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Detection and Classification of Crop Leaf Diseases using Machine Learning Algorithms

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ABSTRACT
Disease recognition and categorization are critical endeavours in crops, and they are a serious difficulty in today's agriculture and food processing situations as they affect crop inputs and yields. A quicker and more precise forecast of agricultural leaf diseases could aid in the formulation of a prompt remedial procedure, significantly lowering economic losses and yield losses. The use of machine learning technological advances have made it possible investigators to substantially enhance the performance and accuracy of object identification and recognition systems. Our major goal is to uncover a way to develop a more relevant machine learning framework to suit the proposed duties. In this paper, we suggest a machine learning-based approach for detecting crop leaf diseases in a variety of plants using photographs of plant leaves. As a result, we evaluated the detection and classification processes accurately. The suggested crop leaf disease forecasts contain four stages: preprocessing to enhance and shrink images using the contrast stretching approach; For segmentation, Otsu's thresholding-based k-means clustering technique is employed; for feature extraction, grey level co-occurrence; and for classification, convolutional neural network and support vector machine techniques have been implemented. Following that, we identified numerous segmentation features, classifier performance metrics, and statistical and structural features of the projected disease type and displayed them in the dialogue box. Finally, we compared the obtained results to existing approaches and discovered that the suggested plant disease prediction method is both accurate and efficient.
Keywords: *Agriculture, Crop Disease Detection, Machine Learning Algorithms, Support Vector Machine, GLCM*

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INTRODUCTION

Machine learning (ML) as well as artificial intelligence (AI) are increasingly employed in agriculture in a variety of ways, including finding the disease type, monitoring the soil and its quality, weed control, pest diagnosis, computer vision and drones for crop analysis, and weather forecasting. Agronomy accounts for 18% of the Indian economy's GDP. Agriculture is the primary source of income for a huge proportion of India's people [1]. As a result, crop yield is crucial to India. Crop leaf illness would not only diminish productivity but also pollute the ecosystem. Plant diseases have a negative impact on agricultural productivity. Plant diseases generate 10-15% of productivity losses [2-3]. In severe circumstances, it might reach 40-50% or even no revenue, causing agriculturalists who have laboured tirelessly for a whole year to suffer significant economic losses. Farmers, on the other hand, generally do not know enough about crop illnesses, so they are unable to completely comprehend the manifestation of each and every disease besides the definite looks of illness spots, and so they are unable to assess the condition and apply treatment appropriately. As a result, detecting leaf diseases through visual observation necessitates a team of professionals as well as continual crop surveillance and visual assessment of symptoms or results from experiments obtained by growing microorganisms in laboratories. The process of visual assessment is a qualitative and prone-to-mistakes procedure [4]. As a result, it is very expensive, time-consuming, and less trustworthy, and it is a subjective technique that is prone to error. As a result, too much, too little, or even the incorrect drug will be given, delaying illness treatment and harming the soil and environment. As a result, it is vital to identify the infectious disease and determine its nature immediately as feasible [33-34].

Particular diseases of leaves continue to pose a problem for agricultural production, not only by reducing crop yield but also by lowering nutritional value. Alternaria alternate (AA), anthracnose, cercospora leaf spot (CLS), and bacterial blight (BB) are certain of the most prevalent leaf illnesses. In the beginning phases, several leaf diseases may appear quite similar, making them difficult to detect with the naked eye [5]. We can use machine learning approaches to do automatic, quick, and accurate leaf disease identification and categorization. A number of researchers in this discipline have been working together to create a model that can foresee the presence of leaf disease in various plants. Feng Jiang and Yang Lu et al. [6] proposed a deep learning and SVM-based rice leaf image detection and recognition system. This SVM algorithm was used to categorise and forecast a specific disease using 10-fold cross-validation and a penalty value of one. Ahmed Khattab et al. [7] developed a cognitive monitoring system that employs IoT to forecast early plant sickness and control epidemic diseases. They created an artificial intelligence system that can provide disease-hazard alerts for end clients.

