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Plant leaf disease detection using computer vision and machine learning algorithms

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ABSTRACT

Agriculture provides food to all the human beings even in case of rapid increase in the population. It is recommended to predict the plant diseases at their early stage in the field of agriculture is essential to cater the food to the overall population. But it unfortunate to predict the diseases at the early stage of the crops. The idea behind the paper is to bring awareness amongst the farmers about the cutting-edge technologies to reduces diseases in plant leaf. Since tomato is merely available vegetable, the approaches of machine learning and image processing with an accurate algorithm is identified to detect the leaf diseases in the tomato plant. In this investigation, the samples of tomato leaves having disorders are considered. With these disorder samples of tomato leaves, the farmers will easily find the diseases based on the early symptoms. Firstly, the samples of tomato leaves are resized to 256×256 pixels and then Histogram Equalization is used to improve the quality of tomato samples. The K-means clustering is introduced for partitioning of dataspace into Voronoi cells. The boundary of leaf samples is extracted using contour tracing. The multiple descriptors viz., Discrete Wavelet Transform, Principal Component Analysis and Grey Level Co-occurrence Matrix are used to extract the informative features of the leaf samples. Finally, the extracted features are classified using machine learning approaches such as Support Vector Machine (SVM), Convolutional Neural Network (CNN) and K-Nearest Neighbor (K-NN). The accuracy of the proposed model is tested using SVM (88%), K-NN (97%) and CNN (99.6%) on tomato disordered samples.

1. Introduction

Developed Technologies have provided the ability to produce sufficient food to meet the demand of society. But still, the safety and security of the food or crops remained unattained. Factors like change in climate, the decline in pollinators, Plant disease, and others are challenging to the farmers. An important foundation for these factors needs to be attained on a priority basis [1,2]. Making use of analysis and detection processes using present technology helps the farmers to get rid of such problems. During pandemic situations like COVID 19 the nation is dependent on the recent technologies to prevent address the issues to reduce the transmission of the diseases [2–5]. As plant diseases are a significant threat to human life as they may lead to droughts and famines. In turn it results causing substantial losses, where farming is accompanying in commercial purpose. The use of technologies like Computer vision and Machine Learning (ML) helps to fight against diseases [6–8]. In this paper, we are using ML to give a solution to Plant Diseases. In this method, we have divided the process into three stages Identity, Analyse and Verify with the Available database [9].

The key issues and challenges [10,11] are identified by the researchers and the scientists, while analysing the leaf diseases of plant. Some of them are as follows

1 The quality of the leaf image must be high.
2 Publicly available Dataset requirement.
3 Noisy data affecting the leaf samples.
4 Through the process of segmentation, diseases may be identified but the samples must undergo training and testing.
5 Classification is one more challenge, in the stage of detecting the leaf diseases.
6 Color of the leaves may be varied due to environmental effect.
7 Variety of diseases can be seen in various kinds of plants, so detection of disease is quite difficult.

Based on the challenges discussed above and combined techniques using image processing (IP) and ML, the proposed model provide better accuracy. Keeping all these things in mind, in this paper an algorithm based on ML and IP tools to automatically detect leaf diseases is proposed.

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The contribution for the above proposed framework is done in three stages. Firstly, the HE and K-means clustering are employed to maximize the quality and segment the leaf samples. Based on the K-means clustering response, the leaf is diseased or not can be predicted at the early stage of operation. Secondly, The DWT, PCA and GLCM are used to extract the informative regions/features of the samples. Lastly, as a part of machine learning approaches the SVM, KNN and CNN are used to classify the features

Section 2 describes the detailed description of existing leaf disease techniques. The leaf disease detection model is discussed in section 3. The results of proposed model on tomato leaf samples having six disorders are analysed in section 4. The leaf detection model is concluded in Section 5.

2. Literature survey

Lot of work has been devoted to the detection of leaf diseases using image processing in the history and it continues to attract research to carry out their research work in this field. Automatic crop disease detection using image processing and machine learning has been gaining prominence in recent years.

P. Krithika et al., [9] pre-processed by image resizing, contrast enhancement and color-space conversion. The K-Means clustering for segmentation and feature extraction using GLCM is performed. Classification was made using multiclass SVM. R. Meena et al., [10] performed color space conversion followed by enhancement process. The primary colors of leaves are converted into L*A*B*. The K-Mean clustering algorithm is used for segmentation. The GLCM and SVM are used for feature extraction and classification respectively. Bharat et al., [12] acquired images using digital camera and median filter is used for image enhancement. K-Mean clustering is used for segmentation. SVM is used for classification. Pooja et al., [13] segmentation is done to get the areas of interest that is the infected region. It is done using k-Mean clustering algorithm, Otsu's detection converting RGB to HSI later segmentation is done using boundary and spot detection algorithm. Rukaiyya et al., [14] performed pre-processing by contrast adjustment and normalization. The conversion of color transform into YCBCR and Bi-level thresholding is performed. The GLCM, and HMM are used for features extraction and classification [15].

