Design and Analysis of Pepper Leaf Disease Detection Using Deep Belief Network

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Abstract

The quality of crop yield is reduced due to leaf diseases in agriculture. Therefore, it is possible to automate the recognition of leaf diseases to improve yield in the farming sector. However, most systems lack in performance due to different patterns of leaf disease that influence the precision of detection. In this paper, a computer vision framework is developed by framing a model that consists of image acquisition, feature extraction and image classification. A deep learning classifier namely Deep Belief Network (DBN) is used for classification of real-time images. The experimental results on pepper plant leaf disease detection show that the proposed method has improved rate of classification than other existing methods. The classification result shows that whether the leaf is diseased or not.

Keywords - *Real-time image acquisition, Artificial Neural Network, leaf disease detection, pepper plant*

I. INTRODUCTION

Plant disease detection plays a significant role in agriculture sector as it indirectly affects a country's economy. Care should be taken to detect and identify the disease of plants at an early stage. Image processing technology has made it possible to detect diseases in plants with less human intervention. The issue of effective plant disease protection is closely linked with sustainable farming and climate change [1]. Research indicates that seasonal change in climate can affect pathogens and the rate of its development, because of which host resistance can also be altered and host-pathogen interactions can physiologically change [2]. It complicates the situation, now that diseases are transmitted more easily around the world than before. New diseases may arise where they have not previously been identified and where, intrinsically, local expertise is not available to combat them [3].
Long-term pathogens can develop resistance and seriously decrease the fighting capacity through unsuspected use of pesticides. As stated in [4], 'The timely and accurate diagnosis of plant diseases is one of the pillars of precision farming'. Financial and other resources should not be wasted unnecessarily and production should be better addressed by addressing the problem of developing long-lasting pathogenic resistance and reducing the adverse effects of climate change.

In this changing environment, adequate and prompt identification of plant diseases, including early prevention, plays a significant role in agriculture. Various ways of identifying plant pathologies are available. Certain diseases have no apparent symptoms or the effect is too late to work on and in these situations a sophisticated analysis is necessary. However, most diseases cause some kind of manifestation on the visible spectrum, so that the primary technique that can be used for plant disease detection is trained professional testing. In order to obtain accurate diagnostics of plant diseases, a plant pathologist should possess excellent observational skills for identifying characteristic symptoms [6]. Variations in sick plant symptoms may lead to inadequate diagnoses, as amateur and hobbyists may find it harder than professional pathologists to determine the defect. An automated system designed to identify the conditions and visual symptoms of the plant as a verifier of disease diagnoses can provide amateurs in gardening and trained professionals with significant advantages.

Developments in Computer vision technology provide opportunities to expand and consolidate precise plant protection practices and to expand the market for precise agricultural computer vision applications. The use of common digital imaging techniques, such as color analysis and thresholds [5], was used to detect and classify plant diseases.

Deep learning is a new trend of machine learning with cutting-edge results in many fields of research, including the field of computer vision and bioinformatics. Differing approaches to deeper learning are currently used for plant disease detection and the most common are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Deep Belief Network (DBN), etc. The ability to use raw data directly without handmade materials [7] is the primary advantage of deep learning [8] [9].

In this paper, we aim at introducing a deep learning approach for classifying plant diseases, focusing mainly on diseases present in the leaf images. In this paper, a computer vision framework is developed by framing a model that consists of image acquisition, feature extraction and images classification. A deep learning classifier namely Deep Belief Network (DBN) is used for classification of real-time images. The experimental results on pepper plant show that the proposed method has improved rate of classification than other existing methods. The classification result shows that whether the leaf is diseased or not.

II. RELATED WORKS

Sladojevic, S., et al. [6] discussed an approach to deep classification for identifying herbal diseases based on image leaf classifications. New methods of training were used to make system implementation quick and easy. The models developed for 13 types of plant diseases distinguished diseased plant leaves from that of healthy plants. Krishnakumar, A., [10] presented an imaging approach for classifying a sort of disease in a plant and measuring the severity of the spots that are caught in a leaf under real circumstances. Brahimi, M., et al. [11] used a pepper leaf dataset. The study introduced deep classification to form the classification system as a learning algorithm. One of greatest benefits of deep classification is the self-extraction of features through raw image processing. Zhang, S., et al. [12] proposed a new approach for the recognition of Cucumber disease, including three pipelines: K-means segmentation of disease, information extraction of shape and color lesions, and sparse sheet image classification. The classification can efficiently reduce calculation costs and increase reconnaissance performance which the authors claim as one of the main advantages of the approach.

