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Managing The Tomato Leaf Disease Detection Accuracy Using Computer Vision Based Deep Neural Network

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Abstract: Development of leaf disease in the agricultural sector would decrease crop yield output. Thus, leaf disease identification can be achieved in an automatic way to increase the yield in the agriculture sector. However, most of the disease recognition system works with poor disease recognition due to varying patterns of leaf disease which impair detection accuracy. In this article, we are managing this issue by designing a computer vision model that assists in building a system that involves real-time image detection, feature extraction and image classification. The findings are given by the classifier, whether the leaf is diseased or not. In this paper we use Deep Neural Network (DNN) for real-time image classification. The experimental findings on tomato plant indicate that classification rates have increased with the proposed system relative to other current methods.

Keywords: Real-time Image Acquisition, Artificial Neural Network, Leaf Disease Detection, Tomato Plant

1. INTRODUCTION

The problem of successful protection of plant diseases is closely related to sustainable agriculture and climate change [1]. Research suggests that climate change can shift pathogens and concentrations, host tolerance can also be altered and interactions between host and pathogen can shift physiologically [2]. Now that illnesses are spread more quickly across the world than ever, it complicates the situation. New diseases can occur where they have not been previously established, and where local expertise is not inherently available to combat them [3].

Long-term pathogens, through the unintentional use of pesticides, may build resistance and significantly decrease combat capability. One foundation of precision farming is the timely and reliable diagnosis of plant diseases [4]. Financial and other resources should not be unnecessarily wasted and development should be better handled by solving the issue of developing long-lasting pathogenic resistance and reducing the adverse effects of climate change.

Adequate and timely detection of diseases, including early prevention, was never more important in this changing climate. There are different ways of recognizing pathologies of plants. Some diseases have no obvious effects, or the impact is too late to function and a detailed study is needed in these circumstances. However, most diseases cause some type of manifestation on the visible spectrum, so that specialist testing is trained as the primary technique for plant detection.

A plant pathologist should possess excellent analytical skills for recognizing characteristic symptoms in order to obtain correct diagnoses of plant diseases [6]. Variations in sick plant symptoms may lead to incorrect diagnosis, as it may be more difficult for amateurs and hobbyists to assess than trained pathologists. An automated device designed to recognize the plant's conditions and visual symptoms as a verifier of diagnosis of disease can offer considerable benefits to amateurs in gardening and qualified professionals.

The advances in computer vision provide opportunities [10]-[16] for extending and consolidating precise plant protection activities and increasing the demand for precise agricultural computer vision applications. Popular digital imaging techniques, such as color analysis and thresholds [5], have been used to detect and identify diseases of plants.

Deep learning is a recent trend in deep learning that provides cutting-edge results in many research areas, including computer vision and bioinformatics. There are currently varying approaches to deeper learning for plant disease detection and the most common are convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Deep Belief Network (DNN), etc. The ability to directly use raw data without hand-made materials [7] benefits from deep learning [8] [9].

In this paper we intend to incorporate a deep learning method for the classification of plant diseases, concentrating primarily on the diseases present in the images of the leaf. A computer vision paradigm is developed in this paper by framing a model consisting of image acquisition, extraction of features, and classification of the images. A deep learning classifier called Deep Neural Network (DNN) is used for real-time image classification. The experimental findings on tomato plant indicate that classification rates have increased with the proposed method relative to other existing methods. The outcome of the test indicates whether or not the leaf is diseased.

The outline of the paper is given below: section 2 provides the related works, section 3 provides details of the proposed classification engine. Section 4 evaluates the entire work. Section 5 concludes the work.