Chaitali et al., [16] segmentation of image is applied for background subtraction. The classification approach is carried out by KNN, ANN and SVM method. In KNN, it classifies samples using nearest distance between trained and testing subjects [17]. Varun et al., [19] has developed model for extraction thresholding technique and morphological operation. Then multiclass SVM is used as classifier. For segmentation, based on a set of marks generated by analysis of the color and luminosity components of different regions of image is L*A*B* color spaces. The GLCM is used for feature extraction. Vijai Singh et al., [19] considered samples of plant leaves like rose/beans (bacterial disorder), lemon (sun burn disorder), banana (early scorch) and beans (fungal) that are captured using a digital camera. The green regions as background using thresholding algorithm. Finally, the genetic algorithm is used to get the segmented image. The color co-occurrence is adapted for useful extraction of features from the segmented images. The Minimum Distance Criterion and then SVM classifier is used for classification purpose. The average accuracy of 97.6% has been recorded.

Sa'ed Abed et al., [20] performed scaling and stretching (min-max linear) process for the input samples to improve the quality. The creation of HIS model is completed and the same is segmented later. The techniques of combined Euclidean distance and K-mean clustering is performed for segmentation of the samples. The GLCM and SVM are used for feature extraction and classification respectively. Arya et al., [21,22] takes input RGB image and creates color transformation then conversion of the input samples to HIS format. Finally, segment the components using Otsu's method. Nema et al., [23] images of 81 were included in the database and analysis was performed in L*a*b color space. Segmentation of the leaf disease was carried using k-means clustering and the classification of the disease was performed using SVM. Statistical information such as mean, median, mode, standard deviation was used by authors to record their findings. Vidyashree Kanbur et al., [24] developed the model for leaf detection disease using multiple descriptors. The model was tested on local leaf database and the performance of the model was superior., but it can be tested on publicly available dataset.

Pushpa et al., [25] Indices Based Histogram technique is used to segment unhealthy region of the leaf. The authors have surpassed other segmentation techniques such as slice segmentation, polygon approximation, and mean-shift segmentation. Kaleem et al., [26] considered pre-processed to resize them into 300*300 sized images, remove background noise, enhance brightness, and adjust the contrast. The K-means clustering for segmentation and the useful features are extracted using Statistical GLCM and SVM classifier is used for classification of leaf disorders.

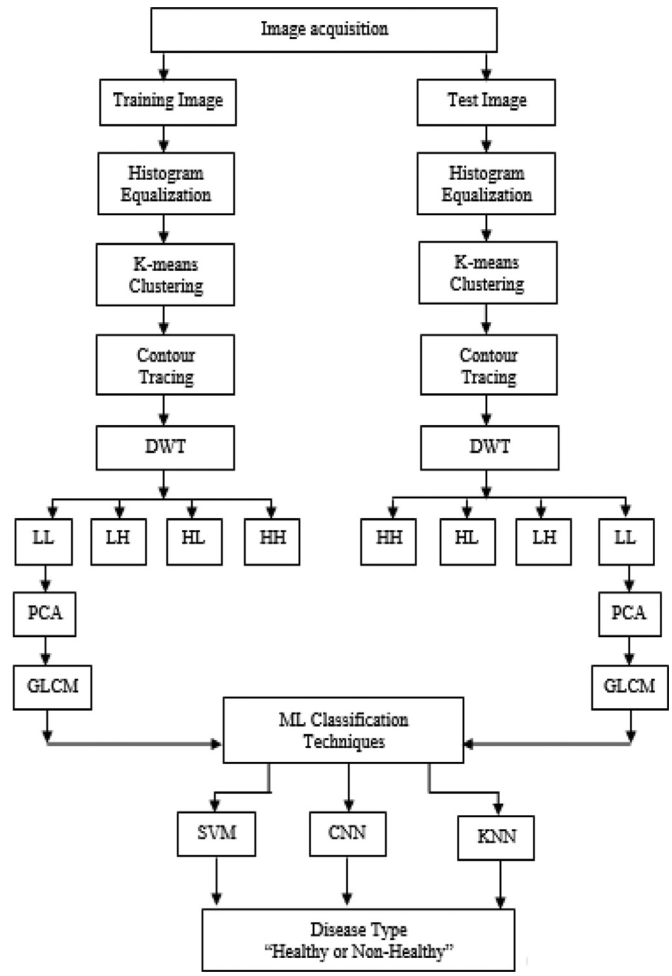

Fig 1. Proposed model.