Lu, Y. et al. [13] proposed a rice disease identification method based on a deep classification technique. The deep classifier is trained to identify 10 common rice diseases, including 500 natural photos of rice and stalks captured in diseased and healthy rice leaves. Reference [17] discusses about the use of Genetic algorithms in automatic identification of plant leaf diseases. The authors present an extensive survey on the various plant leaf diseases and propose a novel image segmentation algorithm for the detection and classification of plant leaf diseases. The green pixels above a particular threshold are masked and those with pixel values less than the threshold are assigned zero to identify the outliers from the green pattern which indicates disease in the leaf. They considered bacterial diseases in the leaves of plants like rose, beans, sun burn disease in lemon plant, scorch disease in Banana plant for testing their algorithm and have shown improvement in classification accuracy over existing algorithms. They state, a further improvement in classification accuracy can be obtained if Artificial Neural Network, Bayes classifier, and fuzzy logic is used.

Monishanker Haldar et.al., [18] presented a detailed survey on various leaf disease identification using Image processing techniques based on algorithms like K-means clustering, support vector machine, ANN, Fuzzy logic etc,. Based on their survey it is noted that identification of plant leaf disease using Machine learning approach yielded the highest accuracy of 95%. In [19] the authors proposed a histogram based segmentation to calculate the threshold for image segmentation in leaf disease detection and used multiple linear regression technique for improving the classification performance. An extensive survey on crop disease detection presented in [20] suggests that performance of algorithms can be greatly enhanced when compared to that of image processing methods by adopting techniques like artificial intelligence, machine learning, Deep learning, transfer learning, hyperspectral imagery and internet of things.

III. METHODOLOGY

The automated framework used in Figure 1 is used to classify the pepper plant disease. This framework consists of a range of operations including 1) image acquisition 2) pre-processing 3) extraction 4) classification. The classifier has been designed to classify between a normal leaf and an abnormal pepper leaf. The images acquired after pre-processing is segregated as train images and test images. The images that has been segregated as train images are used to train the network with the leaf disease features and the normal features for classifying as diseased and not diseased. If the image at the input is a test image then the features are extracted and given to the DBN classification system to classify the leaf as diseased or not. The steps involved in the classification of pepper leaf as diseased or not is described below

A. Image Acquisition

In the image acquisition process, leaf images of the pepper plant are captured using digital camera in different orientations. The acquired images are of different dimensions, different background, varying illumination and different positions

B. Pre-processing

In the inventory data of either local or global repositories, a large number of images of healthy and infected leave can be found. There are three RGB channels in each image. Both RGB images and gray images were used in our experiment to test the applicability of our approach. To this end, each image in our dataset becomes a grid of 256 x 256 pixel in the pre-processing step. The various steps followed in the pre-processing stage for removing noise from the samples collected is summarized below.

the size of window is enlarged in order to allow the processing of corrupted pixels

the median value is calculated using the corrupted pixels

the corrupted pixel is replaced with the median value and the process is repeated for all the corrupted pixels in the window

the window is then moved to the next pixel and the process is repeated. The size of window may be extended to accommodate the corrupted pixel if any.

