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Particle Swarm Optimization Based Support Vector Machine (P-SVM) for the Segmentation and Classification of Plants

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ABSTRACT With the rapid growth in urbanization and population, it has become an earnest task to nurture and grow plants that are both important in sustaining the nature and the living beings needs. In addition, there is a need for preserving the plants having global importance both economically and environmentally. Locating such species from the forest or shrubs having human involvement is a time consuming and costly task to perform. Therefore, in this paper, a novel method is presented for the segmentation and classification of the seven different plants, named Guava, Jamun, Mango, Grapes, Apple, Tomato, and Arjun, based on their leaf images. In the first phase, both real-time images and images from the crowdAI database are collected and preprocessed for noise removal, resizing, and contrast enhancement. Then, in the second phase, different features are extracted based on color and texture. The third phase includes the segmentation of images using a k-means algorithm. The fourth phase consists of the training of support vector machine, and finally, in the last phase, the testing is performed. Particle swarm optimization algorithm is used for selecting the best possible value of the initialization parameter in both the segmentation and classification processes. The proposed work achieves higher experimental results, such as sensitivity = 0.9581, specificity = 0.9676, and accuracy = 0.9759, for segmentation and classification accuracy = 95.23 when compared with other methods.

INDEX TERMS Computational and artificial intelligence, imaging, image classification, image segmentation, particle swarm optimization, support vector machine.

I. INTRODUCTION

Plants are the life support system for the livings organisms as they provide oxygen. They are an integral part of this sector as they are the lone providers of livestock. Plants are also important in serving and balancing biological aspects of the environment. Plant parts and their products like fruits, flowers, cereals, stem, leaves etc. are consumed in different ways by humans and animals. There are a number of practices in which plants play a major role, but primarily they are used for the preparation of food items, medicine, manufacturing of mustard oil, making of biofuel etc. Plants are also characterized and recognized by their features like height, shape, size or color of plant or its subsequent parts. The identification or classification of the plant is more often done with the help of leaves visually based on the attributes like color, texture, shape, and size of them. Traditionally, this task involves human intervention and experts known to be plant pathologist for the suitable selection of them [1]–[4]. But this process is time consuming, costly, and also comes with the chances of human error due to the similarities in their visual characteristics for example, in the agricultural fields, when crops are grown some unwanted plants (weed) also grow with them. More often the weeds are having similar features as the crop and therefore cannot be differentiated by the naked eye. They reduce the nutrient content of soil and thus distressing crop quality and productivity.

Computer vision concepts, image processing, and machine learning algorithms are predominately used in various applications including pattern recognition, classification, segmentation etc. [5], [6] due to their simplicity in terminology as shown in Fig. 1. From the past few years, automatic detection of plants has attracted many researchers in different domains. Learning is a prevalent phenomenon since the existence of life. Over the years, generations of living beings have evolved, so have their learning skills. Machines these days

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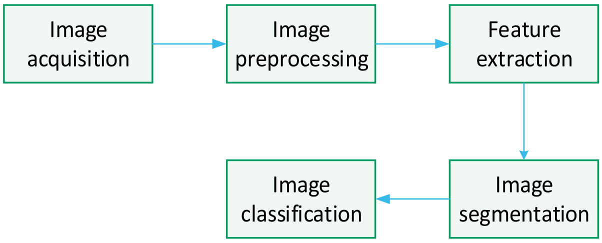

FIGURE 1. Flowchart of plant identification in computer vision.

learn the same way as humans do. This learning process of machines is also called the training of a machine to make it intelligent. Various computer vision algorithms pave a way for making machines intelligent due to their capability to interpret the visualized data [1], [2]. The machine does this by using two important mechanisms known as pattern recognition and classification.

The identification of plants is based on the observation of its morphological features such as the structure of the stem, roots, leaves, fruits. Leaves share a significant amount in contributing to the design of automatic systems due to their prolonged existence. A leaf is characterized by its texture, color, and shape. Computer vision concepts try to eradicate the conventional practices and introduced new methods for segmentation of plants. The automatic or computer-aided plant segmentation approaches and methodologies designed are of much importance these days. The automatic detection systems mainly consist of two phases. First, the plant leaf images are captured using the digital cameras or drones, followed by the segmentation and classification of plant achieved through different steps; extracting the region of interest, obtaining the images representing common features from the database and then classifying them with the others having distinct features [7]–[10].