3. Proposed model

The model is developed based on the IP and ML approaches for detection of leaf disease in presented in this section. The proposed model (DWT+PCA+GLCM+CNN) using computer vision and machine learning approaches for leaf disease detection is shown in Fig. 1.

The tomato samples having six disorders are considered to evaluate its accuracy and to recognize the leaf disease as Healthy or Unhealthy. As a part of image processing, the samples of tomato are resized to 256 × 256 pixels to maintain equal in their size throughout the exper-

Fig 2. Sample of tomato having disorders.

Fig 3. K-mean clustering.

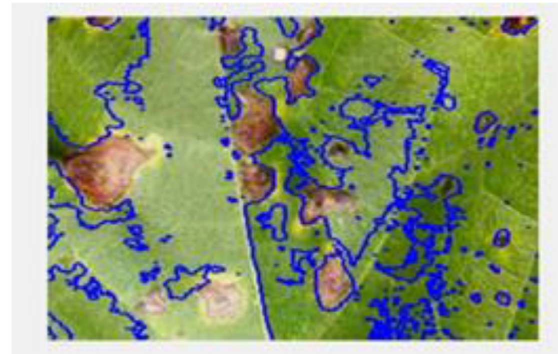

Fig 4. Contour tracing.

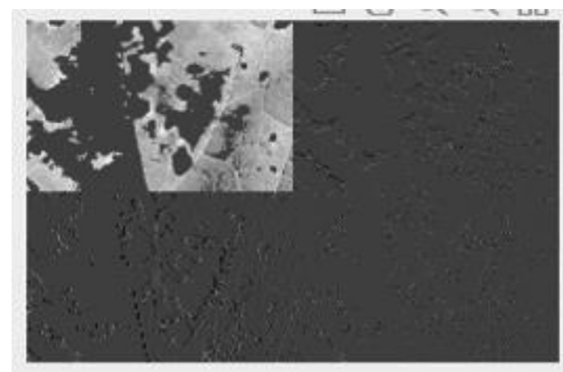

Fig 5. DWT decomposition.

iment. The HE and K-means clustering are employed to maximize the quality and segment the leaf samples. Based on the K-means clustering response, the leaf is diseased or not can be predicted at the early stage of operation. The boundaries of the leaf samples can be extracted using contour tracing.

The DWT, PCA and GLCM are used to extract the informative regions/features of the samples. In the next stage as a part of machine learning approaches the SVM, KNN and CNN are used to classify the features and the performance of the model is recorded.

3.1. Dataset

The village database of tomato leaf [15,34] is considered, the plants which are affected from variety of diseases. The images of tomato leaf having six disorders are taken to carry out the experiments for detection of leaf disease. The samples of leaf images in the database are shown in Fig, 2.

3.2. Preprocessing

K-means clustering technique [17–21] is applied on leaf images to find out the infected region. The K-mean clustering is used to get the data centre of the image and make the clusters of that image and calculates the centre distance from the other cluster. Samples of leaf after applying k-mean clustering algorithm [20] is shown in Fig. 3.

Contour tracing [21,22]is performed on digital leaf samples to extract their general shape information. After extracting the contour, its characteristics is analysed and used for pattern classification. It often helps for determining the efficiency of feature extraction process [19,20]. The images appeared after performing contour tracing is shown in Fig. 4.

3.3. Feature extraction

Discrete Wavelet Transform: The DWT [23] is applied on enhanced tomato samples to extract the useful features. The DWT decomposes into sub-bands of lower (LL, LH, HL) and higher frequency (HH) components. The LL component of DWT carries maximum availability of information when compared with higher frequency components of DWT as shown in Fig. 5.

Gray Level Co-occurrence Matrix: The optimal features are selected obtained from wavelet decomposition is carried out by Principal Component Analysis [24,25]. The GLCM uses in the distribution of higher order of gray values that are defined with neighborhood criterion [26,27]. The several properties are derived from the GLCM technique for extraction of leaf features.