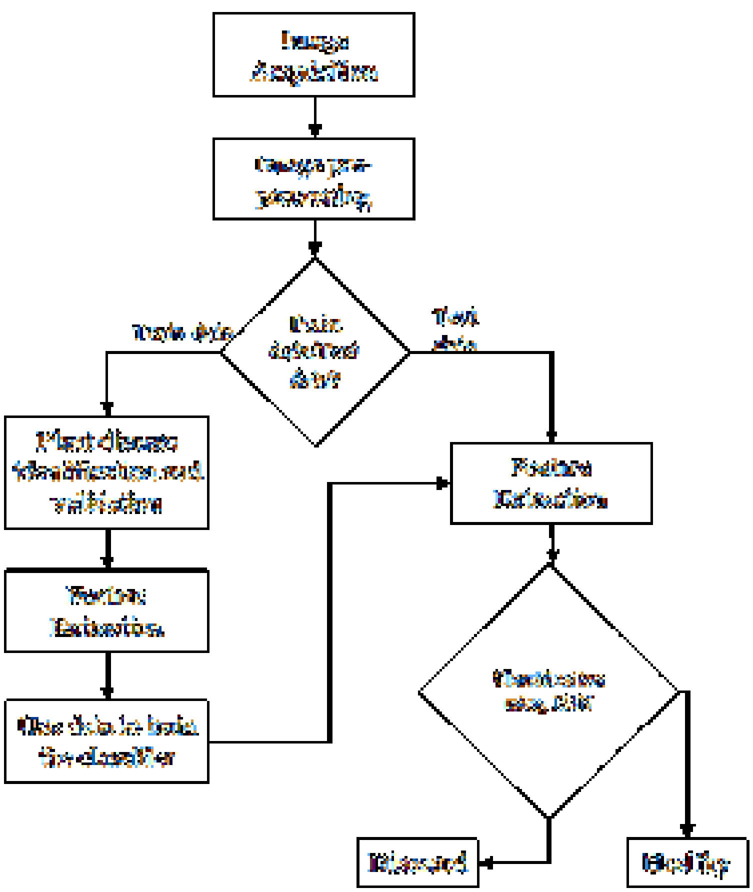


Figure 1: Architecture of Detection using RBNN model

C. Feature Extraction

Gray Level Co-occurrence Matrix (GLCM) with 256×255 matrices is used in extraction of features, where each matrix position is obtained by applying Scale Invariant Feature Transform (SIFT) in a scaled image.

D. Classification

The proposed approach has four major components given below:

Pre-Training Phase: In this phase, deep architectures are trained using large dataset like ImageNet. This phase is intended to initiate network weight for the next phase.

Training: The pre-trained network with two classes of pepper leaf namely diseased and not diseased is used in updating the current output with new set of pepper leaf images.

Disease classification: The test leaf images are classified as diseased and not diseased using Deep Belief Network.

Visualization: After the process of classification, the user is allowed to visualize the leaf image regions of a plant that displays the disease characteristics. The user is also provided with the estimation of disease spread in the pepper plant.

DBN is regarded as a deep learning method, which is used mainly for the process of feature extraction and classification. The DBN learning method acquires the weight w and these weights are used to iteratively train the entire network through the series of weights $W = w_1, w_2...w_l$. Finally, connection weights are linked with the back propagation learning algorithm using unsupervised Restricted Boltzmann machine (RBM). This learning allows suitable gradient determination using the labelled training datasets and adjusts the parameters for optimal classification from the output layer and offering it as a feedback for gradient reduction. Finally, the DBN is used to obtain a minimum error while predicting the instance for classification.

To detect the anomaly in the general leaf pattern of pepper plant when it is diseased, free energy concept of RBM based on probabilistic model [15] is used. If v is a set of visible variables and h is a set of hidden variables that describes a system, the energy associated with the state of the system described by the joint configuration (v, h) is given by E(v, h/Θ) as stated in equation(1). The energy values are functions of the weights of the links between the variables and bias terms related to the variables.

$$E(v,h \mid \theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i w_{ij} h_j \tag{1}$$

where

θ - RBM parameter = {w_{ij}, a_i, b_j},

w - weight of connection in a layer

a - visible layer neuron bias

b - hidden layer neuron bias.

Hence the joint probability distribution between the hidden layer (h) and the output layer is represented as follows:

$$P(v,h \mid \theta) = \frac{e^{-E(v,h|\theta)}}{Z(\theta)} \tag{2}$$

$$Z(\theta) = \sum_{v,h} e^{-E(v,h|\theta)} \tag{3}$$

The conditional probability distribution of a and b is represented as:

$$P(h_j = 1 \mid v, \theta) = sigmoid\left(b_j + \sum_i v_i w_{ij}\right) \tag{4}$$

$$P(v_j = 1 \mid v, \theta) = sigmoid\left(a_j + \sum_i h_i w_{ji}\right) \tag{5}$$

Using equation (3), the probability of hidden layer being in an active state is derived. In RBM, the probability of the activation state of a visible layer neuron and hidden layer status h tends to be a symmetrical feature. The probability of activation is therefore determined with equation (4).

IV. RESULTS AND DISCUSSIONS

The implementation was done in a high-end computer system using the MATLAB platform. Classification performance using DBN is evaluated through pepper leaves experiments consisting of 1500 pepper leaf images with both healthy and diseased leaves. The system is also trained and tested with pepper leaf [14], out of which 300 images are healthy and 35 are diseased. Figure 2 illustrates the leaves used for classification.