Related Works

As described in [17] the Diamante Max tomato variety contains three most common diseases, namely the Phoma Rot, Leaf Miner and Goal Leaf Spot. Phoma Rot disease is a popular in subtropical tomato production in the region. On the leaves, the symptoms of disease occur as a small black spot on the surface of the leaf which enlarges around 0.5 in. In diameter, looking irregular to circular in somewhat sunken form and even zonate, both foliar and fruit spots clearly grow black pycnidia with lens of the eyes. Leaf Miner is typically found in numerous plants in the green houses, home gardens, and landscaped field. It is the larval (maggot) stage of a family of insects and can be found in the lower and upper portion of leaves. It is not normal to have 6 or more maggot per leaf that cause damage that may limit the growth of the plant.

Goal Leaf Spot is easy to spread to all leaflets and other leaves, resulting in the leaves turning yellow, decaying and dying. There are marks on the roots too. They are slender and long. On the fruit can also appear small , light brown spots with dark margins. Its effect is that plants lose their leaves because of the fungus; it's a major disease. If infection is present before the fruit grows, yields are poor. In Pacific island countries this is a widespread tomato disease. The illness occurs in the field and in the screen shelter.

Meanwhile, the disease favors temperatures between 29 degrees Celsius and 32 degrees Celsius with a 55 per cent and above comparative humidity. Goal Spot disease turns up on all areas of the tomato plant above ground. The Foliar lesions begin on the upper surface as small, tiny, water-soaked spots which also gradually increase the size and become oval, often ringed and pale brown with yellow hollows. It influences the harvest of crops, too. To prevent overfitting when implementing deep neural networks, the device applies data annotation and increase to the input image. The collection of hyper-parameters, the regularization of the method or a number of images used for testing are often referred to as fitting[17]. Other studies have recommended providing a server side component containing the trained model and a smart mobile device framework with additional features such as viewing known diseases on many plant types based on leaf photographs. The photos are shot using a sensor on the cell phone. Moreover, by incorporating aerial photos of larger lands[18], datasets could be expanded.

There are several new developments and innovative strategies for sustainable crop safety that include fustigation, agronomy, pesticides, seed care, and development of biotechnology and the use of renewable knowledge to detect the crop disease as early as possible. The response is crop enhancement and security outcomes based on paramount global standards and the available emerging technologies[18]. S. Sladojevic et al.[18] uses AlexNet architecture and collected online pictures of plant diseases with 13 plant diseases and obtained 96.6 percent test accuracy. Detection of diseases in a tomato leaf using Convolutionary Neural Networks (CNNs) which is a class of a deep neural network. Transfer learning was performed using ResNet 50 model[19] for classifying various forms of malware. They use byte plot grayscale images, using the pre-trained model that was trained on the ImageNet dataset. The weights for the initial layers were frozen, and the final fully attached layer was fine-tuned to accommodate the definition of malware. The model they developed was able to accurately distinguish with 98.62 per cent accuracy.

India is in third place as a Tomatoes manufacturer and exporter worldwide. For growing tomato crops, the nation covers the largest property. About 3,50,000 hectares of land has 53,00,000 tons of production quality[20] was estimated. Owing to diseases, the tomato crops are destroyed last year. Diseases range from leaf to fruit. Detecting the diseases on the plants' leaf at an early stage is important. Therefore the volume and consistency of nutrition is adequately present in the fruits. Prajwala TM et al.[20] Explains the modification model created on the CNN for the identification of tomato leaf disease, and modifies the LeNet model. The photographs of the tomato leaf were taken from the dataset on the plant village. CNN 's design, which was a basic one used in this project, has a minimal number of classification levels. The experiment was carried out using various techniques of learning and optimization. Modified model accuracy was 94-95 percent.

C. Sabarinathan et al.[21] Developed a model for the identification of fifty different medicinal plants for classification based on the CNN which demonstrates the uses of medical applications using the MongoDB database. For identifying purposes the leaf pattern was used. The suggested approach beats the best attribute of the medical plants datasets used in this work in classification such as SVM and on-hand designed. The study was conducted in such a manner that it is considered non-specific so researchers would train the network to identify many other plants other than medicinal plants. You may use this method in any other sector where classification is needed. The approach suggested in the paper relates to the most common diseases found in the tomato plant such as, Bacterial leaf spot and Septorial leaf spot, Yellow Leaf Curl among many others. Any picture of the leaf provided as input may be categorized as one of the types of illness, or may be considered good. A subset of Plant Village[22], a repository that includes 54,306 photographs of 14 crops infested with 26 diseases, is the database used for assessment. The section contains about 18160 pictures of diseases from the tomato leaf.