The most used texture-based features are as follows. Homogeneity, Autocorrelation, Dissimilarity, Entropy, Sum of squares, Average, Variance, Entropy [28,29]. The features obtained using DWT, GLCM and PCA are combined to form feature vector which are provided as an input sample to the classifiers to recognize classify the images.

3.4. Classification

The techniques such as SVM, KNN and CNN are used for classifying the samples. The CNN [30–32] is a type of ANN which is designed to process the data. The architecture of CNN includes input (IL), output (OL) and hidden layers (HL), which are multiple in its nature. The HL includes convolutional layers, RELU layer i.e., which performs activation function, pooling, fully connected and normalization layers [33,34]. It is having mathematically evident that its architecture is cross correlation rather than a convolution and demonstrates significance for the indices in the matrix [35]. Regular 3-layer network is shown in Fig. 6.

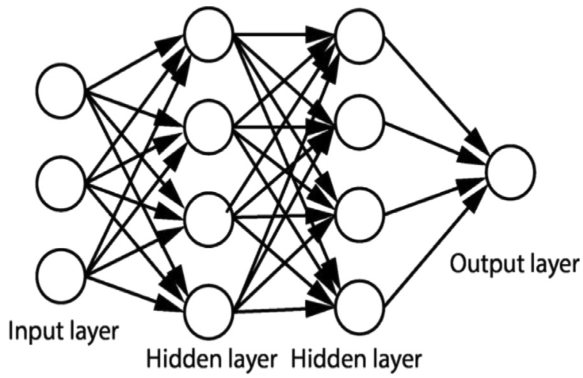

Fig 6. A regular 3-layer Neural Network.

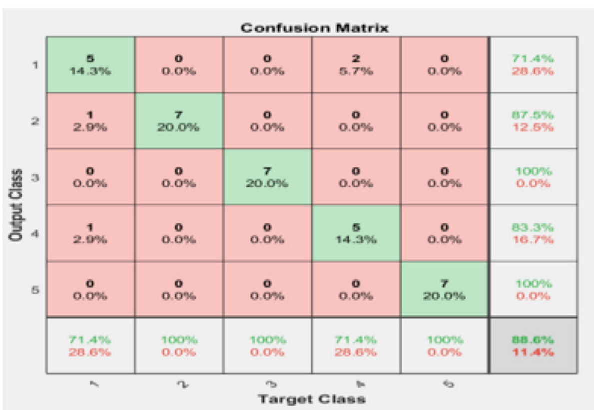

Fig 7. CNN Confusion matrix.

The confusion matrix [36,37] for CNN having output class and target class is shown in Fig. 7. The progress of training samples of leaf features classified using CNN to know the accuracy and errors are shown in Fig. 8.

3.5. Evaluation of Leaf disease

The parameters such as Precession, Recall and F-measure [38] for the proposed model is calculated and is given in Eqs. 1,2, and 3.

$$\text{Precision Measure (\%)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \text{X100} \tag{1}$$

$$\text{Recall Measure (\%)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \text{X100} \tag{2}$$

$$\text{F} - \text{measure} = \frac{2* \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \text{X100} \tag{3}$$

4. Experimental results

The samples of tomato leaf of village dataset is considered to carry out to evaluate the proposed model. The 100 samples of healthy leaf is taken to test on the proposed model. The model results in idetifying 99 samples with an accuracy of 99%. In the 100 Mosaic virus tomato samples, the model recognizes 100 samples with an accuracy of 100%. For leaf mold category, the model results in the accuracy of 100%. For the 100 samples of yellow curl, the model performed 99%. Similarly, the Spotted spider mite and Target Spot results in 99% and 100% respectively. Overall 600 samples of tomato village dataset is tested on the proposed model for evaluation, as a result, the model provides an better accurcay of 99.5%.

```
training started...Wait for ~200 seconds...
training started...
Elapsed time is 2.033151 seconds.
Elapsed time is 2.239313 seconds.
...training finished.
testing started....
test error is
Elapsed time is 1.085832 seconds.
CNN Accuracy  =99.0909
CNN Precision   =0.9913
CNN Sensitivity   =0.99091
CNN Specificity   =0.99773
CNN Confutionmatrix   =

confmatrix =

    22     1     0     0     0
     0    21     0     0     0
     0     0    22     0     0
     0     0     0    22     0
     0     0     0     0    22
```

Fig 8. Performance of CNN Classifier.

