% and 94.7% respectively. The enhanced images presents high clarity and offers best quality in comparison with the original image. The prime colors in the color image are red, green and of blue color. The implementation of RGB color model for the application is very difficult as their range lies in between 0 to 255. Therefore the RGB model converts the RGB color to grey images. The histogram equalization is then applied to the RGB converted image which further distributes the intensities of image for enhancing the diseases in image. (Márquez-Martín et al., 2011) have developed an approach for detecting the disease in plant along with the fruit grading by using image processing. Their work includes the creation of two databases, one consists set of images which comprised of already stored images of diseases and other set consists of query images for the implementation purpose. The weight adjustment for the training datasets is carried out through back propagation. The authors have considered three features termed as color features, textures features and the morphology. Their experimental result presents that the morphological feature provides best of results when compared with other two features.

(Huang et al., 2014) designed a plant disease detection scheme where authors have gathered leaf images of chilli plant. These collected images of chilli plants are processed for analyzing the health of chilli plant. With the help of their approach the chemicals are applied to the diseased plants only which ensures the health of diseased plant. The extraction of features and recognition of images is carried out through image processing using MATLAB. Fourier filtering is implemented for the image pre-processing, edge detection and for the morphological operations. The classification of objects is based on the computer vision which is an extension of image processing process. The graphical user interface is built by making use of LabVIEW software platform where the images are captured using the digital camera. In order to achieve the extraction of features from the image, the image segmentation of input image is an essential step. (Jhuria et al., 2013) proposed a method for disease prediction and the authors have compared k-means clustering and otsu threshold method which are used for the analysis of leaf infection. The experimental results shows that k-means clustering offers

less extracted values for features in comparison with Otsu method. On the other hand the k-means clustering is more accurate in comparison with other method for its clarity. The identification of disease is carried out using RGB image. In their approach, authors have applied k-means clustering approach for the identification of green pixels and then the extracted pixels are further subjected to next step where Otsu approach is applied for obtaining the varying threshold value. Color co-occurrence approach is implemented for the extraction of features. The RGB input is subjected to the HIS color space model for its conversion and translation (Khirade and Patil, 2015). The texture statistics is computed based on this SGDM matrix is created and then the features are calculated by using GLCM function. (Prakash et al., 2017), have developed a system for monitoring the plant diseases and controlling plant diseases by making use of DSP and FPGA system. FPGA is utilized for processing the collected field image and videos for the regular monitoring and detection of diseases. DSP system is utilized for the purpose of encoding the image and video data. (Al-Hiary et al., 2011), presented an approach for the identification of diseases in rice by implementing the pattern recognition method. The author have described a prototype for the detection of disease in rice on the basis of rice plant infected image. The authors have implemented HIS color model at the interested region of image for image segmentation and based on this spots and boundaries are detected for the identification of leaf infected part.

There exist many work for different applications using IoT like smart farming. The prediction of diseases in crops using image processing is very helpful in increasing the overall crop yield. The work presented by (Zhang et al., 2010) utilized color and pattern analysis approaches for the identification of multiple diseases in leafs and fruits. (Phadikar and Sil, 2008) have designed a framework which combines cloud computing along with the Internet of Things for the possible detection of crop diseases. (Channe et al., 2015) have presented the importance of IoT in smart agriculture by designing an approach which regulates water in the agriculture field. (Suciu et al., 2019) have presented the discussion about the fast growth in the field IoT and its applicability in agriculture domain and its modernization. Their discussion helps in terms of realization with increasing demand of IoT as it provides a smart solution for agriculture and more efficiently solves the issues associated with farming. The advantages of implementing smart devices and IoT for farming increases the production and provides more efficient solutions for meeting the requirements of agriculture (Boursianis et al., 2020). The adoption of image processing for the detection of various crop diseases is discussed by (Balamurugan et al., 2016). (Rekha et al., 2017), have proposed an approach for the visualization and tracing the products of agriculture in supply chain. The work presented by (Muangprathub et al., 2019), discussed the use of network, hardware architecture along with the software process to design a smart agriculture system for precision irrigation system. (Garg and Alam, 2020), have discussed the importance of cloud computing and Internet of Things for the application of agriculture and forest environment monitoring.

3. METHODOLOGY

The three features are computed for the classification of images. The color features, morphological features and texture features are utilized for the extraction of features for the learning of dataset images. The features are termed as low level features.