In [22] deep convolutionary neural networks were learned to classify 26 diseases in 14 different crop types. Mobilenet [23] was introduced in 2017 and comes with python keras kit. It is 32 times smaller than VGG16, and the performance is also close. The bigger the network, the smoother it runs and the less battery capacity it requires. The compression of convolution layers is achieved by sorting the weights and tossing the smallest weights. Mobile net also uses depth-wise separable convolutions that render the function 9 times quicker with equal precision as compared to conventional neural networks. In this building blocks of separable convolutions, normalization of the Relu and Batch is used. Mobile network has 17 such blocks accompanied by global average pooling and a segregation layer (28 layers if we consider depth wise and point wise convolution as different layers). We also tried to use transfer learning with mobilenet and found it provided 63.7 percent accuracy on our tomato disease issue of 10 class with 1000 epochs. This may be attributed to the already large network with a limited number of groups triggering overfitting.

Machine learning algorithms are implemented in diverse fields but the core challenge remains function engineering. With the advent of deep neural network, the promising findings are possible without the laborious function engineering for plant pathology. Deep neural networks meaningfully improve the precision of image recognition.

2. METHODS

The DNN classification framework illustrated in Figure 1 is utilized for the classification of tomato plant disease. The classification framework includes: image acquisition, image pre-processing, feature extraction and classification. The classifier is designed in order of classifying the leaf into a normal or a malignant tomato leaf.

a. *Image Acquisition*: These images are shot using a digital camera of various orientations, different dimensions, backgrounds, lighting and poses.

b. *Pre-processing*: You will find a large number of photos of safe and sick leave in the inventory data of either the local or global repositories. Each picture has three RGB channels. To this end, in a pre-processing phase each image in our dataset becomes a grid of 256×256 pixels. Noise is removed from the collected image samples when the pixel is selected for cleaning purposes.

c. *Laplacian Filtering Method*: In this paper, we use the Laplacian filter to eliminate the noises from the image. The study uses Partial Differential Equation:

$$\frac{\partial u}{\partial t} = -sign\left(\nabla^2 u\right) \times |\nabla u| \qquad (1)$$

The standard adaptive is utilized in this filter for forward differencing for expressing the upwind derivatives. Here, the Laplacian expression sign is represented as:

$$\frac{\partial u}{\partial t} = -|\nabla u| \qquad (2)$$

In addition, the filter is applied with the minima and it suits if the Laplacian is negative:

$$\frac{\partial u}{\partial t} = |\nabla u| \qquad (3)$$

The results of the filter offers dilation round the maxima region. Therefore the images tends to get sharper with the operations filter. The expression of disintegration and dilation operations is considered to be isolate and the expression of the Eqn.(4) to Eqn.(8):

$$\nabla u = \sqrt[2]{\left(u_x^2 + u_y^2\right)} \qquad (4)$$

where

$$u_{x^2} = \left\{ \min\left(\frac{\left(u_{i,j} - u_{i,j-1}\right)}{h_x, 0} \right) \right\}^2 + \left\{ \max\left(\frac{\left(u_{i,j+1} - u_{i,j}\right)}{h_x, 0} \right) \right\}^2 \qquad (5)$$

$$u_{y^2} = \left\{ \min\left(\frac{\left(u_{i,j} - u_{i,j-1}\right)}{h_y, 0} \right) \right\}^2 + \left\{ \max\left(\frac{\left(u_{i,j+1} - u_{i,j}\right)}{h_y, 0} \right) \right\}^2 \qquad (6)$$