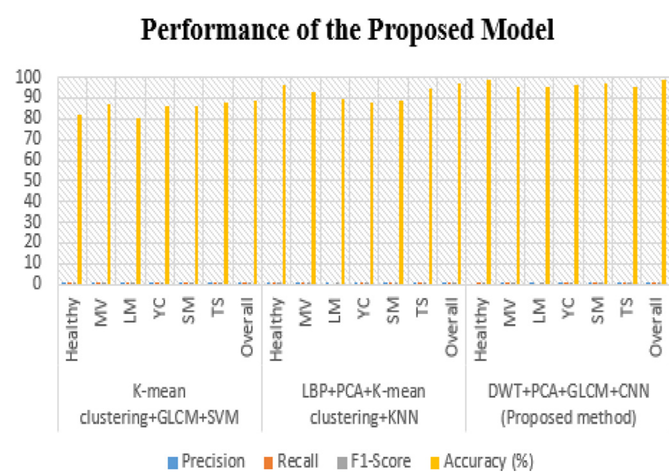

Fig 9. Comparison of Proposed model.

The model is validated by training/testing the dataset samples. The hardware and software specifications are recommended to carry out the work. ie., operation system: Windows10, Core: GPU-NVIDIA, language: Python, Libraries: Image data generator, Open Cv, Kera's, tensor flow, NumPy, Mat plot, Dataset: Plant village dataset having Tomato samples (Six disorder). The parameters such as Precision, Recall and F1 score are used to evaluate the performance of proposed model.

The proposed model is tested on tomato leaf disease dataset with an overall 600 samples. Fig. 9 shows the comparison of proposed model with the existing models. The precession, recall and F1-scores of SVM, KNN and CNN is tabulated in Table 1.

The result of proposed model is compared with existing models. It is observed that, the accuracy of Proposed model (DWT+PCA+GLCM+CNN) provides better accuracy of 99.09% compared to the other existing models.

The proposed model (DWT+PCA+GLCM+CNN) using computer vision and ML classification technique is compared with the methodology explained by Hossain et al., [22] and Vidyashree et al., [24] and Thanjai Vadivel et al., [34] and is tabulated in Table 2. The accuracy obtained

Table 1
Comparison of different classification techniques.

Techniques	Disorders	Precision	Recall	F1-Score	Accuracy (%)
K mean clustering + GLCM + SVM	Healthy	0.983	0.834	0.881	81.9
	MV	0.913	0.722	0.821	86.8
	LM	0.895	0.817	0.896	80.2
	YC	0.811	0.889	0.992	86.3
	SM	0.977	0.861	0.985	85.9
	TS	0.987	0.898	0.994	87.9
	Overall	**0.967**	**0.978**	**0.915**	**89**
LBP+PCA+K mean clustering+ KNN	Healthy	0.858	0.998	0.905	95.9
	MV	0.834	0.852	0.932	92.8
	LM	0.722	0. 844	0.916	89.6
	YC	0.817	0.985	0.892	87.7
	SM	0.889	0.876	0.915	88.9
	TS	0.861	0.928	0.958	94.8
	Overall	**0.978**	**0.975**	**0.952**	**97.3**
DWT+PCA+GLCM+CNN**(Proposed method)**	Healthy	0. 985	0.984	0.979	98.9
	MV	0.949	0.945	0.962	95.3
	LM	0.932	0. 934	0.956	95.5
	YC	0.938	0.968	0.979	96.4
	SM	0.953	0.919	0.899	97.2
	TS	0.967	0.978	0.898	95.5
	Overall	**0.995**	**0.995**	**0.988**	**99.09**

Table 2
Comparison of existing methodologies with proposed model.

Authors	Methodologies/Descriptions	Accuracy (%)
Hossain et al., [22]	Based on univariate statistical features test + SVM	90
Vidyashreeet al., [24]	K-mean clustering + GLCM + SVM	90
Thanjai Vadivel et al., [34]	Fast Enhanced Learning Method	99
Proposed Model	**DWT+PCA+GLCM+CNN**	**99.09**

by the proposed method is better compared with the existing methodologies.

5. Conclusion and future scope

The proposed model uses computer vision techniques including RGB conversion to gray, HE, K-means clustering, contour tracing is employed in preprocessing stage. The multiple descriptors Discrete Wavelet Transform, Principal Component Analysis and GLCM are used to extract the informative features of the leaf samples. The machine learning approaches such as SVM, K-NN and CNN are used to distinguish diseased or non-diseased leaf. The analysis of the proposed model is well suited for CNN machine learning classification technique with a desired accuracy compared to other state of the art method. In future, the model can be improved using fusion techniques for extraction of significant features and examined for other leaf samples of datasets.

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