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ORIGINAL RESEARCH

Automatic methods for classification of visual based viral and bacterial disease symptoms in plants

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Abstract In this research, machine vision system is developed for the automatic identification of plant disease symptoms, from color images. Visual symptoms based identification of viral and bacterial diseases in plants using image processing and pattern classification is presented. Viral and bacterial plant disease symptoms affecting leaf, stem and fruit are segmented and features are selected based on co-occurrence based multispectral approach and co-occurrence based color moments approach. The artificial neural network (ANN), support vector machine (SVM) and convolutional neural network (CNN) are deployed for image-based disease symptoms classification. The maximum mean classification result of 90.72% is achieved using co-occurrence based color moments approach with SVM, on the held-out dataset comprising 4000 images of 20 plant disease symptoms. The method developed has shown applications in building intelligent systems which can be used automatically to identify the visual symptoms of plant disease and assist farmers.

Keywords Plant disease · Image analysis · Co-occurrence based methods · Classifiers

1 Introduction

India's agriculture is mainly composed of many grains, primarily rice and wheat. The major cereals are wheat, maize and jowar. The most popular fruits are banana, apple, orange, sapota and grapes. The main commercial crops are groundnuts, sugarcane, chili and cotton. The country retains over 210 million acres of farmland and about 80% of its population relies on agriculture for their food and fodder needs. Few years back plants were used to cater humans and animals, but in the present scenario plants play a vital role in all forms of livelihood. Plants are the sources of energy which improves the living conditions of human beings. Nevertheless, plants are affected by many diseases that lead to substantial ecological losses and cause great harm to socio-economic development of the country. Excessive uses of pesticides in agriculture are harmful and results in increase of costs.

Timely and accurate identification and diagnosis of plants diseases is important to avoid such loses. From the past, naked eye observation is the usual practice adopted by the people who are engaged in farming and agriculture to monitor plant diseases. The plant disease diagnosis developed from visual inspection leads to bias, prejudice, mental stress and evaluation results often turn out to be inconsistent among individual experts [22]. The initial symptom of plant diseases has to be identified in the early stages by means of computer technology particularly in remote areas [7]. The identification of plant disease using machine learning for pattern recognition in images has been successfully achieved in the recent past.

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Automating disease identification in plants is a fast and proven method to estimate plant disease condition. The direct consultation between agricultural experts and farmers can be avoided by this practice. The accurate plant disease diagnosis and prediction is the main advantage of using computer technology compared to manual observation. Automatic plant disease identification significantly reduces rapid growth of plant diseases, which improves the quality and quantity of food production and benefits in decreased production costs. A literature survey is undertaken to perceive the state-of-the-art detection of plant diseases and related works. The core of publications is as follows.

In Cui et al. [8], have adopted various segmentation methods for quantifying rust disease intensity of soybean plant leaves using multi-spectral images. The threshold-setting method performs well in laboratory settings for determining soybean rust severity, while the centroid-locating method performs best in the field.

Expert system has been developed by Abunaser et al. [1], for the early identification of plant diseases. The two methods have been adopted for diagnosing plant disease based on descriptive and visual representations of plant disease symptoms, namely, botrytis and powdery mildew. It is found that graphic depiction is better adapted for diagnosis of plant diseases relative to descriptive form.

In Bauer et al. [6], have proposed image processing techniques for identifying sugar beet leaf diseases such as cercospora beticola and uromyces betae. In comparison to the k-NN classifier, the experimental results show that an adaptive bay classifier using Gaussian mixture models performed better.

The image processing system presented by Dubey and Jalal [10], apple diseases such as apple rot, scab and apple blotch are considered for detection and classification. K-means clustering technique is used to segment the images of disease affected apple. The experimental results achieved classification accuracy of 93% using multi-class SVM with local binary patterns.

In automated identification, classification and quantification of disease intensity in plants by Barbedo et al. [5], demonstrated many image processing techniques. For researchers, who provide a comprehensive analysis of vegetable pathology and automated detection of plant diseases, these methods are supposed to be useful.

The support vector regression based on radial basis function developed by Omrani et al. [20], for detection of apple diseases, namely, apple black spot, alternaria and apple leaf miner pest are considered. K-means clustering is applied to detect affected regions. Features are extracted from affected regions using color, texture and wavelet. The SVM and ANN are used as classifiers.

Several image processing methods for recognizing and classifying fungal disease symptoms have been addressed by Pujari et al. [22]. Different fungal disease symptoms caused by agriculture and horticulture crops have been considered. Using different image processing methods, early identification of fungal disease symptoms is carried out.

In Mohanty et al. [19], have developed deep learning technique for crop disease identification. The trained overall classification efficiency of 99.35% is reported using 54,306 images experimented with 26 plant diseases.

In Singh et al. [23], have presented detection of diseases affecting plant leaves using soft computing techniques. Plant disease detection is done using genetic algorithms.

In Golhani et al. [13], have demonstrated the potential of hybrid system comprising neural network and hyperspectral data for early detection and diagnosis of plant diseases.

In Mishra et al. [18], have discussed and critically reviewed the prevailing image processing tools, techniques, key issues and challenges for leaf disease detection.

Ma et al. [17], have demonstrated a deep learning model for the identification of cucumber diseases affecting leaf. With traditional classifiers such as random forest and SVM, they contrasted the results obtained from DCNN. They achieved 93.4% recognition performance.

In Dhingra et al. [9], developed a novel neutrosophic approach using computer vision techniques for identification of leaf disease. The disease affected area is separated from healthy leaf using fuzzy extended form neutrosophic logic. Texture and color histogram features are extracted from segmented regions to identify leaf as diseased or healthy. The system has produced an average of 98.4% classification accuracy using nine different classifiers.

A CNN model for the detection of leaf diseases is proposed by Geetharamani and Pandian [12]. The developed CNN model is trained using 39 various categories of leaves. An average classification accuracy of 96.46% is reported for the dataset constructed using 6 different data augmentation techniques.

Edge and color based methods are used by Poornima et al. [21], to identify plant disease symptom and multi-class SVM to classify plant disease symptoms. They have considered plant disease symptoms like bacterial, fungal and viral for identification and classification.

In Khairnar and Goje [16], have proposed image-based approach for recognition of cotton plant leaf diseases. The k-means segmentation technique is used to separate the affected part of leaf. The color and texture features derived from segmented image are used to train SVM classifier.

In Ferentinos [11], have developed CNN model to classify 58 various combinations of plant diseases from 25 different plants. Overall classification efficiency of 99.53% is reported.