3.1. Color

The color of object is one of the strongest parameter that humans requires and considers for the discrimination of different objects. The working of image processing based on color images is divided into three categories:

1. The transformation of color (includes mapping of color image).

2. The processing of spatial features of individual color plane.
3. The processing of color vector features.

The RGB color features of an image adversely affected by the intensity of light and the angle of the captured images. So in order to avoid this affect HSI color space is implemented where the RGB features are transformed to HSI color model:

$$H = \begin{cases} \theta & \text{if } B < G \\ 360 - \theta & \text{if } B > G \end{cases} \quad (1)$$

where:

$$\theta = \cos^{-1} \left\{ \frac{\frac{1}{2}(R - G) + (R - B)}{\left[\left[(R - G)^2 + (R - B)(G - B) \right]^{1/2} \right]} \right\} \quad (2)$$

$$S = 1 - \frac{3}{(R + G + B)} \left[\min(R + G + B) \right] \quad (3)$$

$$I = \frac{1}{3}(R + G + B) \quad (4)$$

3.1.1. Algorithm for the Computation of Color Feature Vector

The closest relevant feature from the matching dataset along with the query image presents the least feature of distance metric. Equation 5 is implemented for the computation of distance metric where the exact match is featured along with the zero distance metric:

$$hist_{dist} = \sum_{j=0}^{255} \left[hist(j)_{database} - hist_{query} \right] \quad (5)$$

where:

- j indicates the grey level features;
- $hist_{query}$ represents the query image histogram value;
- $hist(j)_{database}$ represents the histogram value of database image; and
- $hist_{dist}$ represents the difference in error.

The histogram equalization for all the images is computed and then saved in database in advance which further processed in order to compare to the query image with the images that are saved in

database. In the next step H, S and V plane are computed considering the level 8, 8, 4 respectively. The levels are considered in order to provide less importance towards V plane and offer less computational time.

3.2. Morphology

Morphology operation is carried out for extracting components of images which are further utilized for the representation and description shape features of region, like boundaries and edges. The implementation of morphology, brings the extraction of shape feature vector of disease which are extracted from the healthy leaf and healthy fruit. Considering color plane, RGB color model is further subjected to next stage for its conversion to HSI color plane which is quantized in H, S and I planes at the levels of 30, 30 and 20 respectively.

3.2.1. Algorithm for the Computation of Feature Vector Using Morphology

For each plane, utilizing images from the databases the boundaries are obtained by using the concept of erosion. This operation involves rule based classification which is responsible for measuring the state of pixel value of the output image and it is also observed that the output pixel value is measured as the minimum of the computed values for all the pixel values measured as the input pixel's neighborhood computed by using Equation 6:

$$Erosion = \left\{ \frac{T}{B} z \in A \right\} \quad (6)$$

$$Image\ Boundary = Original\ image - Eroded\ image \quad (7)$$

From this equation, erosion of A by B (which represents the database images with the input image) is defined as the set of all points of T such that value of B, can be translated by T, which is contained in A. DCT transform is implemented as the morphology which is hereby used because it contains the complete information about shape considering few coefficients.

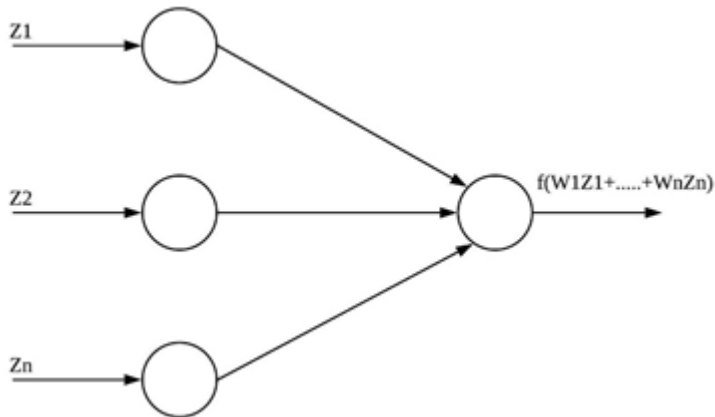
3.3. Texture

The property of extracting texture features describes the visual patterns, where each of the pattern comprised of the properties of homogeneity. 2-D wavelet packet decomposition approach is implemented for the computation of texture features. Whereas the identification of particular texture features present in an image is computed primarily by the modeling of texture feature as a 2-D grey level variation as represented in Equation 8 and 9:

$$\varphi^{ab}(x) = |a|^{-\frac{1}{2}} \varphi\left(x - \frac{b}{a}\right) \quad (8)$$

$$w_{\varphi} = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \varphi\left(t - \frac{b}{a}\right) dt \quad (9)$$

Figure 1. General model of Neural Network



After the process of extraction of features, neural network is implemented for learning database of images. The computed feature vectors are considered as the input neurons for artificial neural network. The output of an artificial neural network represents the function as the weighted sum of computed inputs along with a bias. The working function of complete artificial neural network is understand as the evaluation of outputs for all the input neurons (Figure 1).