Rumpf T et al. [8] suggested an early identification and differentiation method for sugar beetroot diseases based on SVM with a radial basis function (RBF) as the kernel and spectral vegetation indices for particular disorders. Through deep learning approaches, Konstantinos P.F. [9] recommended the use of CNN models for recognising plant diseases and diagnosing them using modest leaf photos of healthy and diseased florae. Although Abdul Waheed et al. [10] developed a DCNN (dense convolutional neural network) model that is optimised to identify and classify maize leaves. These DCNN architectures had considerably fewer parameters and computational time. Zahid Iqbal et al. [11], Prabhira Kumar S. et al. [12], and Vijay Singh [13] examined various computer vision algorithms utilised for autonomously diagnosing diseases of plant leaves. Yanfen Li et al. [14] used several deep convolutional neural networks (DCNN) to develop a crop pest recognition (CPR) technique that accurately recognises ten prevalent kinds of crop pests. Gonzalez Camacho et al. [15] examined the use of machine learning (ML) in the selection of genomes of wheat-rust-resistant crops. In addition, Azadbakht et al. [16] employed machine learning (ML) to classify wheat diseases. ML approaches such as SVM (support vector machines), KNN (k-nearest neighbour), DF (decision forests), LDA (linear discriminant analysis), NBC (naive Bayes classifier), CNN (convolutional neural networks), RNN (recurrent neural networks), and others have been used to classify wheat diseases. [17–21]. When compared to alternative feature selection-based approaches, SVMs and decision forests (DFs) fared better. Deep learning models (DLM) do not necessitate explicit feature extraction, which can be accomplished as part of the learning process. E. Sasikala et al. [22] developed a system to identify and classify plant leaf ailments using an experimentally tested software approach. Machine learning is being utilised to create new evolutions. ML has been applied to crop disease detection. The basic purpose of ML approaches in this context is to grasp the material provided to be trained and integrate it into computational models that can prove advantageous for individuals. Khanna V et al. [23] created a new method for illness characterization that was integrated into the weed identification algorithm. The similarity measure is used to distinguish between normal leaves, damaged leaves, and weeds. Iqbaldeep Kaur et al. [24] used image processing approaches to investigate plant leaf disease detection and classification. They began by working on fundamental image processing techniques such as collecting RGB colour-based disease-affected leaf images, enhancing contrast with histogram equalisation, segmenting with K-means clustering, and extracting features of leaf disease symptoms by maintaining GLCM and classification by SVM. At the final stage, ant colony optimisation is used for concept optimisation. Akhila M et al. [25] proposed three significant detecting categories called Faster region-based CNN, Region-based FCN, and SSD, all of which effectively identified different types of diseases while dealing with challenging circumstances in a plant's area. Using image processing techniques (IPT) and machine learning (ML). Kishori Patil et al. [26] suggested a system for disease identification and categorization. From the above literature, it is observed that, the crop leaf disease findings offered different ML & AI and image processing algorithms by general procedural steps of any abnormal detection such as acquisition, pre-processing, extraction of features, feature designation, disease forecasting, and fertiliser recommendation are all part of the process. The result allows farmers to offer the most effective disease prevention service.

The primary objectives of this investigation endeavour are to create a model for detecting plant leaf disease using machine learning (ML) techniques and provide smart and intelligent systems (IS) to farmers to assist in smart decision-making (SDM). Because it is still difficult, it has been the primary focus of research for reliable identification of diseased areas. This paper makes two significant contributions. (1) To identify crop illnesses, a method is proposed in this research that combines k means, Otsu's, and HSI colour conversion with machine learning algorithm that is SVM classifier. Also, noteworthy because the model can reliably and effectively diagnose agricultural ailments. (2) The study's findings suggest that the ideal blend of features and model parameters can't merely enhance convergence speed but also have higher recognition accuracy than conventional models such as feature extraction and illness recognition directly using SVM.

This paper is organised into four different sections. First it provides outlines agricultural diseases and their impact on yield and output, as well as a literature review. Later it includes methods and resources such as the dataset gathering procedure, block diagram, preprocessing methods, and machine learning models. Then after presents the experimental findings and comparisons of the machine learning models to the provided dataset. At last, it describes the conclusions and subsequent research.

METHODS AND MATERIALS

This section presents dataset and the methodology used for plant leaf disease detection. The samples of infected and healthy plant leaf photos were collected at various locations throughout Kadapa, Andhra Pradesh, India. Some of the images were also collected from the public Kaggle website [32].

Block Diagram of the Crop Leaf Detection and Classification

The proposed system's methodology is presented using the block diagram demonstrated in figure 1. The following steps explain the methodology:

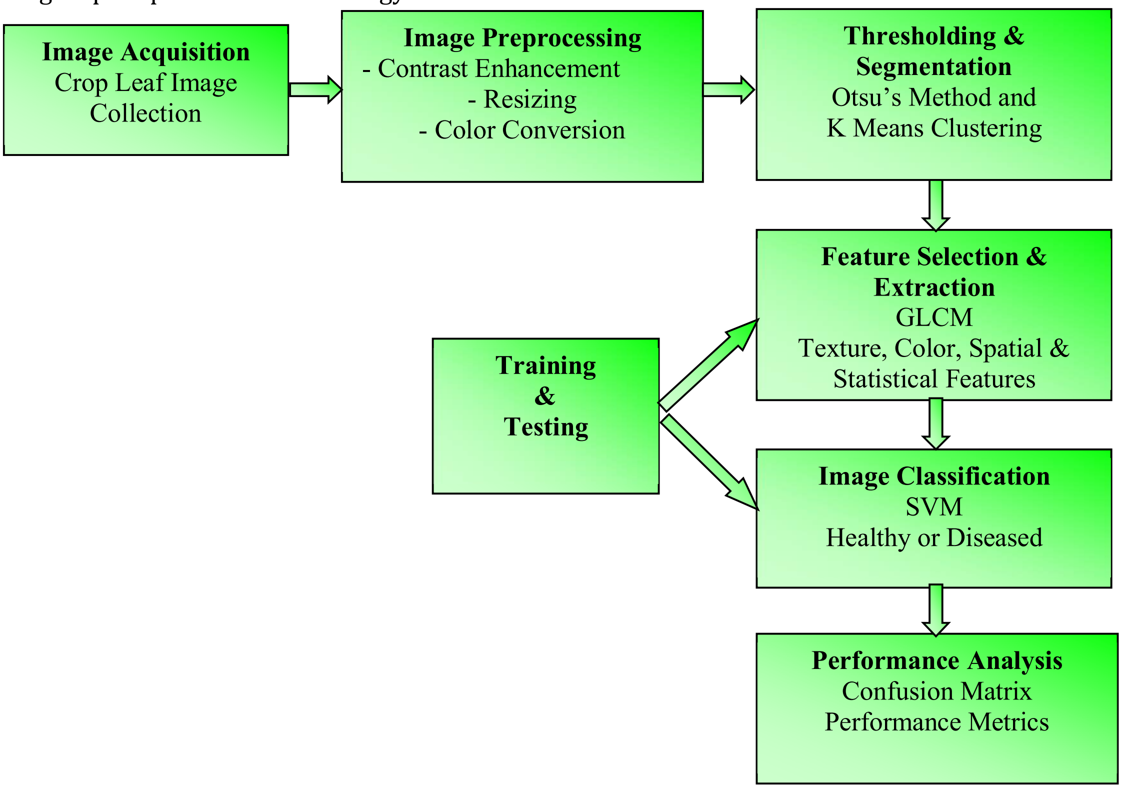


Fig. 1. Block diagram of crop leaf disease prediction

Image Acquisition: Specifies the acquisition of raw agricultural information such as input crop leaf photos from publicly available sources. *Image Preprocessing:* Increases the contrasting qualities of captured crop leaf photos by employing the contrast stretching technique, as well as making resize and colour conversions, which aids in the smooth and easy processing of subsequent phases of implementation and results in superior visual qualities compared to the original. *Thresholding and Segmentation:* Otsu's thresholding (OT) and k-means clustering (KMC) methods are used to segment the preprocessed image, and it provides an excellent way to find various features of the segmented image. *Feature Selection and Extraction:* Determines the statistical, texture, colour, and other properties of the segmented image by selecting the ROI (region of interest). Image Classification: The category of the leaf image is classified as healthy or unhealthy by observing the features obtained. *Training and Testing:* To learn a technique and fit the parameters for a classifier, the dataset must be trained. The sample photos obtained from databases are then validated and tested. It should be noted that the probability distribution (PDF) in the test dataset is the same as in the training dataset. as the training dataset but is independent of it. *Performance Analysis:* Develop the confusion matrix along with additional performance indicators, then compare the proposed methodology to existing methods to evaluate its precision and effectiveness.

Contrast Enhancement

Contrast enhancement methods are applied to the acquired diseased crop leaf images. Many of the collected input images have low contrast and develop just a small portion of the available brightness range. Stretching the image will help to improve the problem. The contrast stretching process is a 'point operation,' indicates that every single pixel in the source image relates to a pixel in the resultant image.

Two kinds of enhancement that are global and lobal stretching methods for contrast are observed. A global contrast stretch intended to provide detail in dark areas will almost certainly saturate the bright parts, and vice versa. The dynamic adjustment range of global contrast stretching is extremely narrow. This method is rarely used to apply image processing techniques. Local contrast stretching balances out the contrast across the image, making it easier to perceive image detail in areas that were previously very light or very dark. It will increase the visualisation of structures in two shades of the image [27].