The Laplacian term sign is considered in Eq.(6) is negative i.e. the operation is considered dilation. If the operation is erosion, equations below is applied:

$$u_{x^2} = \left\{ \max\left(\frac{\left(u_{i,j} - u_{i,j-1}\right)}{h_x, 0} \right) \right\}^2 + \left\{ \min\left(\frac{\left(u_{i,j+1} - u_{i,j}\right)}{h_x, 0} \right) \right\}^2 \qquad (7)$$

$$u_{y^2} = \left\{ \max\left(\frac{\left(u_{i,j} - u_{i,j-1}\right)}{h_y, 0} \right) \right\}^2 + \left\{ \min\left(\frac{\left(u_{i,j+1} - u_{i,j}\right)}{h_y, 0} \right) \right\}^2 \qquad (8)$$

Discrete Laplacian solution is given below:

$$\nabla^2 u = \frac{\left\{u_{i+1,j} + u_{i-1,j} + u_{i,j+1} + u_{i,j-1} - 4 \times u_{i,j}\right\}}{h^2} \qquad (9)$$

Combining the above expressions, the equations for filtering is expressed below:

$$\frac{\partial u}{\partial t} = \frac{\left(u_{i,j}^{k+1} - u_{i,j}^{k}\right)}{\nabla t} \qquad (10)$$

d. Feature Extraction

Gray Level Co-occurrence Matrix (GLCM) is for the feature extraction, where the position of matrix is counted using Scale Invariant Feature Transform (SIFT).

e. Classification using DNN

DNN needs structured data, and further outputs with more data sets are produced by understanding these structured data, and if the desired output is not obtained then human intervention is needed. Whereas, the deep learning network works on ANN layers as shown in Figure 2 and is learning by their own errors. Therefore they don't need any human intervention. One of the advantages of Deep Learning is its ability to learn and capture high-level features from the provided data in an incremental order that eliminates the need for the domain expertise.

Due to their scalable structure deep learning techniques are gaining popularity. DNN is a modification of traditional neural networks in which the input effect on the hidden layers and output of the network decays exponentially when rotating across the recurrent networks. This is again changed by altering the arrangement of the secret neurons in DNN in Long Short Term Memory (LSTM)

Long Short Term Memory Models (LSTM): LSTM is on a recurrent neural network (RNN) evolution. Standard RNN modules have last layer output over a single Tanh feature while LSTMs use feedback loops and gates to remember. The LSTMs have four dynamic NNs layers in each module and consist of a cell, an input gate, an output gate and a forgotten gate where the cell recalls values over self-assertive time intervals and the three gates guide the data progression into and out of the cell. Using sigmoid gates, LSTM can add or delete data from module state (which is the main data flow chain. The Fig.3 stands for a basic LSTM cell architecture.

Long Short Term Memory Model is a form of supervised deep learning that is highly efficient in processing prediction of the time series. Here, information is transmitted via a process into certain cell states. In this way LSTM decides selectively on which data to maintain. In this step, we train deep architectures with powerful machines on a large dataset like ImageNet. The goal of this process is to activate network weight for the next step. From step one the resulting network is enhanced. We also have a new output level which replaces the pre trained network output layer with two classes of tomato leaf disease. Using the DNN the user uses a leaf picture in this process to evaluate the condition. Upon classification, the user may display the regions of the leaf image which characterize the leaf.