The convolution neural network (CNN) models developed by Jadhav et al. [15], identified soybean diseases like bacterial bacterial blight, frogeye leaf spot brownspot and non-disease (healthy) images. Overall classification efficiency of 97% is achieved using CNN models.

From the literature review, it is revealed that much work has been cited for identification of plant diseases using image-based approaches in the field of agriculture and horticulture. The study carried out is, however, concentrated on generic plant diseases. Also, in much of the work cited the number of plant diseases identified is limited. In the proposed work, machine vision system is developed that identifies large variety of viral and bacterial disease symptoms, which can be of great benefit to the farmers. For this purpose, feature extraction is done on plant disease infected image samples. In order to validate the accuracy of correctly identified image samples, classification models are used. The research finds automated use in the identification of plant disease symptoms. The paper consists of four sections. In Sect. 2, the proposed methodology is given. Section 3 gives experimental outcomes. Section 4 gives conclusion.

2 Proposed methodology

In this research, the machine vision system is built to identify and distinguish viral and bacterial diseases based on visual symptoms affecting different parts of plants such as leaf, stem and fruit. The disease infected color image samples acquired are segmented and features are extracted from target region. Further, classification of plant disease symptoms is performed using ANN and SVM classification models. The Fig. 1 demonstrates the view of the method proposed to identify symptoms of plant disease automatically.

2.1 Image dataset

The dataset of 4000 sample images for the purpose of experimentation are taken from University of Agricultural Sciences (UAS), Dharwad, India. A total of 20 symptomatic categories are considered for research work (consisting of 10 bacterial and 10 viral symptoms). For identification and classification purposes, an image dataset of 4000 images (comprising 100 images per symptomatic category i.e., 20 categories × 200 images per category = 4000 images) is considered. To optimize the computing time needed for further processing as well as its storage on the medium, the image size is reduced to 400 × 400 pixels. Image format JPEG is used in all cases. The viral disease symptoms include mosaic leaf pattern, crinkled leaves, yellowed leaves, plant stunting, veinal chlorosis, fruit malformation, sterility, witches broom, leaf distortion and phyllody. The bacterial disease symptoms consists of rots, wilts, leaf blight, bacterial blight, leaf spot, canker, shepherds crook stem, scabs, leaf streak and leaf stripe. The sample images of viral disease symptoms observed on various plants are shown in the Fig. 2. The Fig. 3 depicts some of the sample images of bacterial disease symptoms observed on various plants.

2.2 Segmentation

The diagnosis of plant disease becomes complicated because symptoms are similarly analyzed if sample images are taken in an unregulated outdoor lightning setting. In this study, k-means clustering technique is used to separate plant disease infected regions from healthy [3]. It is revealed from experimentation that k-means clustering provides better segmentation results compared to other segmentation techniques for the present work. Based on visual inspection, the images has three 3 distinct clusters and k-means is deployed with the value of k = 3, for segmentation of the image. The diseased parts are identified from segmented image. The Fig. 4 shows disease infected region obtained using k-means clustering technique.

2.3 Feature selection

The features are derived from detected infected areas obtained from segmentation. The areas of study images showing visual signs of viral or bacterial plant disease are the regions affected with the disease. In this work, color and texture features are extracted from the disease infected area of the segmented image based on co-occurrence matrix method. The feature extraction is performed using co-occurrence based multispectral approach and co-occurrence based color moments approach.

2.3.1 Co-occurrence based multispectral approach

Six co-occurrence matrices are constructed, three for intra-channel information (R, R), (G, G) and (B, B) and three for inter-channel information (R, G), (R, B) and (G, B) [4]. The six color combinations of color planes considered in RGB color space take into account the correlation between channels. The co-occurrence information is calculated by considering a pixel from first plane (R) and its neighbor from second plane (G) in (R, G) pair. Similarly, co-occurrence information is calculated for (R, B) and (G, B) pairs. Using uniform quantization technique all the channels are quantized to 32 Gy levels. When the image is scanned from top-to-bottom and left-to-right, the co-occurrence matrix method calculates how many pairs of grey pixel levels are discriminated by a certain distance (d) and