The back propagation algorithm is implemented in the recurrent process. After the frozen of trained network weights, these weights are further utilized for the evaluation of output standards for each query image that are not present in learning database (Figure 2).

4. RESULTS AND ANALYSIS

The operation of the proposed methodology has been conducted on the dataset gathered from the tomato plants. It consists of around images belonging to ten dissimilar classes of diseases for tomato and leaf. A neural network API written in Python, has been used for the model implementation. Out of the 15621 images, 4200 images were set aside for testing and 11421 images were utilized for the purpose of training. In order to increase the dataset, automatic data augmentation techniques has been used by randomly rotating the images by a small amount of 20 degrees, horizontal flipping, vertical and horizontal shifting of images. The optimization was carried out using Adam optimizer with categorical cross entropy as the loss function. Batch size of 20 has been used and the model has been trained for 30 epochs. The initial learning rate has been set to 0.01 and it is reduced by a factor of 0.3 on plateau where the loss stops decreasing. Early stopping has also been used in order to monitor the validation loss and stop the training process once it increases. All the experiments were performed on Intel Core i3-4010U CPU.

For the performance evaluation of our proposed approach, we have considered a set of performance measures which comprised of precision, recall, accuracy and F-Score (Figures 3-5). The observed results are presented in Table 1 which shows that the values of each quantitative measure is computed until the belonging epoch number is computed.

The relation between the table and Figures 6 and 7 is that, the Table 1 represents the observed values of accuracy, precision, recall and F-score for each number of epochs. Whereas the Figure 6 and Figure 7 presents the results in terms of train and test accuracy and the loss for each epochs.

A highest value for the validation accuracy of around 94.34% is achieved for over 40 epochs for training vectors, whereas a high 98.26% of the accuracy in training is achieved. Overall, 94% of average accuracy for validation has been achieved. It is observed that this is an effective measure for

Figure 2. Back propagation network

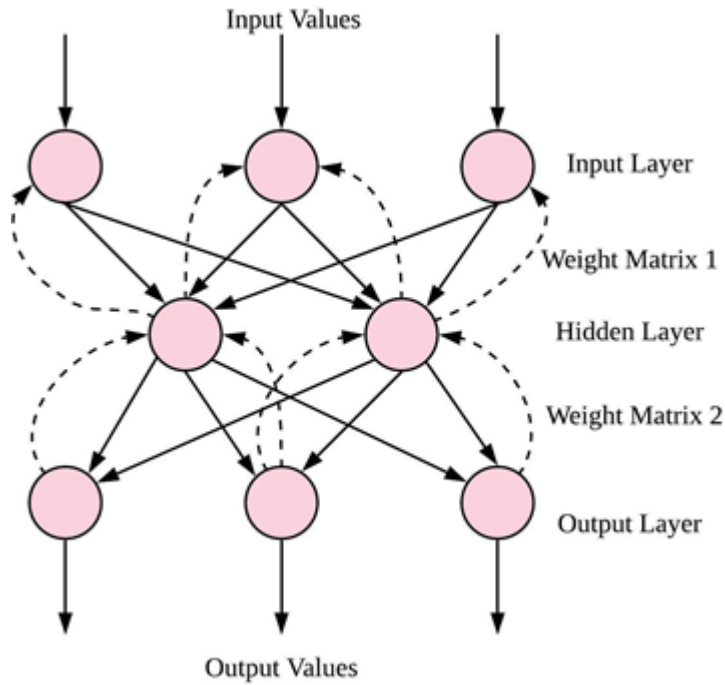


Figure 3. Septoria Leaf Spot



the classification that is made by model of deep learning. Figure 6 represents the accuracy plots of training and testing also loss against the epochs in measured as the means of indication, visualization as the convergence model speed. It can be observed that the model achieves better stability of around 20 epochs and the metrics does not reflects a substantial advancement for the last 10 epochs. The experimental results presents that the proposed model performs better on the dataset and can be