Image Thresholding and Segmentation

Otsu's Thresholding: We employ thresholding based on intensity. It is the most essential computer vision and image processing technique. It converts the grayscale image to a binary image, which makes extracting the relevant information from the MRI image easier. It is used to distinguish the contaminated area from the background. This step's output image has a high processing speed and little storage space [28]. For the grey level, M ranging from 0 to M-1, g_h represents the number of pixels with grey level j. The following equation is applied for determining the probability:

$$q_j = \frac{g_j}{P}, \quad q_i \geq 0, \quad \sum_{j=0}^{M-1} q_j = 1 \quad \text{where where} \quad P = \left(g_0 + g_1 + g_2 + \dots\dots + g_{M-1}\right) \tag{1}$$

Let, (i). *l* is no. of clusters, (ii). *l-1*is selected threshold (maximum number of thresholds considered), (iii) y_l is the cumulative probability, and (iv) μ_l is the mean gray level for each cluster, c_l is computed by given expression (2):

$$y_l = \sum_{j \in d_l} q_j, \quad \mu_l = \sum_{j \in d_l} j \cdot \frac{q_j}{y_l} \quad l \in \{0,1,2\dots\dots, L-1\} \tag{2}$$

Let μ_U mean intensity and $\sigma_C{}^2$ class variance of entire image which are calculated by given expressions (3) and (4) respectively:

$$\mu_U = \sum_{j=0}^{M-1} j \cdot q_j = \sum_{l=0}^{L-1} \mu_l \cdot \omega_l \tag{3}$$

$$\sigma_C{}^2 = \sum_{l=0}^{L-1} j \cdot q_j = \sum_{l=0}^{L-1} \omega_l \cdot \left(\mu_l - \mu_U\right)^2 \tag{4}$$

K-Means Clustering: K-means a most basic unsupervised learning algorithm (USLA). With its easy computational mechanism, it uses for solving well-known clustering problems. This algorithm is guaranteed to converge, although it may not produce the best result [29].

i. Take into account the number of clusters, K.

ii. Initialization: For each cluster, set the centroid v_k. The v_k is represented in Eq (5).

$$v_k = \sum_{i=1}^{N} u_{ki} \cdot x_i \Big/ \sum_{i=1}^{N} u_{ki} \tag{5}$$

iii. Assign each data point to the cluster centre that is closest to it. Calculate each membership matrix, U. If data point xi is closer to cluster ck based on the Euclidian distance function, set uki = 1, otherwise set uki= 0.

iv. Using Eq. (5), calculate the new cluster centres for clusters getting new data points and clusters losing data points.

v. Repeat steps ii and iii until all cluster centroids are the same.

Feature Extraction

GLCM: The most traditional texture-based attribute extraction technique is GLCM. It establishes the textural link between pixels by performing a function in the segmented image based on second order statics. The grey intensities of pixels in pairs can be used to determine the second ordered grey intensity probability distribution for the texture image. As a result, it's known as co-occurrence distribution. The texture feature computations make use of the GLCM contents to offer a calculation of the intensity dissimilarity in significant pixels. This covariance matrix is estimated using two key factors. The relative spacing between its pixel pairs d defined the pixel number and relative orientation, such as 0° horizontal; 45° diagonal; 90° vertical; and 135° diagonal [30].

Classification

SVM: According to Vapnik and Cortes, the most successful supervised learning (SL) and pattern categorization (PC) tool is the support vector machine. SVM classifier (SVMC) was used in this study to determine if a plant leaf was healthy or diseased. SVM is a binary classifier (BC) that takes a collection of input data and divides it into two separate classes [31]. The power of SVM resides in its capacity to transform data into a high-dimensional space (HDS) where it can be divided using a hyperplane and distinguished between two classes by maximising the distance or margin between two classes, as seen in figure 2.

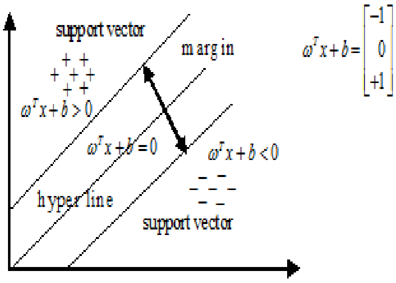


Fig. 2. Representation of SVM

The hyperplane is defined as $\omega^T x + b = 0$ separates the image pixel intensities, where ω^T is normal to hyper plane and *b* is the bias of the from the origin. The learning set provides pairs of (X_i, Y_i), where *i*=1,2,....,*n* feature vector and y=±1 are class labels. They must satisfy $\omega^T x + b > 0$ if $Y_i = +1$ and $\omega^T x + b < 0$ if $Y_i = -1$. SVM has the unique virtue of minimising classification error while maximising geometric margin in both linear and non-linear data classification.

RESULTS AND DISCUSSION

This section, initially provided the example samples of crop leaf images with healthy and diseased conditions. Late offered the system specifications of our presents experimentation, the simulation results and performance analysis. The sample images are given in figure 3.