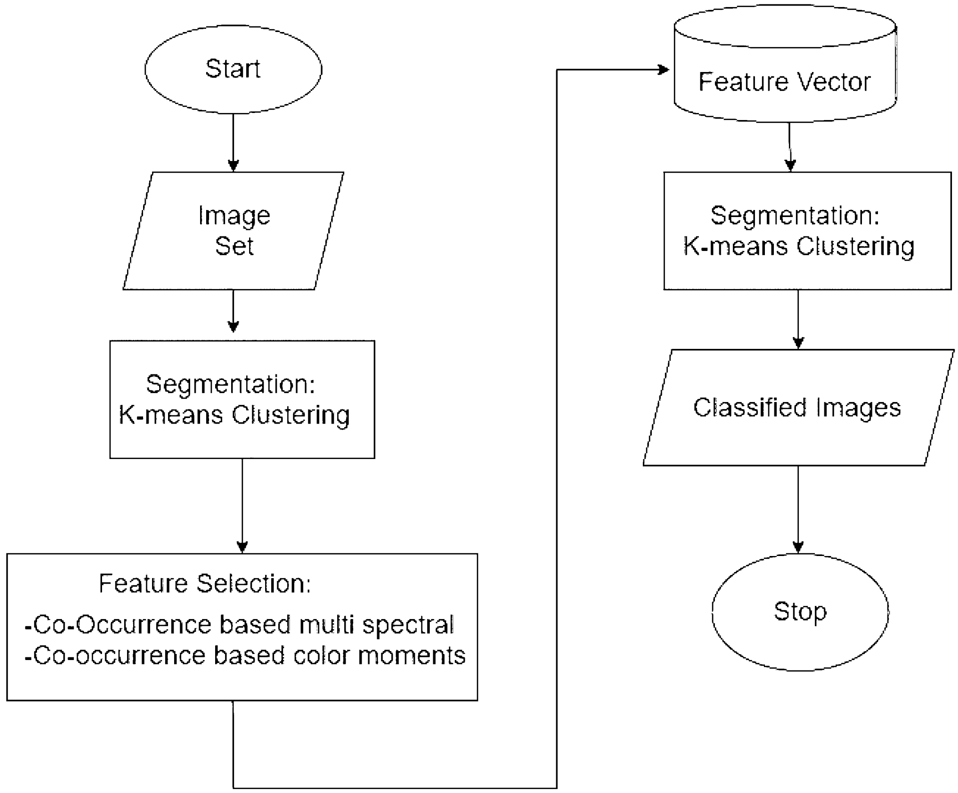


Fig. 1 Schematic flow chart of the work proposed

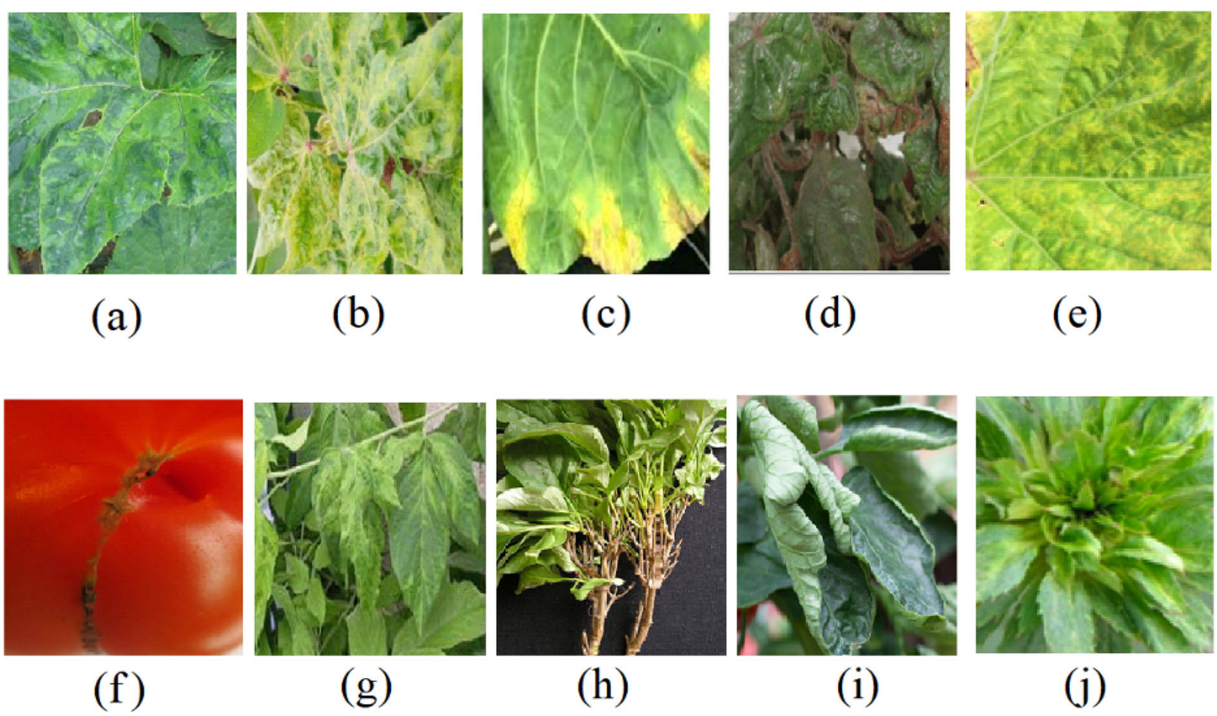


Fig. 2 Viral disease symptoms: **a** mosaic leaf pattern, **b** crinkled leaves, **c** yellowed leaves, **d** plant stunting, **e** veinal chlorosis, **f** fruit malformation, **g** sterility, **h** witches broom, **i** leaf distortion, **j** phyllody

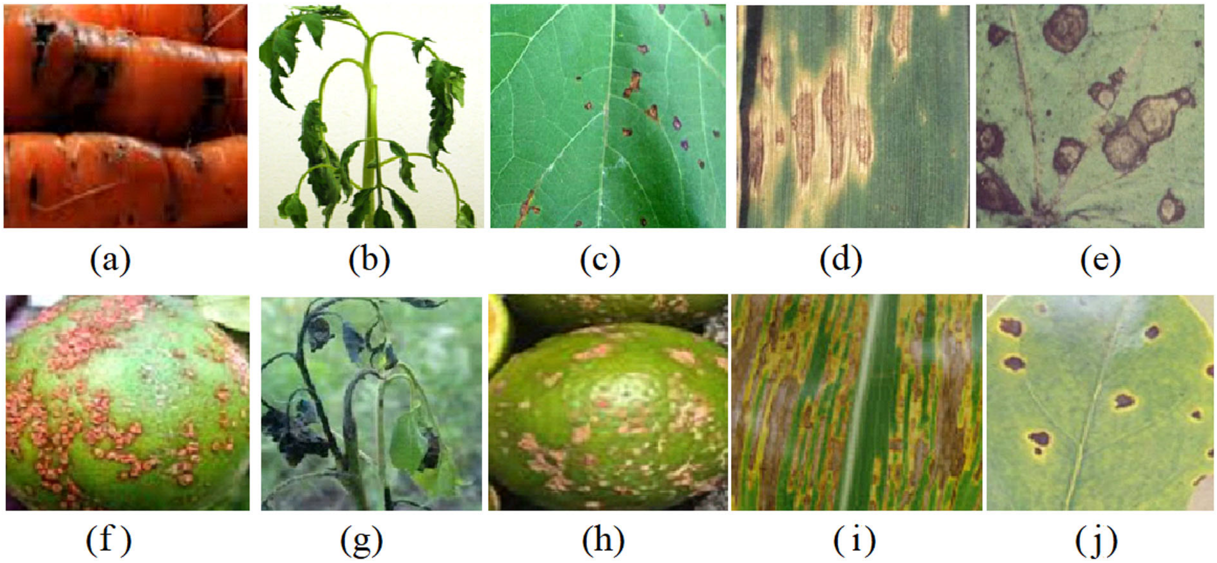
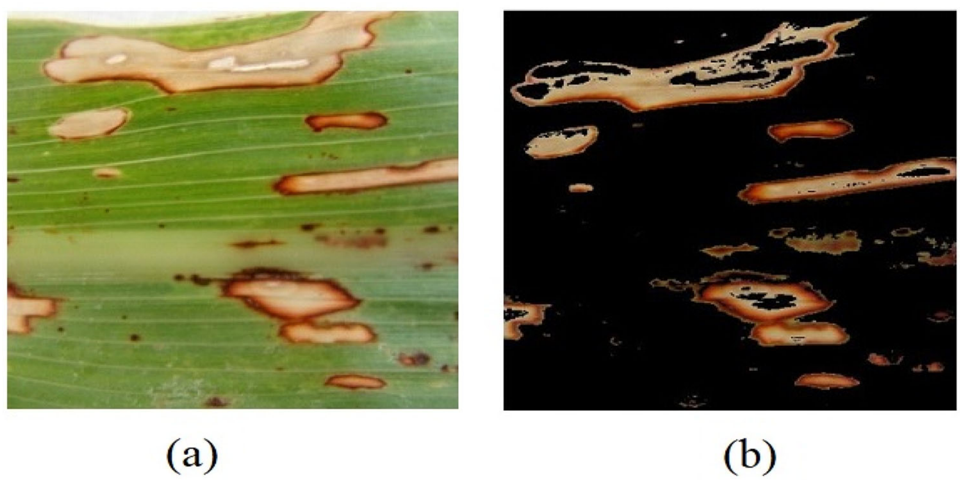