In this work, a novel methodology is proposed for the segmentation and classification of seven different plants named as Guava, Jamun, Mango, Grapes, Apple, Tomato and Arjun. The presented methodology includes image acquisition step for real-time data collection, followed by pre-processing consists of noise removal, resizing, and contrast enhancement. After this step, the features are extracted based on color and texture using $L*a*b$ color space and LBP method. Then in the next step segmentation is performed by using a k-means algorithm. The training of the SVM classifier is accomplished using training data. Finally, with the help of testing data, the classification of the proposed method will be validated. PSO algorithm is used for setting up the initialization parameters of k-means and SVM. Because of this, the proposed method achieves higher accuracy and speed. The highlights of the proposed work are:

1) This work presents a novel approach for the segmentation and classification of seven different plants with global importance among different classes based on the characteristics of leaves.
2) The key concept of the proposed method is the inclusion of an optimization technique that helps in the initialization of the k-means and SVM algorithms for segmentation and classification respectively.
3) The feature extraction process is carried out with the help of the $L*a*b$ color space for color features and LBP for texture features.
4) Because of the similarities in the visual characteristics among plant species classification and sorting are difficult task to perform especially from the dense area. So, this work can be of great help in conserving and saving the plants that are useful in maintaining the food supply chain and fulfilling the demand emerging due to the growing population.
5) The important aspect in designing this model is to preserve forests by locating the useful and evergreen plants, thus balancing the environment.

The organization of this article: introduction in I is followed by related work given in II that includes the various studies associated with the proposed work, followed by the proposed work description and flowchart given in III, then IV presents the various concepts and theories incorporated in this article, V presents the results given separately for segmentation and classification, followed by the conclusion and the future work in VI, ending up with references.

II. RELATED WORK

The recognition and classification of plants is an arduous task. Leaves are the abundant and easily available entities of a plant and at the same time are most difficult to distinguish due to their morphological characteristics. Various computer vision approaches are designed and implemented by researchers to address this issue. In this section, some of the existing intelligent approaches used for plant recognition are encapsulated. The TABLE 1 shows the number of related computer vision methods used in plant recognition and classification.

SVM, because of its property of convex optimization, is best suited for finding the global minimum. With the radial basis function being its kernel, it is beneficial for both linearly and nonlinearly separable data and is thus predominantly used in plant recognition. Not only SVM, but other classifiers such as NN, DT, Linear Models, AdaBoost, and Naive Bayes Classifiers are also in action. From the survey, it can be retrieved that authors have mainly focused on plant recognition via leaves. Authors have implemented Multiscale Fusion Neural Network for leaf identification. A fusion of SVM and ANN was used for weed detection in crops by Bakeshipour and Jafari [13]. Akbarzadeh *et al.* [28] discriminated plants with the help of Normalized Difference Vegetation Indices (NDVI) and SVM. Leaf features were classified by Saleem *et al.* [22] on the basis of geometrical features for feature extraction and KNN, MSM for classification.

The condition of bounds predominantly affects the working of an algorithm. In segmentation approaches, most of them converge to local minima. To solve this issue certain optimization and reduction algorithms like particle swarm optimization, spider monkey optimization, genetic algorithm, many more are incorporated with the conventional methods

TABLE 1. Literature survey.