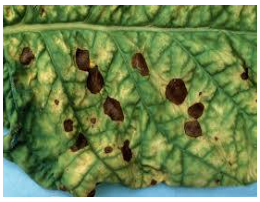
			
(a)	(b)	(c)	(d)

Fig. 3. Example of sample crop leaf images: (a) & (b) are diseased and (c) & (d) are healthy

System Specification

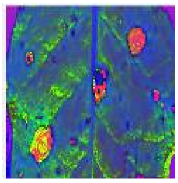
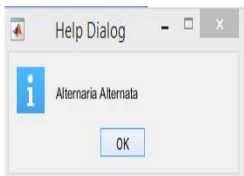
The complete project work was manifested and trained using MATLAB 2016a with several image processing toolboxes, and it was performed on an Intel i3-5005U processor with 4GB RAM (installed memory) supporting Windows 8.1 and a CPU speed of 2GHz. Image processing (IP) on leaf pictures is conducted, and features are collected from the disease-affected cluster using the k-means clustering algorithm. This project effort takes into account both healthy and sick pomegranate leaf photos. Sixty pomegranate samples are collected to test for diseases such as bacterial leaf spot and target spot. Likewise, fifteen pomegranate samples are collected for Alternaria alternata and anthracnose. Cercospora leaf spot and bacterial blight Machine learning methods are used to classify pomegranate leaf diseases.

Simulation Results

The simulation results of our project work were performed on 75 photos using k-means clustering (KNN) - based SVM and convolutional neural network (CNN) classifiers; however, here we are mainly showing four executions with two images, one diseased and one healthy.

Processing of Diseased leaf image using K-Means and SVM based disease prediction system

Figures 4 and 5 shows the simulation results of the Alternaria alternata disease-affected pomegranate leaf loaded from the database using K-Means clustering with SVM and convolutional neural network respectively. Here also is the K-means-based support vector machine. But in addition, here we are doing Otsu's thresholding to get the binary image to separate the background and object. The HIS image was also obtained by applying the HSI conversion method. These are also useful in smoothing out the segmentation and classification.

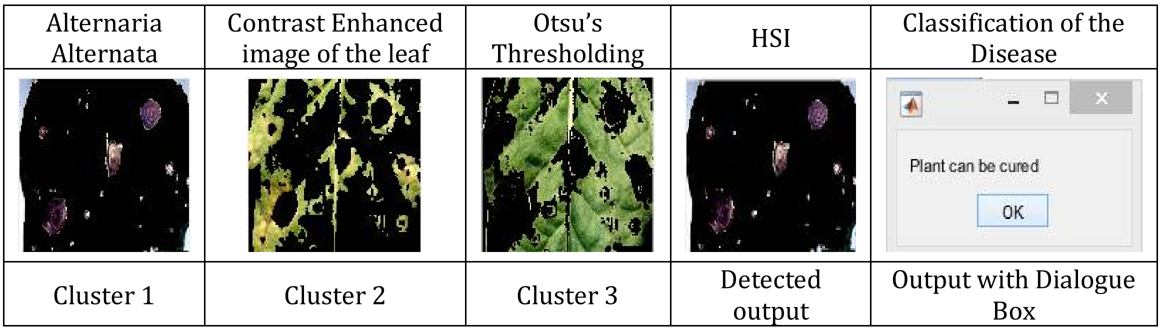


Fig. 4. Processing of Diseased leaf image using k-means and SVM based disease prediction system

Processing of Diseased leaf image using K-Means and CNN based disease prediction system