Fig. 3 Bacterial disease symptoms: **a** rots, **b** wilts, **c** leaf blight, **d** bacterial blight, **e** leaf spot, **f** canker, **g** shepherds crook stem, **h** scabs, **i** leaf streak, **j** leaf stripe

Fig. 4 Resultant segmented color image using K-means: **a** Original image, **b** Segmented image



oriented in a certain direction (θ). A distance of 1 (d = 1, immediate neighborhood) and four angles (θ = 0°, 45°, 90°, 135°) are taken into account in this work. However, all the readings are recorded into a single co-occurrence matrix, thus achieving rotational invariance. Since the texture features are calculated on this conjugate matrix, only five Haralick features [14] calculated for each co-occurrence matrix constructed, generating 30 texture features in the image. Measurements such as homogeneity, contrast, correlation, entropy and local homogeneity are calculated through co-occurrence matrix using Expressions (1) through (5). The Fig. 5 shows multispectral approach followed to compute texture features. The procedure used in obtaining the texture features using co-occurrence based multispectral approach is given in the Algorithm 1.

$$\text{Homogeneity} = \sum_i \sum_j M\,(i,j)^2 \tag{1}$$

$$\text{Contrast} = \sum_{k=0}^{m-1} k^2 \sum_{i-j=k} M(i,j) \tag{2}$$

$$\text{Correlation} = \frac{1}{\sigma_i \sigma_j} \sum_i \sum_j (i-\mu_i)(j-\mu j) M(i,j) \tag{3}$$

$$\text{Entropy} = \sum_i \sum_j M\,(i,j)\, log\,(M\,(i,j)) \tag{4}$$

$$\text{Local homogeneity} = \sum_i \sum_j M\,(i,j)/1 + (i-j)^2 \tag{5}$$

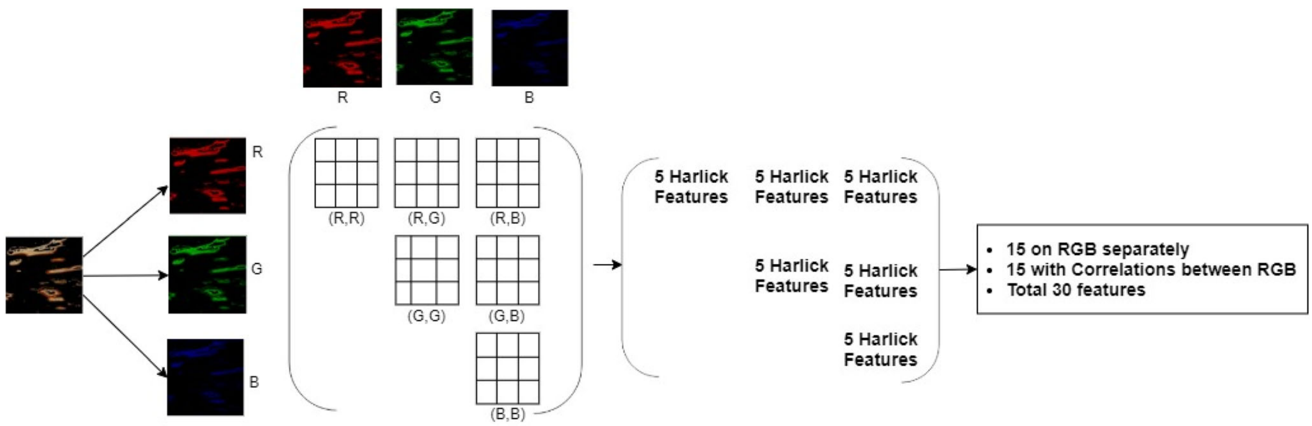


Fig. 5 Schematic block diagram of co-occurrence based multispectral approach followed

Algorithm.1: Feature computation

Input: RGB image

Output: Texture features

Start

Step 1: Read the image

Step 2: Consider six combinations in RGB space i.e., (R,G), (R,B), (G,B), (R,R),(G,G) & (B,B)

Step 3: Compute co-occurrence matrix for one pair (say R,G) for one angle (say 0^0) at d=1

Step 4: Repeat the steps for remaining 5 pairs

Step 5: Form a feature vector comprising 6 pairs i.e., (6pairs x 5haralick features=30 features) and store in database

Stop.

2.3.2 Co-occurrence based color moments approach

Texture features are extracted by computing 5 Haralick features from co-occurrence matrix. The computation is performed for every region in the image using luminance channel of the color space [4]. Color features are extracted by computing first and second order statistical moments for each region on the two chromatic channels given by Expressions (6) and (7). The Fig. 6 shows co-occurrence based color moments approach followed to extract color and texture features. The method used to derive the co-occurrence matrix based texture and color features is given in the Algorithm 2.

$$\text{Mean } \mu \quad 1/N\sum_{i=1}^{N} x_i = \frac{x_1 + x_2 + \ldots\ldots\ldots\ldots + x_N}{N} \tag{6}$$

where, N: total number of pixels, x_i: ith pixel value.

$$\text{Standard deviation } \sigma = 1/N\sum_{i=1}^{N} \sqrt{(x_i - \mu)^2} \tag{7}$$

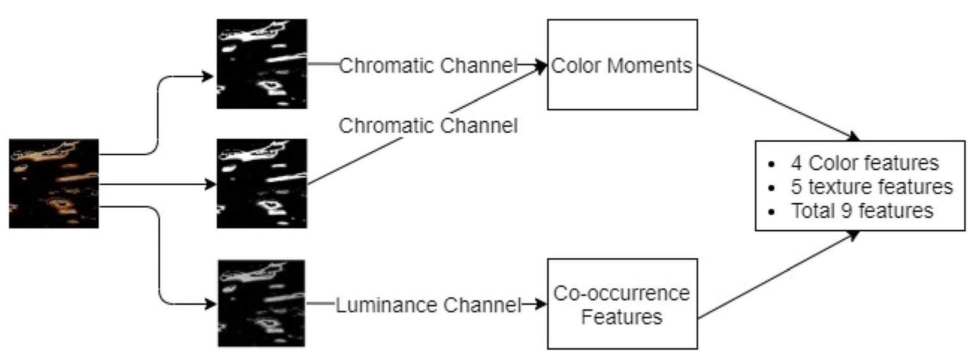


Fig. 6 Schematic block diagram of co-occurrence based color moments approach followed

Algorithm.2: Feature computation

Input: RGB image

Output: Color and texture features

Start

Step 1: Read the image

Step 2: Compute co-occurrence matrix using intensity channel yielding 5 texture features

Step 3: Compute statistical moments on two chromatic channels yielding 4 color features

Step 4: Form a feature vector comprising 9 features and store in database

Stop.