Figure 2. Sample Pepper Leaf images

The study is tested in terms of accuracy, sensitivity, specificity and f-measure against pepper leaf datasets. Accuracy, Sensitivity, Specificity and F-measure are commonly used metrics to describe the performance of a classification system computed using true positive, true negative, false positive and false negative as given in equations 6, 7, 8 and 10 respectively. In our system of pepper leaf disease detection, True positive (TP) represents the number of instances where a diseased leaf is identified as diseased and a True Negative (TN) represents the number of instances where a normal leaf which is not affected is classified as not affected. While, False Negative (FN) represents the number of instances where a diseased leaf is identified as not diseased and False Positive (FP) represents the number of instances where an unaffected leaf is identified as diseased.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

$$Sensitivity(or\ \mathrm{Re}call) = \frac{TP}{TP + FN} \tag{7}$$

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

$$\mathrm{Pr}ecision = \frac{TP}{TP + FP} \tag{9}$$

$$F - measure = 2\frac{\mathrm{Pr}ecision \times \mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call} \tag{10}$$

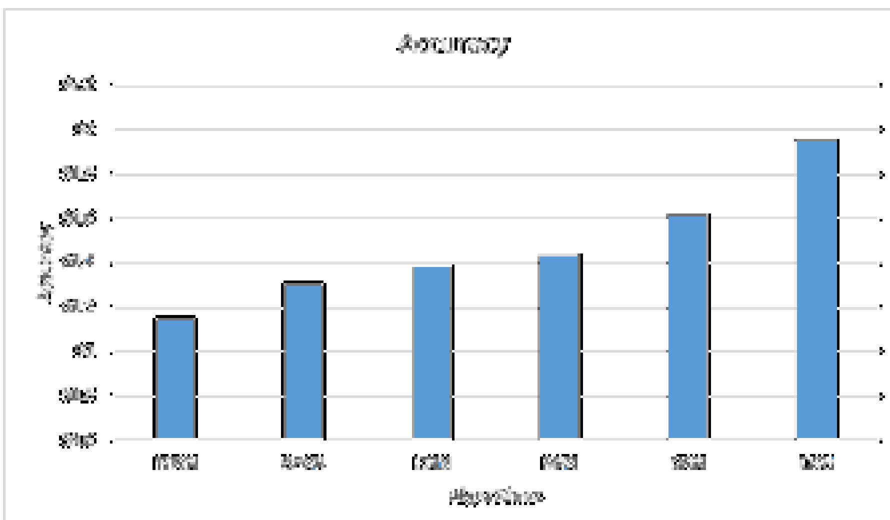
Precision refers to measure which answers the question How many of the pepper leaves are classified as diseased when they are actually diseased. Recall or sensitivity is a measure which answers the question out of the total diseased leaves how many were correctly predicted as diseased. The combination of precision and recall gives F-measure.

The DBN framework is compared against various other classifiers that includes Feed Forward Neural Network (FFNN), Back Propagation Neural Network (BPNN), Deep Neural Network (DNN), Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) for validating the classification accuracy. The accuracy of the proposed pepper leaf disease detection system using DBN is improved by a value of 0.8 when compared to FFNN based classification and by a value of 0.34 with that of the CNN based classification. The sensitivity obtained for FFNN based classification is 65.886 while the sensitivity with the proposed DBN classification is 83.826 which is nearly 18 points greater and 1.6 points more than the CNN based classification system. The F-measure also shows an improvement in the case of DBN based system by approximately 13.6 points in comparison with FFNN based system and 5.5 points more compared to CNN based pepper leaf detection system. The results of accuracy, sensitivity, specificity and F-measure are given in Table 1 for DBN in comparison to FFNN, BPNN, DNN, RNN and CNN and the corresponding graphical analysis is presented in Figures 3 a-d, respectively. The results of simulation show that the proposed method has higher classification rate of 91.956

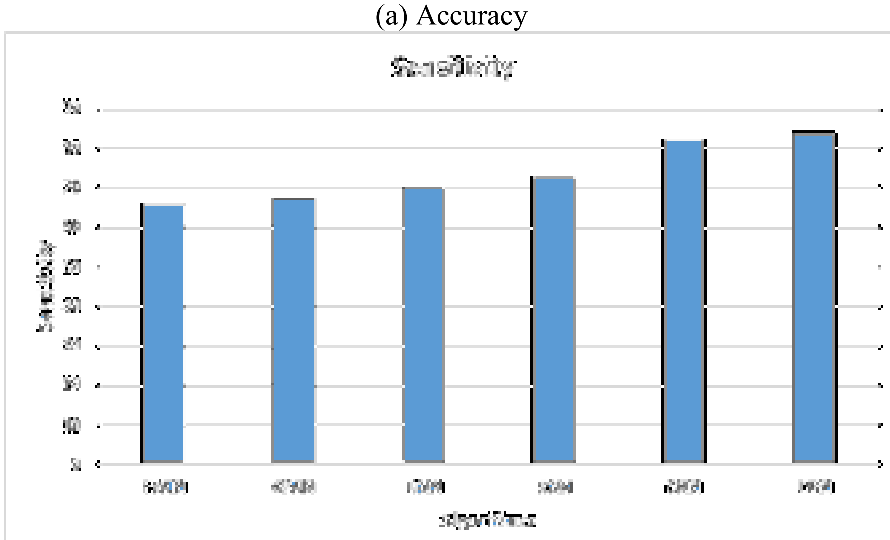
which is a marginal improvement in classification compared to other classifiers namely, FFNN, BPNN, DNN, RNN and CNN.