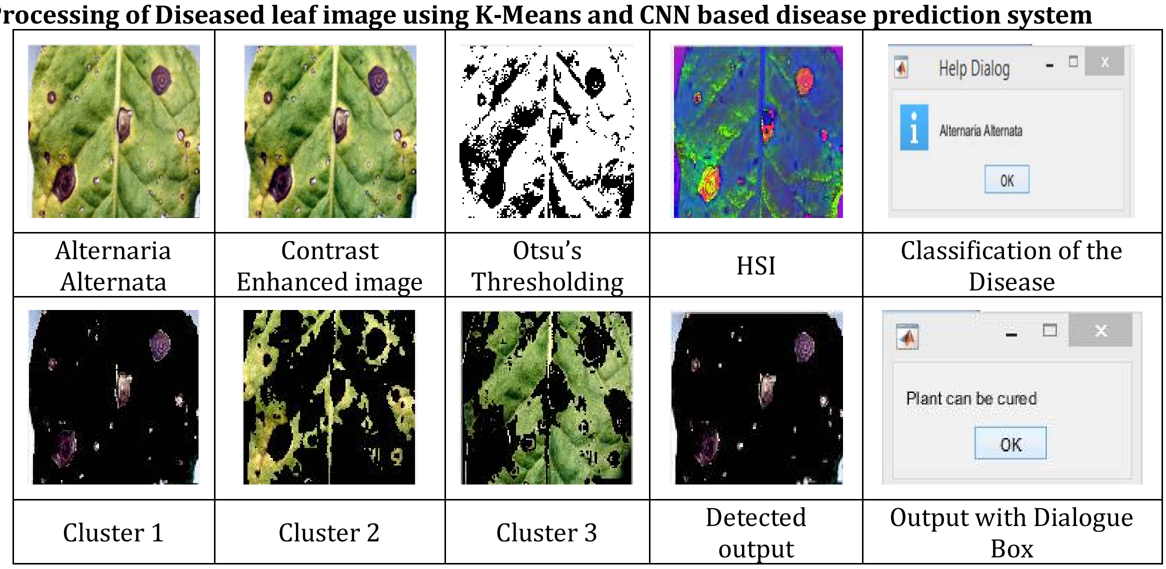


Fig. 5. Processing of Diseased leaf image using k-means and CNN based disease prediction system

The ROI (Region of Interest) is used to select the true portion of the affected clusters for identification of the exact spot of the disease in the leaf, which makes easier the further processes such as extraction and classification by the proposed methodology. Figures 6 and 7 show the simulation results of the processing of healthy images using k-means clustering with SVM and SVM prediction systems respectively.

Processing of Healthy leaf image using K-Means and SVM based disease prediction system

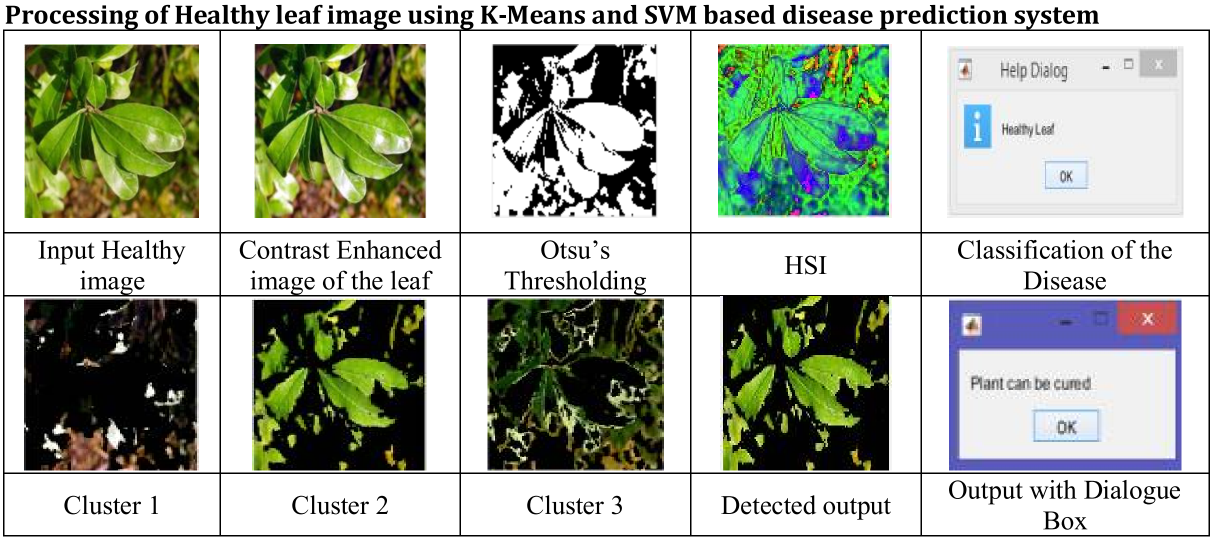


Fig. 6. Processing of healthy leaf image using k-means and SVM based disease prediction system

Processing of Healthy leaf image using K-Means and CNN based disease prediction system