2.4 Classification

The ANN with backpropagation and SVM are used as classifiers in this study. The training and testing of classifiers is done separately. The 30 features obtained using co-occurrence based multispectral approach and 9 features obtained using co-occurrence based color moments approach are used to train and test the classifiers. Half of the image dataset is used for training, while the other half is used for testing. Identification and classification percentage accuracy is defined as the ratio of sample images that are correctly identified to the total number of sample images as implied in Expression (8). The average accuracy is determined as the ratio of the sum of the identification accuracies of all the sample images to the total of the sample images considered using Expression (9). The process of plant disease symptoms classification using ANN and SVM classifiers is given in the Algorithm 3.

$$\text{Identification efficiency } (\%) = \frac{\textit{Correctly identified sample images}}{\textit{Total number of test sample images}} \times 100 \tag{8}$$

$$\text{Average identification efficiency } (\%) = \frac{\textit{Sum of correctly identified sample images}}{\textit{Total number of sample images}} \times 100 \tag{9}$$

3 Experimental results

The algorithms developed in this work are implemented using ANN and SVM tools of MATLAB 2015. The experiments are executed on Intel Core i3-7100U processor with 4 GB RAM and Nvidia GeForce RTX 2070 GPU. The results of plant disease identification obtained using co-occurrence based multispectral approach and co-occurrence based color moments approach with ANN and SVM classifiers are given in Sects. 3.1 and 3.2 .

3.1 Classification using ANN

The ANN training and testing are conducted using 30 features obtained using co-occurrence based multispectral approach. The study has used 30 input nodes and 20 output nodes corresponding to 30 input features and the 20 chosen categories of plant disease symptoms respectively. For ANN training and testing using co-occurrence based color moments approach 9 input nodes corresponds to 9 input features and the 20 chosen categories of plant disease symptoms respectively. The ANN configuration parameter values used for experimentation are presented in the Table 1.

Algorithm 3: Plant disease symptoms identification and classification

Input: Color (RGB) images of viral and bacterial disease infected plants

Output: Images identified and classified

Start

Step 1: Apply Algorithms 1 and 2 to compute color and texture features from a segmented color image

Step 2: Train the ANN & SVM with computed color and texture feature vector stored in the database

Step 3: Repeat Step 1 for all the test images

Step 4: Images are classified using ANN & SVM

Stop.

Table 1 ANN parameters

Parameters	Ideal value
Rate of learning (η)	0.01
Activation function	Sigmoid function
Performance function: MSE	0.01
Momentum constant	0.9
Epochs to train	100
Initial weights	0.1
Input neurons	30,09
Hidden neurons	64
Output neurons	10,10,20
Hidden layers	01
Network type	Feed forward Back propagation
Learning function	Gradient descent with momentum
Training function	Levenberg–Marquardt back propagation

The graph of classification results obtained for images of viral disease symptoms using multispectral co-occurrence based method with ANN classifier is shown in the Fig. 7. It is observed from the graph that the high and low classification accuracies of 86.29% and 80.07% have occurred with images of plant stunting and phyllody respectively. The mean classification accuracy of 82.48% is obtained regardless of the viral disease symptomatic image categories.

The graph of classification results obtained for images of bacterial disease symptoms using multispectral co-occurrence based method with ANN classifier is shown in the Fig. 8. It is observed from the graph that the high and low classification accuracies of 86.61% and 80.39% have occurred with images of leaf stripe and leaf streak respectively. The mean classification accuracy of 83.09% is obtained regardless of the bacterial disease symptomatic image categories.

The graph of classification results obtained for images of viral disease symptoms using color moments co-occurrence based method with ANN classifier is shown in the Fig. 9. It is observed from the graph that the high and low classification accuracies of 91.77% and 83.57% have occurred with images of sterility and phyllody respectively. The mean classification accuracy of 88.51% is obtained regardless of the viral disease symptomatic image categories.

The graph of classification results obtained for images of bacterial disease symptoms using color moments co-occurrence based method with ANN classifier is shown in the Fig. 10. It is observed from the graph that the high and low classification accuracies of 91.31% and 82.51% have occurred with images of canker and leaf streak respectively. The mean classification accuracy of 87.31% is obtained regardless of the bacterial disease symptomatic image categories.

3.2 Classification using SVM

The SVM configuration parameter values used for experimentation are presented in the Table 2.

The graph of classification results obtained for images of viral disease symptoms using multispectral co-occurrence based method with SVM classifier is shown in the Fig. 11. It is observed from the graph that the high and low classification accuracies of 87.02% and 80.76% have occurred with images of plant stunting and fruit malformation respectively. The mean classification accuracy of 84.28% is obtained regardless of the viral disease symptomatic image categories.

The graph of classification results obtained for images of bacterial disease symptoms using multispectral co-occurrence based method with SVM classifier is shown in the Fig. 12. It is observed from the graph that the high and low classification accuracies of 93.39% and 80.43% have occurred with images of leaf blight and rots respectively. The mean classification accuracy of 87.83% is obtained regardless of the bacterial disease symptomatic image categories.

The graph of classification results obtained for images of viral disease symptoms using color moments co-occurrence based method with SVM classifier is shown in the Fig. 13. It is observed from the graph that the high and low classification accuracies of 92.57% and 85.98% have occurred with images of venial chlorosis and mosaic leaf pattern respectively. The mean classification accuracy of 90.07% is obtained regardless of the viral disease symptomatic image categories.