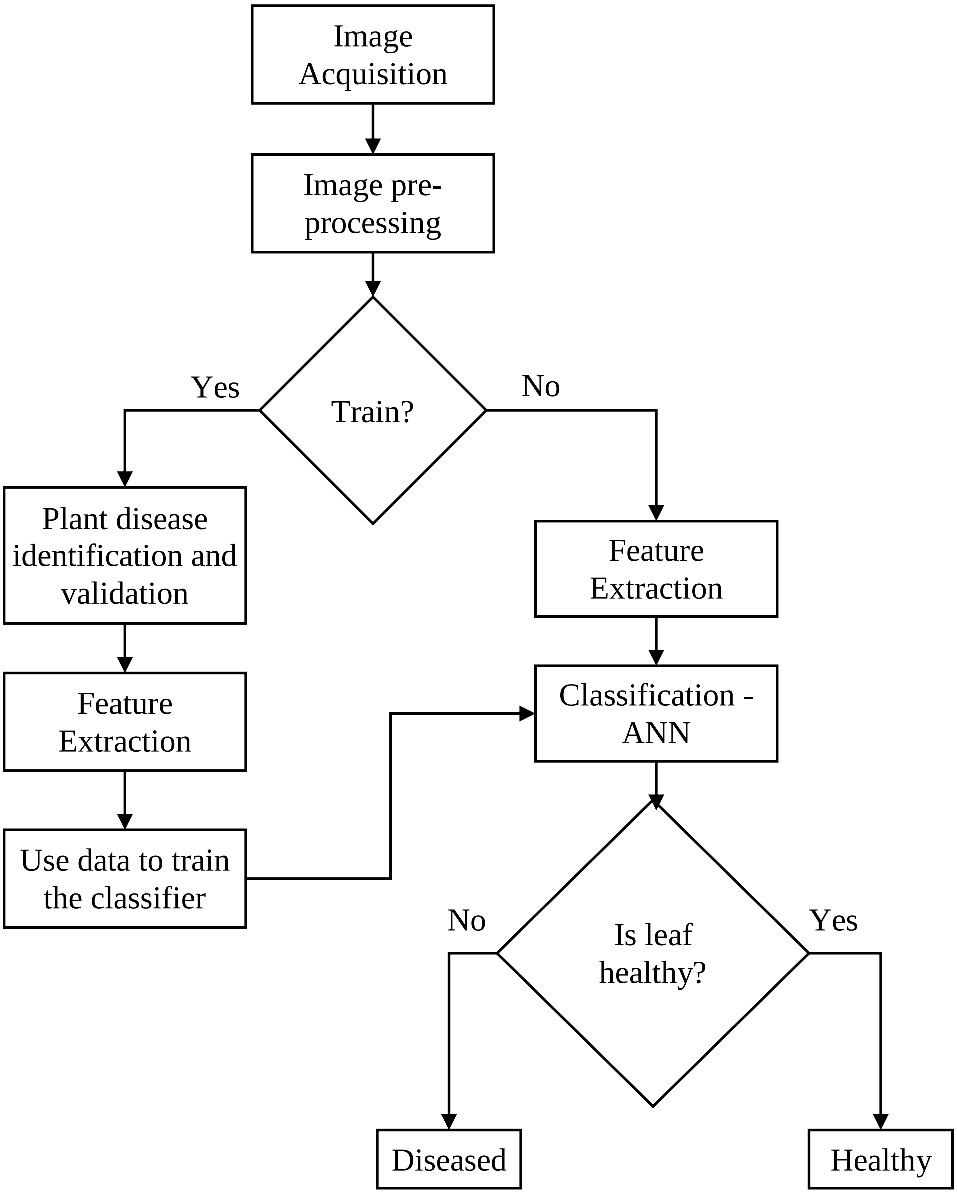

Figure 1: Architecture of Detection using DNN model

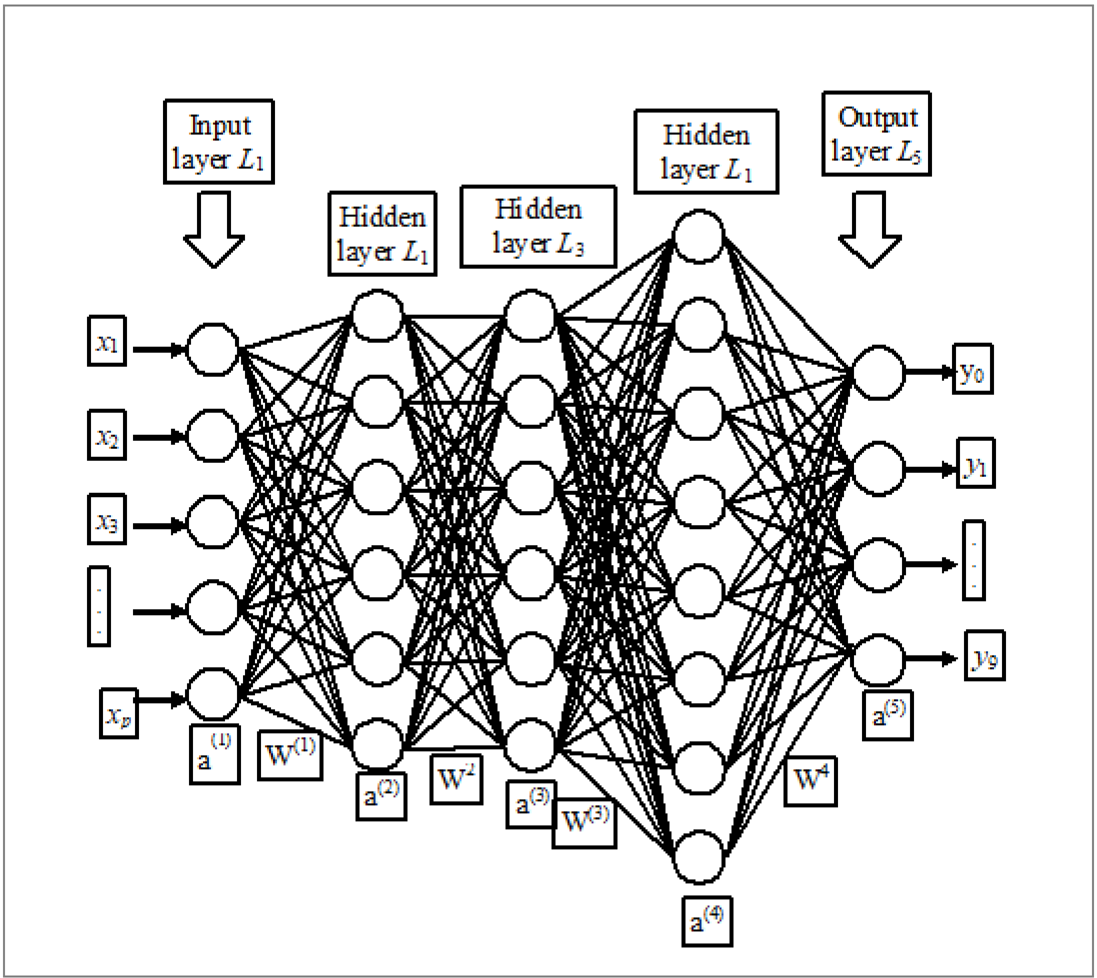

Figure 2. Architecture of DNN

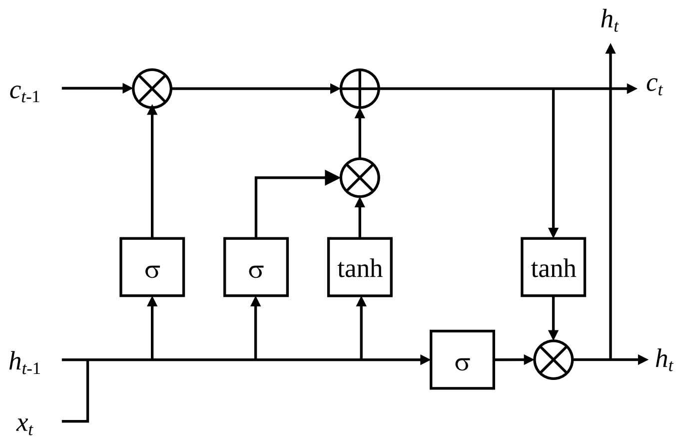

Figure 3: Long Short- Term Memory cell

3. RESULTS AND DISCUSSIONS

This section discusses the evaluation of the proposed classification model in a high-end computing system using the Mat lab platform. DNN classification performance is evaluated on tomato leaves, which consists of 1500 images with healthy and diseased leaves.