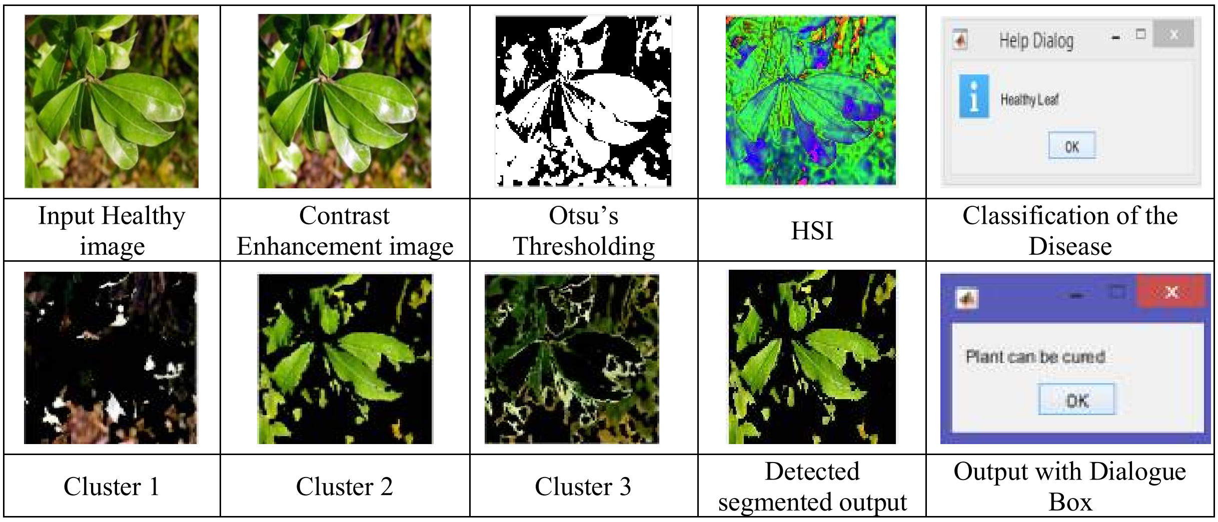


Fig. 7. Processing of healthy leaf image using k-means and CNN based disease prediction system

Performance Measurements of the Classifiers through confusion matrix

A matrix that depicts the class of each occurrence depending on the classifier algorithms used, paving the way for numerous performance measurements that determine the system's tendency. The confusion matrix's dimension is determined by the number of classes. The 5-class model generates a 5-dimensional confusion matrix. It will provide detailed information on the mapping of the correct and incorrect classes. Rows show predicted class labels, whereas columns show actual class labels.

- TP: true positive; it indicates that the sick leaf has been correctly classified.
- TN: true negative; signifies that the healthy leaf was correctly classified.
- FP: false positive; indicates that a healthy crop leaf image was mistakenly identified as a sick crop leaf.
- FN: false negative; indicates that the diseased leaf test image was misclassified as a healthy leaf.

The table 1 represents the confusion matrix, with the details of possible row and column totals, including sensitivity, specificity, and accuracy and other parameters.

Various Performance Parameters

Table 1. Classifier performance prediction table

Total Population		Actual Condition		Row Sum
		Positive	Negative	
Predicted Condition	Positive	TP	FP	TP+FP
	Negative	FN	TN	FN+TN
Column Sum		TP+FN	FP+TN	TP+TN+FP+FN
Parameter		$\text{Sensitivity} = \frac{TP}{TP+FN}$	$\text{Specificity} = \frac{TN}{TN+FP}$	$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$

Table 2. Detailed confusion matrix of classification results of healthy and diseased images using SVM

		Actual				
		Alternaria Alternate	Anthracnose	Cercospora Leaf Spot	Bacterial Blight	Healthy Image
Predicted	Alternaria Alternate	21	0	0	0	1
	Anthracnose	0	23	0	0	0
	Cercospora Leaf Spot	0	0	6	0	0
	Bacterial Blight	0	0	0	9	0
	Healthy Image	1	0	0	0	15

Table 3. Performance parameters determined from Confusion matrix SVM classifier

		Actual Values	
		Positive	Negative
Predicted Values	Positive	58	1
	Negative	2	14

From the confusion matrices represented in table 2 and 3, the TP is 58, FP is 1, FN is 2 and TN is 14. Hence TP, TN, FP and FN, from table 3 determined various performance measures using the expression from (7) to (15). Table 4 provides the performance parameters determined from classification results by using confusion matrix of healthy and diseased images using both CNN and SVM classifiers.

Table 4. Various parameters determined by CNN and SVM

Performance Parameter	**CNN Classifier**	**SVM Classifier**
Sensitivity	0.9508	0.9667
Specificity	0.8667	0.9333
Accuracy	0.9342	0.9600
Precision	0.9667	0.9831
Negative Predictive Value	0.8125	0.8750
False Positive Rate	0.1333	0.0169
False Discovery Rate	0.1333	0.0333
False Negative Rate	0.0333	0.0169
F1 score	0.9587	0.9748

The performance metrics have been determined for both CNN and SVM based classifiers are graphically represented in figure 8. It is observed that the SVM results 96% of classification accuracy whereas the CNN results 93.42% only. The other performance parameters such as sensitivity, specificity, precision, F1-score etc., of SVM classifier provides better results than the CNN classifier.