The graph of classification results obtained for images of bacterial disease symptoms using color moments co-occurrence based method with SVM classifier is shown in the Fig. 14. It is observed from the graph that the high and low classification accuracies of 93.98% and 88.20% have

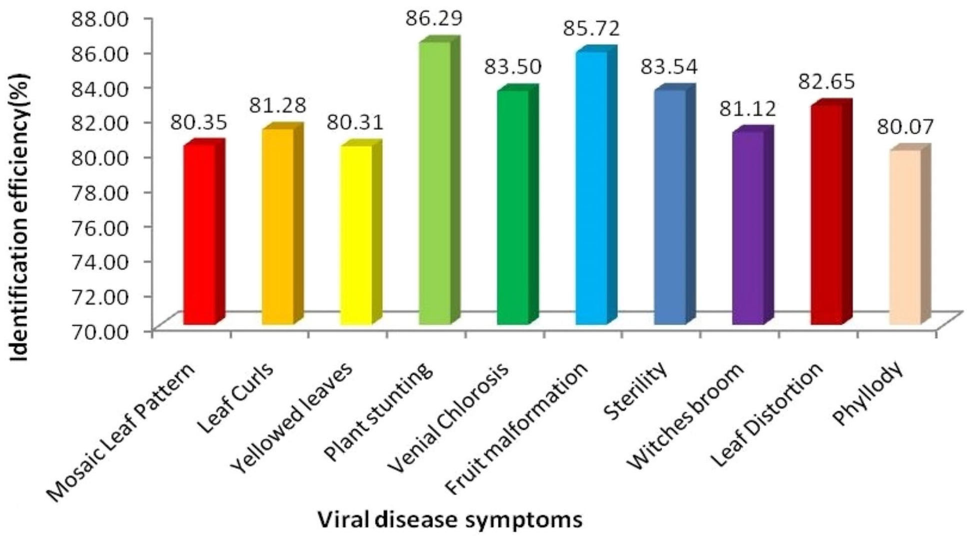


Fig. 7 Classification result using co-occurrence based multispectral approach with ANN classifier

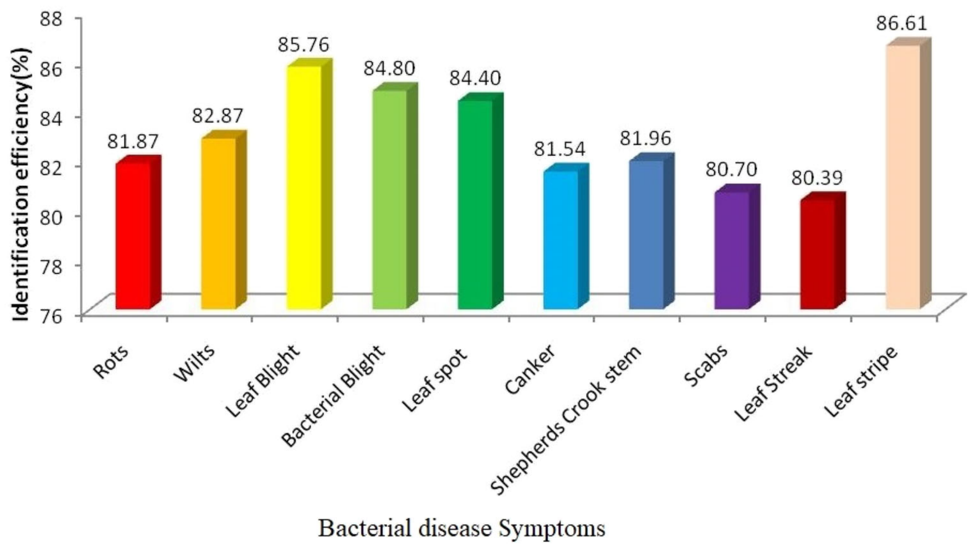


Fig. 8 Classification result using co-occurrence based multispectral approach with ANN classifier

occurred with images of leaf streak and wilts respectively. The mean classification accuracy of 91.37% is obtained regardless of the bacterial disease symptomatic image categories.

3.3 Comparative study

In order to corroborate the efficacy of the developed algorithms using co-occurrence based multispectral approach with ANN and SVM classifiers and co-occurrence based color moments approach with ANN and SVM classifiers, the dataset is experimented using DCNN. In this work, we have used VGG-16 CNN model [2] implemented using deep learning tool of MATLAB 2015, for the classification of viral and bacterial disease symptoms in plants. The VGG-16 CNN model is pre-trained for classification of sample images.

The performances of ANN, SVM and CNN classifiers are compared. The Fig. 15 show the comparison graph of mean classification efficiencies of ANN and SVM classifiers using co-occurrence based multispectral approach and CNN classifier. The comparison result shows that the overall mean classification results obtained are 82.78%, 85.77% and 82% with ANN, SVM and CNN classifiers respectively.

The Fig. 16 show the comparison graph of mean classification efficiencies of ANN and SVM classifiers using co-occurrence based color moments approach and CNN classifier. The comparison result shows that the overall mean classification results obtained are 87.91%, 90.72% and 82% with ANN, SVM and CNN classifiers respectively.

It is observed from experimental results that the SVM using co-occurrence based color moments approach

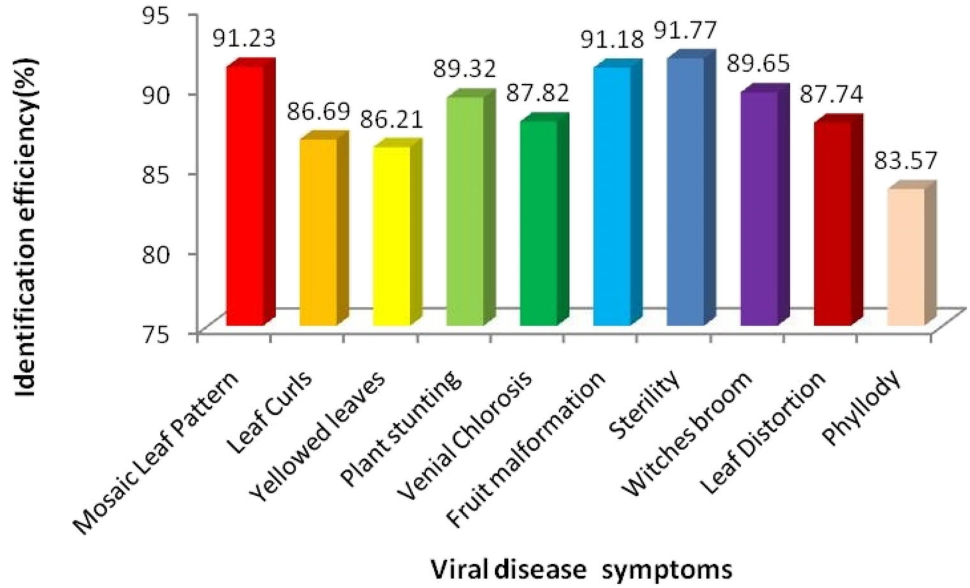


Fig. 9 Classification result using co-occurrence based color moments approach with ANN classifier