The system is initially trained with a set of 1300 image and then tested with 200 tomato leaf [] images.

The DNN classifier is tested against accuracy, sensitivity, specificity and f-measure. The DNN framework is compared against back propagation neural network (BPNN), feed forward neural network (FFNN), Convolutional Neural Network (CNN)and Recurrent Neural Network (RNN) to validate the accuracy of the classifier.

The results of Accuracy, F-measure, G-mean, MAPE, Sensitivity and Specificity are presented in shown in Table 1-3, respectively. The result shows that the DNN has higher classification rate than conventional classifiers. Likewise, the training of the classifier is given in Figure 4 – 6 for various cross-fold evaluation i.e. 70% of training data and 30% testing data, 80% of training data and 20% testing data and 90% of training data and 10% testing data.

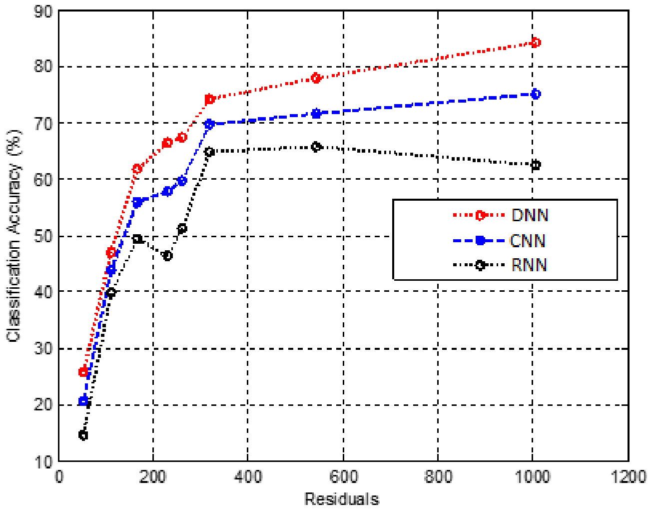

Figure 4: 70% of training data and 30% testing data

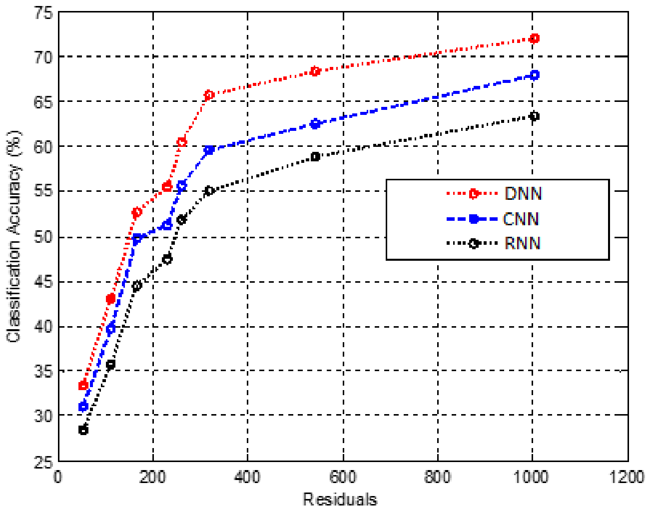

Figure 5: 80% of training data and 20% testing data

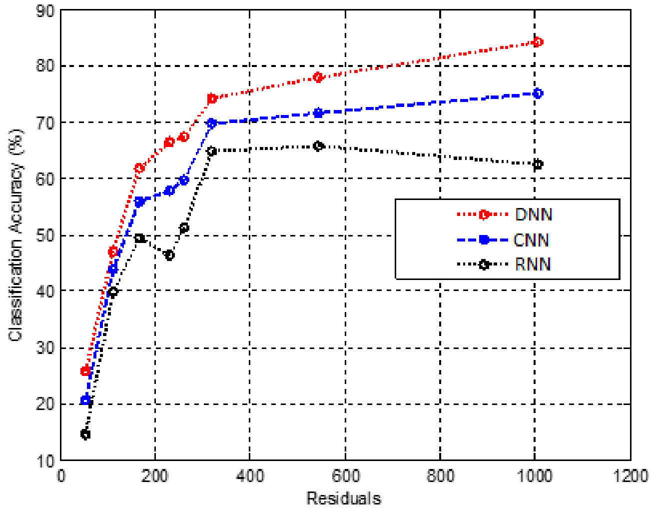

Figure 6: 90% of training data and 10% testing data

Table1. Estimation of various performance metrics with 70% of training data and 30% testing data

Statistical Parameter	**FFNN**	**BPNN**	**DNN**	**RNN**	**CNN**	**Proposed DNN**
Accuracy	56.8956 89	57.1957 19	59.2859 28	59.5469 54	60.9070 9	81.69617
F-measure	39.6179 61	41.7181 71	52.9532 95	53.1133 11	55.4845 48	84.87749
G-mean	73.7623 76	73.9933 99	75.4935 49	75.5335 53	75.9435 94	86.79868
MAPE	29.5529 55	26.6116 61	25.2115 21	22.6302 63	22.0502 05	17.34773
Sensitivity	62.9682 96	66.4796 47	74.3834 38	86.7686 76	87.4287 42	97.47375
Specificity	75.4035 4	75.5935 59	79.1049 1	79.1249 12	80.4960 49	81.33613