Author	Purpose	Feature Extraction / Optimization Method	Classification	Dataset / No. of images	Result
N. Leena and K.K. Saju in [11]	Classification of nutrient deficiency in maize plants.	Color features, GA, symbiotic organism search (SOS)	Multiclass SVM	100 leaf images	86%
Vi Nguyen Thanh Le et al., in [12]	Plant discrimination	Segmentation, Local Binary Patterns	SVM	BCCR-SEGSET dataset	91.85%
Adel Bakhshipour and Abdolabbas Jafari, in [13]	Weed detection	Shape factors, Moment invariant features, Fourier descriptors	ANN, SVM	50 mages from experimental beds of Shiraz University	90.67%
Cuiying Dong and Juan Chen, in [14]	Optimization of anaerobic fermentation of corn stalk	CBP	Least Squares SVM (LS-SVM)	Stalks collected from Shunyi District of Beijing	-
Sandeep Kumar et al., in [15]	Leaf disease identification	Subtractive Pixel Adjacency Matrix (SPAM), Exponential Spider Monkey Optimization (ESMO)	SVM, kNN, LDA, and ZeroR	1000 images from PlantVillage dataset	92.12%
J.M. Guerrero et al., in [16]	Crop/weed identification in maize fields	Combined Vegetation Indices, Color models, Otsu Thresholding	SVM	-	93.1%
Nattane Luiza Costa et al., in [17]	Classification of Merlot Wines	PCA	SVM, Multilayer perceptron model.	Wine samples obtained from markets of Brazil	93.75%
Gittaly Dhingra et al., in [18]	Leaf disease identification and classification	Neutrosophic approach, HIC, DI, DSR, BBP, DSI	Decision Tree, SVM, Random Forest, AdaBoost, Linear Models, Naïve Bayes, K-NN	400 images (200 healthy and 200 non-healthy leaves)	98%
Christoph Romer et al., in [19]	Wheat leaf rust detection	Robust features	SVM	Fluorescence dataset	93%
Diego Sebastian Pérez et al., in [20]	Detection of winter grapevine buds	Computer vision algorithms, SIFT	SVM	Self	-
Faisal Ahmed et al., in [21]	Crop and weed classification using digital images	Color features, size independent shape features, moment invariant features, optimal feature selection	SVM	Images were taken with OLYMPUS FE4000 digital camera	97.3%
G. Saleem et al., in [22]	Visual leaf shape feature classification	Geometrical features, Dimensionality reduction	KNN, Decision Tree, Naive Bayesian, and Multi-SVM	Flavia dataset and 625 self-collected images	96%
Heyan Zhu et al., in [23]	Plant identification	HOG	Linear SVM	PlantView dataset	88.8%
Katerina Horaisov and Jaromr Kukal in [24]	Leaf classification from binary images	Harmonic analysis of TS invariant spectrum (HATSIS), Harmonic analysis of radialized spectrum (HARS)	SVM, Self-Organizing Neural Network	Self and Swedish leaf dataset, Image CLEF dataset, and Czech leaf dataset	97.14%
Koushik Banerjee et al., in [25]	Leaf area index estimation	Supervised image classification and statistical analysis, RMSE	SVM	NA	95%
Milan Sulc and Jiri Matas in [26]	Plant recognition	Image segmentation, deep learning, Texture analysis	SVM	Leaf snap dataset and also dataset of 7content types is created	88.3%
Mónica G. Larese et al., in [27]	Classification of legumes	Unconstrained hit or miss transform	SVM and Random Forests	866 images	92%
Saman Akbarzadeh et al., in [28]	Plant discrimination	Normalized Difference Vegetation Indices (NDVI)	SVM	Self	97%
T. Rumpf et al., in [29]	Detection and classification of plant diseases	Spectral Vegetation Indices	SVM, Multiclass SVM, Decision Trees, ANN,	Handheld non-imaging Spectro-radiometer used for data collection	97%
Xi Qiao et al., in [30]	Underwater sea cucumber identification	Color, texture, shape, dimensionality reduction, PCA	SVM	108 underwater +75 background object images	98.55%
Yunyun Sun et al., in [31]	Tea plant leaf disease saliency map extraction	SLIC	SVM	1308 images	98.5%

for achieving higher performance. These nature or bio inspired algorithms having tendency in converging best optimal solution are well suited with the methods like k-means, support vector machine, and artificial neural networks.

III. PROPOSED WORK

In this work, a novel methodology is proposed for the segmentation and classification of different plants named as Guava, Jamun, Mango, Grapes, Apple, Tomato and Arjun.

TABLE 2. **Algorithm for the proposed work.**

Algorithm
1. Acquire images from real-time condition and crowdAI database
2. Preprocess the images for noise removal, resizing, and contrast enhancement
3. Separate images among train and test dataset
4. Perform segmentation using k-means algorithm optimized with PSO algorithm
*5. Feature extraction and description using L*a*b* and LBP*
6. Train the SVM classifier for the optimized value of classes
7. Test the SVM using a testing database
8. Validate the performance of the proposed model and compare results with other methods

The presented system is revealed by the algorithm given below in TABLE 2. Fig. 2. Shows the flowchart of the proposed work.