Figure 4. Early and late blight tomato images



(a)



(b)

Figure 5. Healthy Leaves

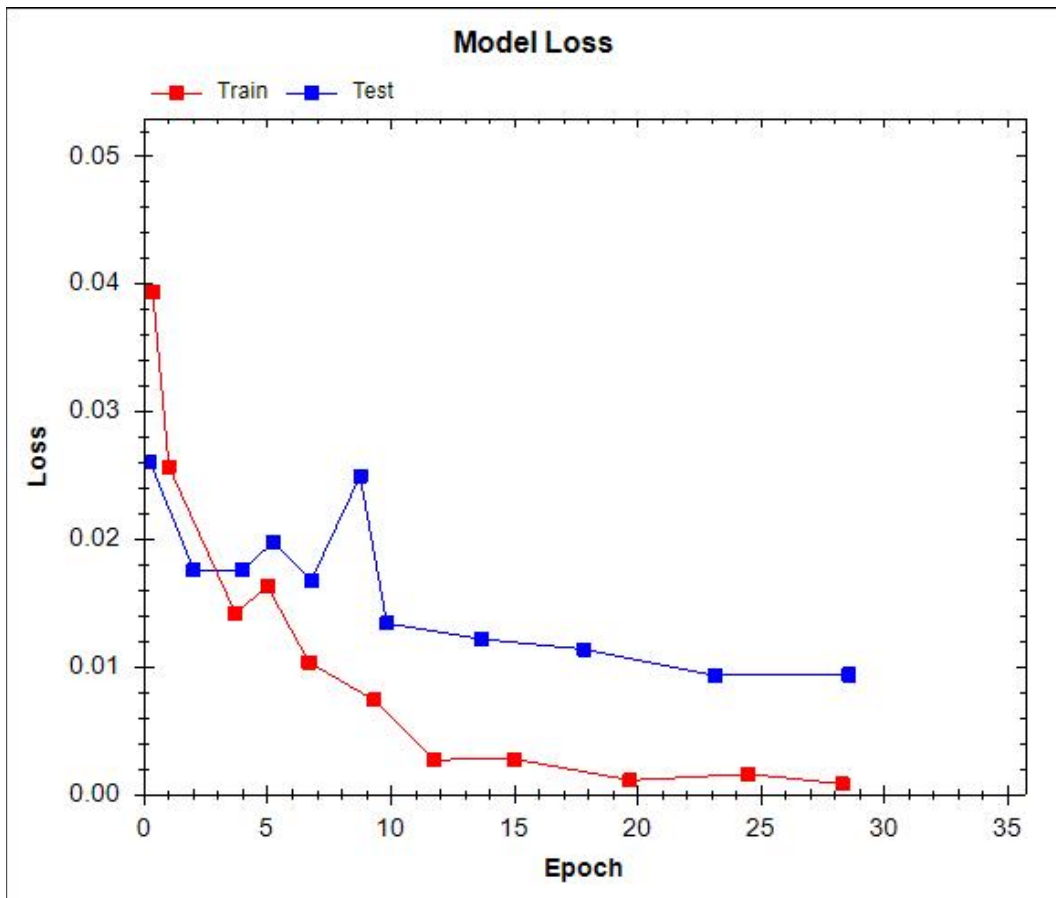


utilized as a classification means for different ten types of tomato leaf diseases where the resource requirements is minimum. Moreover, process of implementation involves least hardware requirements in comparison with large neural networks which generally requires more computational resources or the practice of Graphics Processing Unit. This is because of the last number of training constraints