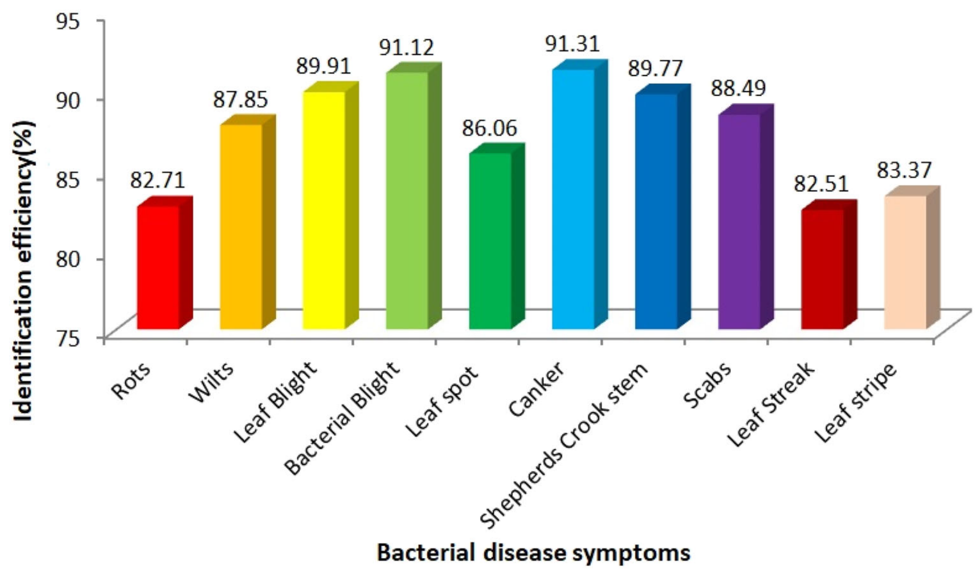


Fig. 10 Classification result using co-occurrence based color moments approach with ANN classifier

improved overall classification results for identifying and classifying viral and bacterial disease symptoms in plants.

3.4 Estimation of computation time

The computation time needed for the analysis using ANN, SVM and VGG-16 CNN classifiers is given in the Table 3. It shows that SVM using co-occurrence based color moments approach is the fastest. On an average, it takes around 291.5 s for each testing image to be compared over the training dataset. The VGG-16 CNN model is the most time consuming. It took around 2 h both for training and testing dataset.

4 Conclusion

The image based identification and classification of symptoms of plant disease is effectively executed in this work. Two distinct plant disease types, namely, viral and bacterial affecting various parts such as leaf, stem and fruit are used. This research employs image processing based algorithms such as segmentation, feature selection and classification. The classifier efficiencies are studied using the test datasets. The experimental results are compared with co-occurrence based multispectral approach with ANN and SVM classifiers, co-occurrence based color moments approach with ANN and SVM classifiers and CNN classifier. It is observed from the results that the co-occurrence based color moments approach with SVM

Table 2 SVM parameters

Parameters	Ideal value
Kernel function	Polynomial
Degree of polynomial function	3
Kernel coefficient (gamma)	10
Penalty/cost (C)	1.0
Cache_size	200
Probability	False
Verbose	False
max_iter	−1
decision_function_shape	'ovr'
Shrinking	True
random_state	None
Tol	0.001

classifier performs significantly better than the ANN and CNN classifiers in terms of overall mean classification and computation time. The outcomes of the research are encouraging as it considers unique symptoms of viral and bacterial diseases. By using various feature selection approaches and classifiers, there is potential for progress in overall classification results. Further, there is scope for increasing the size of dataset and comparing the appropriateness of the developed methods. The method developed finds application in the automatic identification of plant disease symptoms affecting various plant crops.

Fig. 11 Classification result using co-occurrence based multispectral approach with SVM classifier

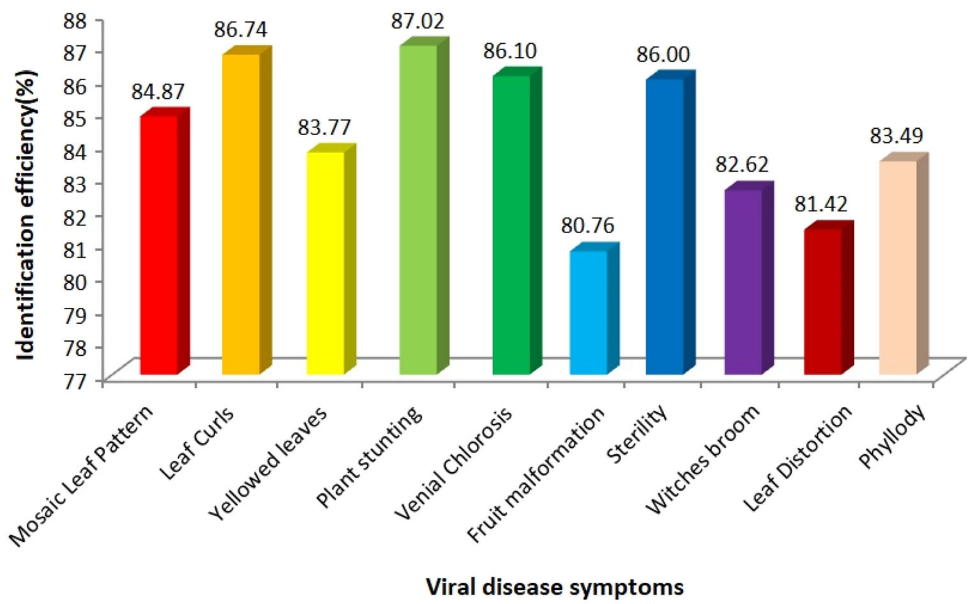
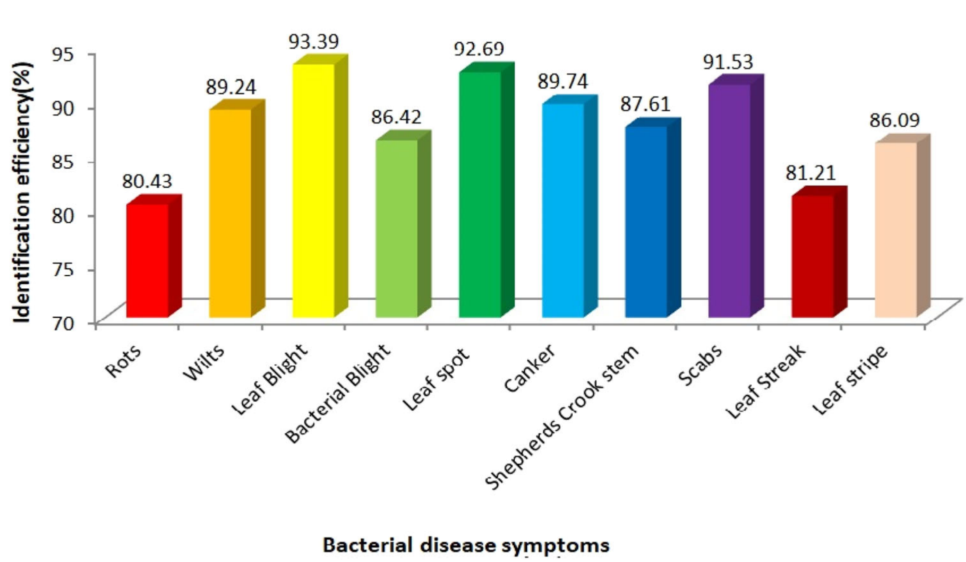