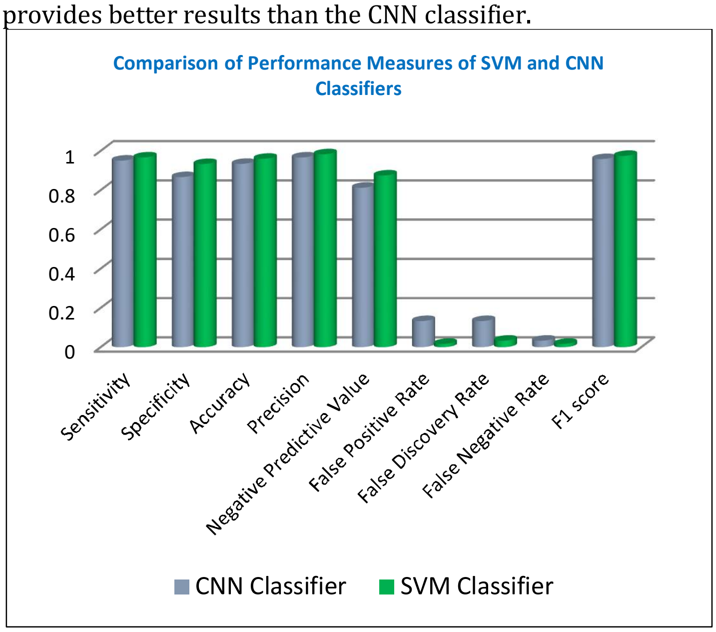


Fig. 8. Comparison of various performance measures of CNN and SVM classifiers

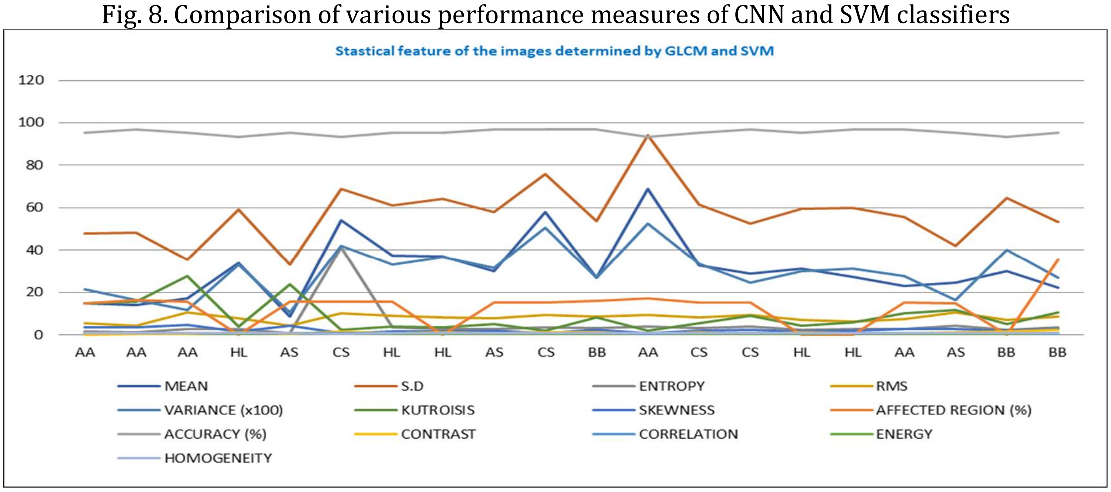


Fig. 9. Various statistical features of the GLCM and SVM

Note that the following are the full forms obtained from the figure 9 such as AA- Alternaria Alternate, HL- Healthy Leaf – HL, AS-Anthracnose- AS, CS-Cercospora Leaf Spot, BB-Bacterial Blight. Figure 9 gives the statistical features, texture features, and performance parameters of the SVM classifier. From these, we observed that the classifier efficiently predicts and detects the diseased and healthy leaves.

CONCLUSION AND FUTURE WORK

Predicting crop leaf diseases with visual assessments is usually challenging and time-consuming for farmers and agriculture sector professionals. In such cases, we choose autonomous crop leaf disease detection techniques to reduce false positives. For crop disease identification and classification, we used a machine learning-based algorithm, SVM, together with k-means clustering and GLCM feature extraction approaches in the proposed methodology. The SVM-based classifier outperformed the CNN-based classifier in terms of performance metrics and statistical characteristics. The proposed machine learning approach demonstrated its high potential; however, it is a matter of increasing the quantity and quality of accessible data to improve the system and make it broader (in terms of plant species and diseases that can be diagnosed) and robust in real-world cultivation circumstances. In the future, the research will be expanded by including and enabling IoT and various hardware circuitries for live capture and spontaneous (at crop location) disease diagnosis and categorization by embedding pest detection and management algorithms.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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