IV. THEORIES AND CONCEPTS

The proposed approach comprises six elementary phases: image acquisition, pre-processing, feature extraction and feature selection, segmentation, classification, and evaluation. The overall architecture of the proposed system is elaborated below:

A. IMAGE ACQUISITION PHASE

This is the first phase of the proposed method. For the proposed work the images are selected from two data sources 1. PlantVillage (CrowdAI) dataset and 2. Self-acquired dataset. The leave images of the four distinct plants namely Arjun. Mango, Guava, and Jamun are captured using the DSLR camera in the laboratory. The acquired images are invariant of angles, light, rotation etc. The number of images used in the work selected from the database is given in TABLE 3.

B. PRE-PROCESSING PHASE

After the creation of dataset, the images are preprocessed for noise removal, resizing, and illumination enhancement in the proposed work.

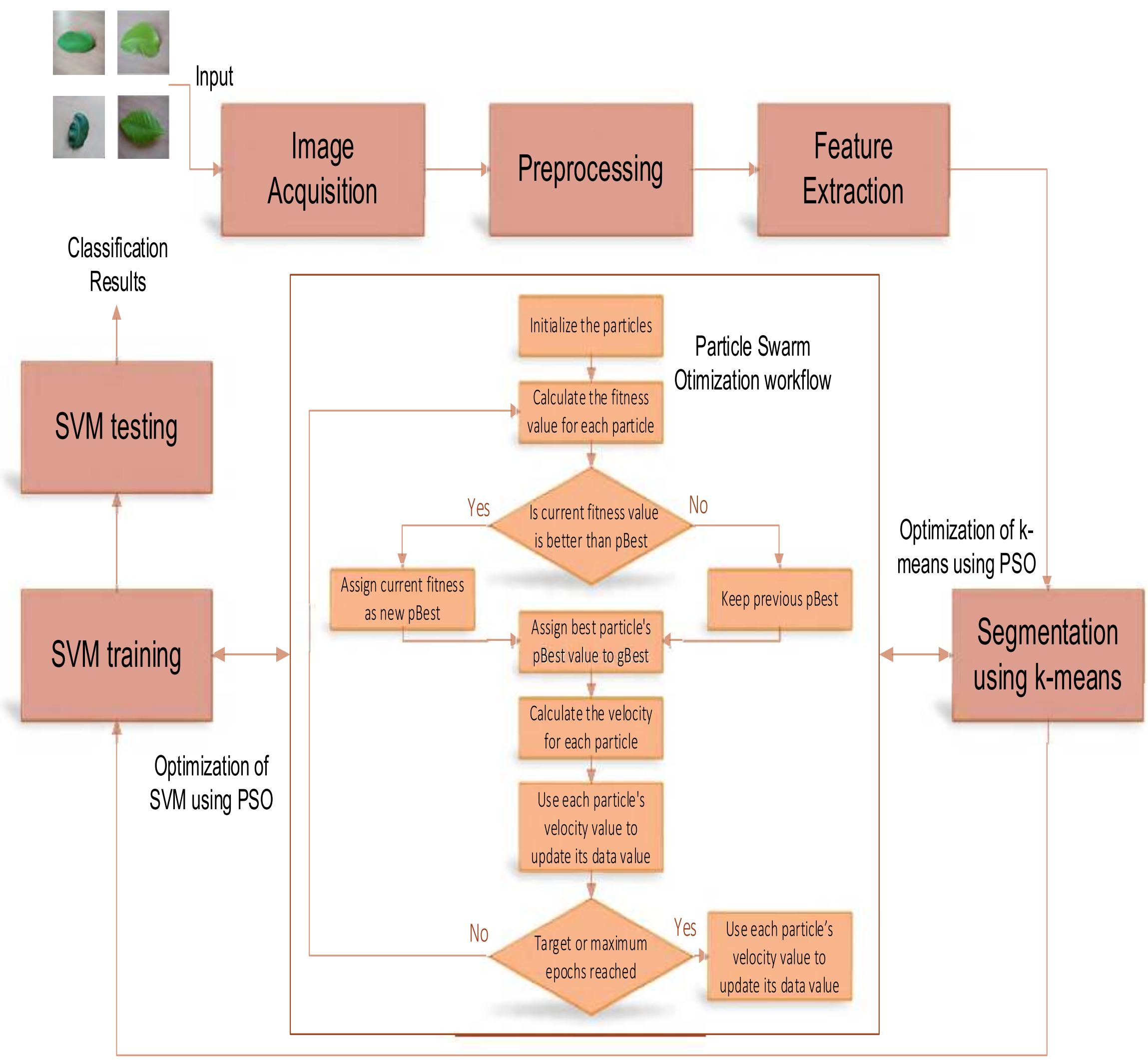

FIGURE 2. **Flowchart of the proposed work.**

TABLE 3. Database information.