Fig. 12 Classification result using co-occurrence based multispectral approach with SVM classifier



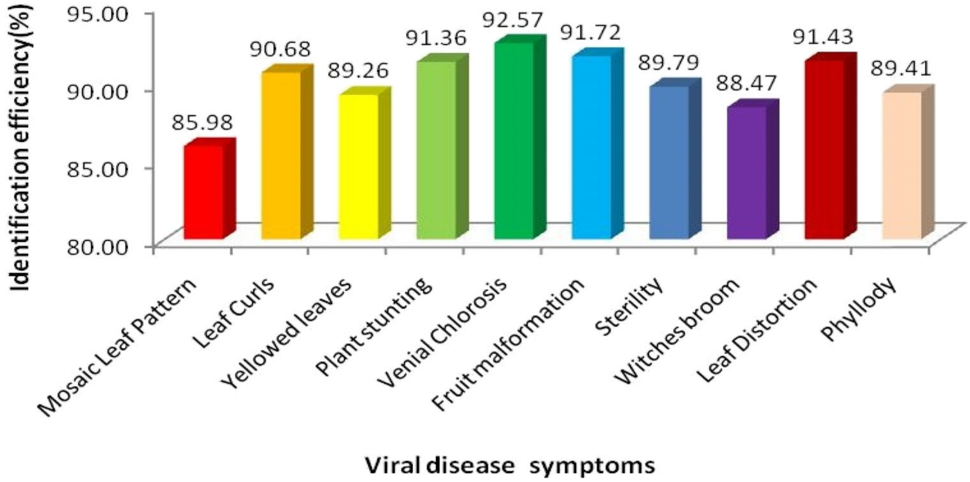


Fig. 13 Classification result using co-occurrence based color moments approach with SVM classifier

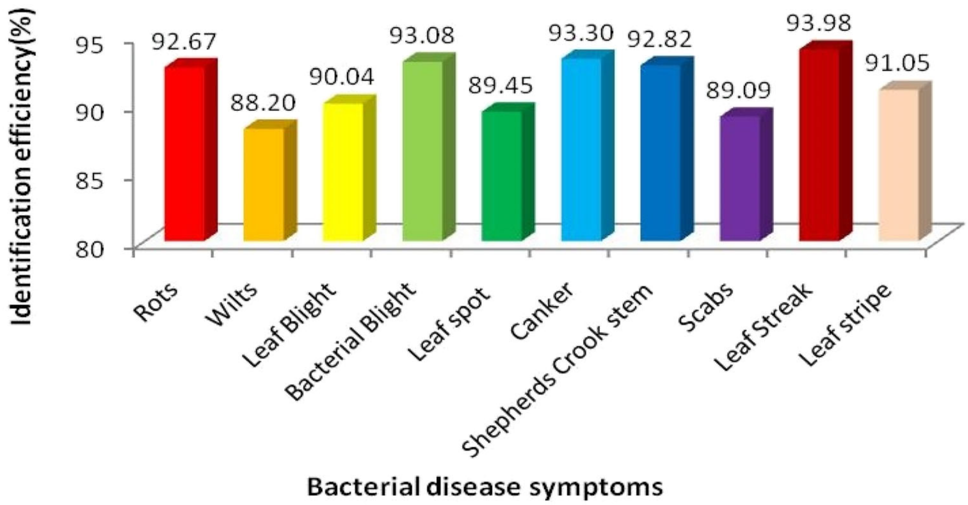


Fig. 14 Classification result using co-occurrence based color moments approach with SVM classifier

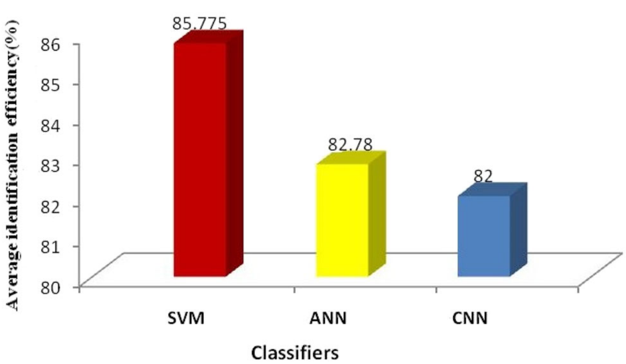


Fig. 15 Performance of SVM and ANN using co-occurrence based multispectral approach and CNN

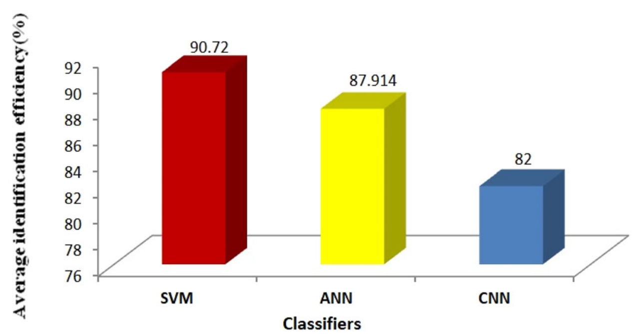


Fig. 16 Performance of SVM and ANN using co-occurrence based color moments approach and CNN

Table 3 Computation times of ANN, SVM and CNN classifiers

Methods	(Training + Testing [per image]) Average computation time in seconds
Co-occurrence based multispectral approach with ANN classifier	360 + 0.8 = 360.8
Co-occurrence based multispectral approach with SVM classifier	300 + 0.6 = 300.6
Co-occurrence based color moments approach with ANN classifier	323 + 0.7 = 323.7
Co-occurrence based color moments approach with SVM classifier	291 + 0.5 = 291.5
VGG-16 CNN model	2 h

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Declarations

Conflict of interest The corresponding author declares on behalf of all the authors that there is no conflict of interest to disclose and that he has earned no financial support for the research.

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