Table 1. Result and analysis

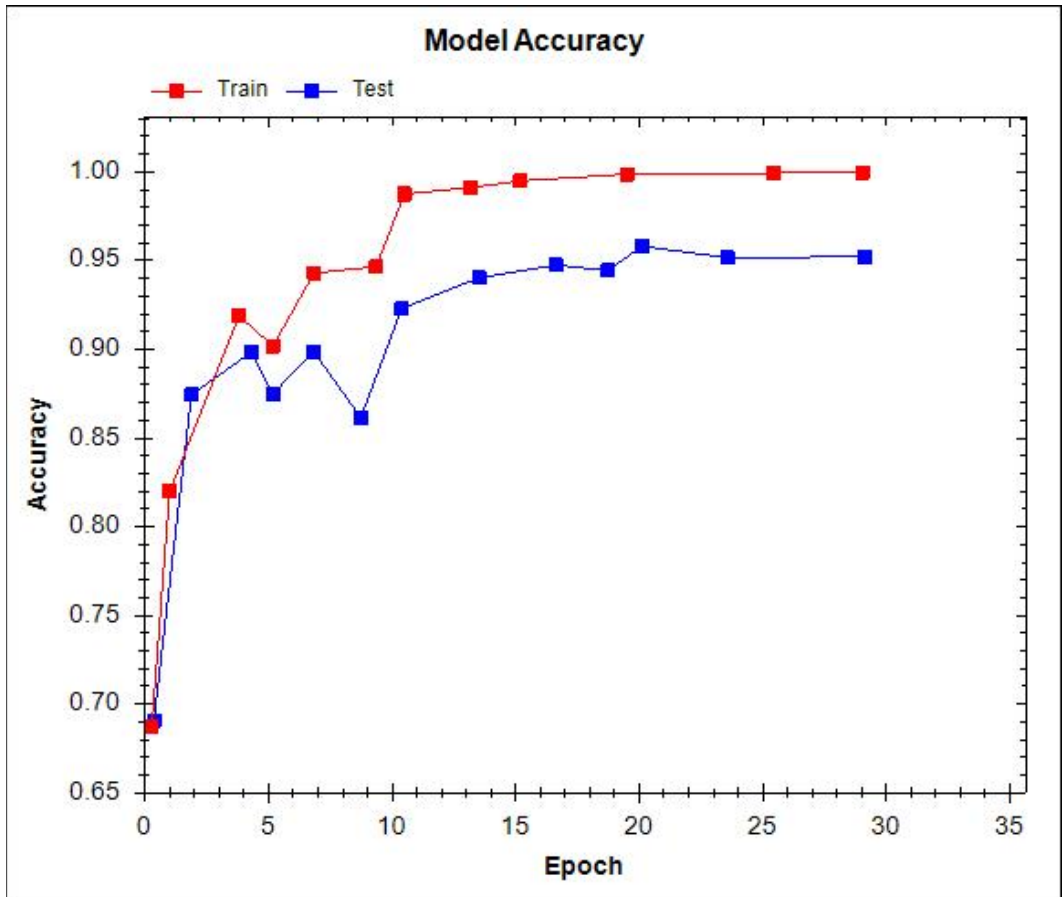
No. of Epochs	Accuracy	Precision	Recall	F-Score
20	93.21	90.23	90.36	90.37
30	92.14	94.58	94.63	94.12
40	94.27	94.37	94.57	94.56

Figure 6. Plot of Model Loss



considering the presence of fewer number of layers with lesser number of filter sizes along with small size train images. In comparison with other existing state of art approaches, the implementation of proposed model can be achieved on CPU with minimum time requirement in respect with simplicity. Also, the major advantage of the LeNet model variation which is adopted is easy to understand and simple for the implementation. The proposed model is capable of providing a simple and effective solution for solving the problem of detecting the diseases in plants at their early stage in comparison with the results obtained from (Huang et al., 2014) where the model presented by authors particularly deals with plant diseases of different crops. With fewer number of resource constraints and lesser data, the proposed model provides comparative results in comparison with traditional existing state of art approaches.

Figure 7. Plot of Model Accuracy



5. CONCLUSION

Agricultural area is still one of the most essential area over which the common of the Indian population depend on. Detection of diseases in crops at early stage is the critically important for growing the economy of nation. Tomato is one of the key essential crops that is produced in huge quantities. Henceforth, the aim of this article is to design an approach that can detect the disease in crop at early stage and is capable of identifying ten different types of diseases of tomato crop. The proposed model implements artificial neural network for the classification of leaf diseases of tomatoes which are gathered from the tomato plants. The architecture utilizes the implementation of simple convolutional neural network with less number of layers for the classification of leaf diseases of tomato considering ten different cases. Dissimilar rates of learning and optimization can also be implemented for experimentation purpose along with the proposed model considering as the future work. The limitation of the proposed model is its accuracy for the training dataset. The future implications can also involves experimentation of this designed approach with newer architectures in order to improve the performance of model for the training dataset. Therefore, the discussed approach can be made by making use of decision tool for helping and providing support to farmers in identifying and detecting the diseases at early stage which can be observed in tomato plant. With the observed accuracy of 94% to 96% the proposed approach can make an accurate prediction of the diseases in leaves with very less of computational effort.

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