TABLE.1. Comparison of DBN classifier performance measures – Accuracy, Sensitivity, Specificity and F-measure, with existing classifiers

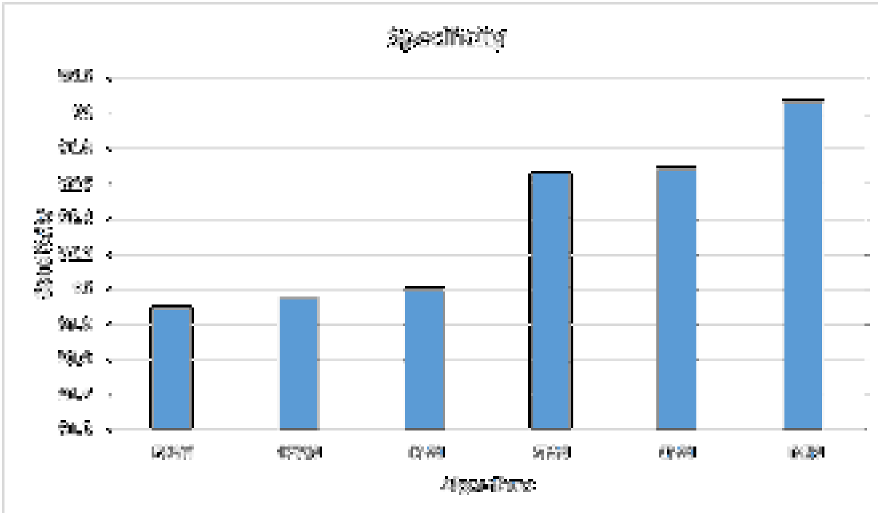
Classifier Types	Accuracy	Sensitivity	Specificity	F-measure
FFNN	91.156	65.886	91.906	63.936
BPNN	91.306	67.286	91.966	66.916
DNN	91.386	70.056	92.006	67.246
RNN	91.436	72.736	92.656	67.486
CNN	91.616	82.186	92.696	72.046
DBN	91.956	83.826	93.076	77.546



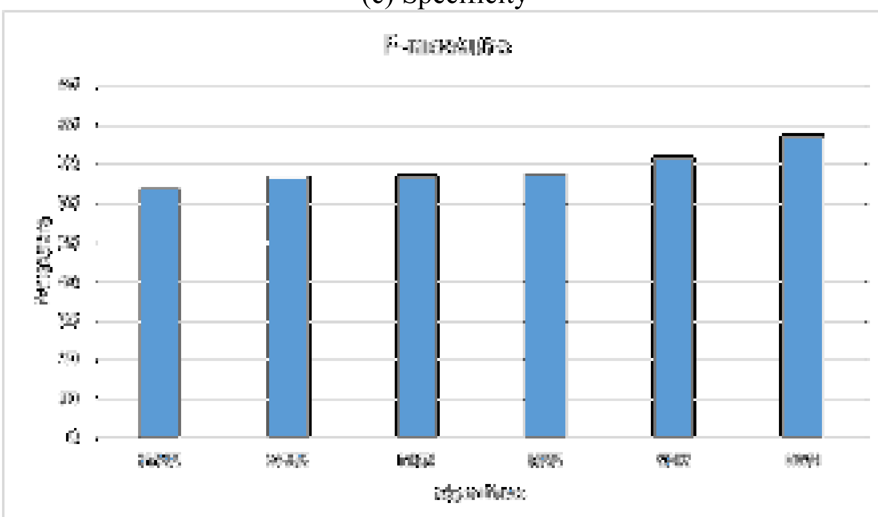
(a) Accuracy



(b) Sensitivity



(c) Specificity



(d) F-measure

Figure 3. Comparison of performance measures of the pepper leaf disease detection system

V. CONCLUSIONS

In this paper, DBN is used to develop a framework that operates on classifying the leaf disease using a series of framework consisting of image acquisition, extraction of relevant feature and classification of pepper plant. The deep learning classifier namely DBN classifies well the pepper leaf images. The results confirm the improved accuracy of DBN than existing deep and machine learning models. It further provides accurate results on classifying the leaf samples than deep learning methods.

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