Table 2. Estimation of various performance metrics with 80% of training data and 20% testing data

Statistical Parameter	**FFNN**	**BPNN**	**DNN**	**RNN**	**CNN**	**Proposed DNN**
Accuracy	97.1337 12	97.1537 14	97.1637 15	97.2537 24	97.2737 26	97.33373
F-measure	78.6048 6	78.7348 73	79.2549 25	80.3360 33	81.0161 01	81.30613
G-mean	80.6560 65	80.8960 89	81.1661 16	82.1662 16	82.4862 48	82.67727
MAPE	32.3742	32.0142	31.4941	29.8829	29.3829	29.06291

	37	01	49	88	38	
Sensitivity	65.6795 67	66.0396 03	66.5596 55	68.1708 16	68.6708 66	68.9909
Specificity	95.9425 93	96.0025 99	96.0426 03	97.2737 26	97.6837 67	98.0338

Table 3. Estimation of various performance metrics with 90% of training data and 10% testing data

Statistical Parameter	**FFNN**	**BPNN**	**DNN**	**RNN**	**CNN**	**Proposed DNN**
Accuracy	98.6628 65	98.6628 65	98.7428 73	98.7428 73	98.7628 75	98.81288
F-measure	87.1697 16	87.2897 28	89.2319 22	89.2619 25	90.6230 61	90.63406
G-mean	95.3185 31	95.3185 31	95.6895 68	95.7595 75	96.0896 08	96.12961
MAPE	72.0722 07	71.8921 89	63.9933 99	62.6622 66	55.3035 3	54.62246
Sensitivity	91.8151 81	91.8151 81	92.6262 62	92.7562 75	93.4963 49	93.56736
Specificity	98.7528 74	98.7628 75	98.8528 84	98.8528 84	98.9428 93	98.94289

4. CONCLUSIONS

In this paper DNN is used to develop a framework that uses a series of frameworks consisting of image acquisition, extraction of relevant feature and tomato plant classification to classify the leaf disease. The DNN deep learning classifier ranks the tomato leaf images well. The results confirm DNN's improved accuracy (86.18%) over existing models. It further provides an accurate results on classifying the leaf samples than other methods.

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