Plant	Number of images
Guava	237
Jamun	241
Mango	287
Apple	294
Grapes	239
Tomato	220
Arjun	295
Total images	1813

1) RESIZING

The images when captured are of different sizes. The region of interest is either clearly visible in some images or not. This issue challenges the performance of any model or approach. To eradicate this problem, all the images of the dataset are resized by using the non-adaptive methods of interpolation. K-nearest neighbor approach is used for resizing of the images.

2) NOISE REMOVAL

Noise is an undesirable byproduct that alters the actual or desired information. In images, noise causes a relatable variation in the brightness and color. It basically alters the actual color and pixel appearance or distribution of the image. Depending upon the nature and the methodology of how an image is captured, the noises are of different types i.e. Gaussian noise, salt and pepper noise, shot noise, quantization noise etc. To remove these noises, various filters are employed depending upon the nature of it. Gaussian filter, Vector median filter, and hybrid filters are some of them employed to remove the impulsive noise in color images [33]. In the proposed work, the median filter is implemented due to its property of preserving edges even after removing the noise.

3) HISTOGRAM EQUALIZATION

To understand the distribution of background and foreground pixels and to differentiate between them, histogram equalization is performed. This also enhances the contrast of the images. It fine-tunes the image intensities and evenly distributes them. This improves the areas of lower local contrast. The global contrast of the images is increased with this method. Histogram equalization spreads out the most frequent intensity values. To improve the contrast of the images, a uniform intensity value to the pixel is assigned using the histogram of an image with the help of the histogram equalization method given by eq. (1) and shown in Fig. 3.

$$G\left(p_{(a,b)}\right) = round\left(\frac{f_{cde}\left(p_{(a,b)}\right) - f_{cde_{min}}}{(I \times A) - f_{cde}} \times H - 1\right) \quad (1)$$

where f_{cde} = cumulative frequency of the gray level, $f_{cde_{min}}$ = minimum value of cumulative distribution function, $f_{cde}\left(p_{(a,b)}\right)$ = intensity of the current pixel, I and A = product

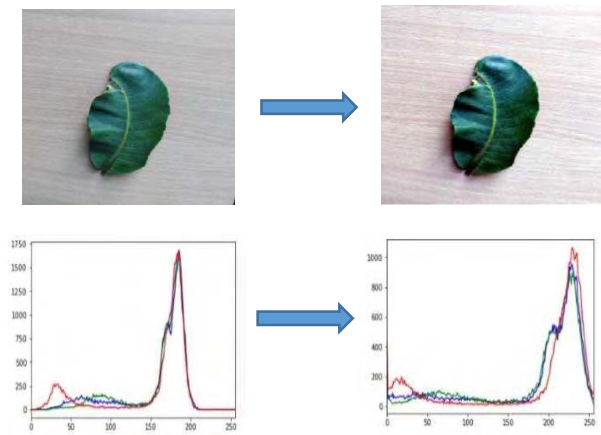

FIGURE 3. (a) Original image with (RGB) histogram (b) enhanced image with (RGB) histogram.

of number of pixels in rows and columns and H = number of intensities.

C. FEATURE EXTRACTION AND FEATURE DESCRIPTION

The feature extraction phase is divided into three steps, depending on the type of the feature to be extracted and the algorithm used. The steps are discussed below:

1) COLOR FEATURES

For extracting the color features, the $L * a * b$ color space is used due to its device-independent property. Developed by *Commission Internationale de Leclairage* (CIE) in 1976 to be used in the industrial applications. Designed in perpetuation with the human vision, this model contains one luminance channel and two chrominance channels defined as the non-linear transformation of the RGB color space. In the $L * a * b *$ channel $a*$ is the green-red axis and $b*$ is the blue-yellow axis. In $L * u * v*$, $u*$ and $v*$ are the non-linear transformations of X and Y channels respectively of XYZ color space [34]. In order to transform the RGB into these two channels, the XYZ color space are adopted as given

For XYZ channels

$$\begin{aligned} \{X &= 0.607R + 0.174G + 0.200B \\ Y &= 0.299R + 0.587G + 0.114B \\ Z &= 0.066G + 1.116B\} \end{aligned} \quad (2)$$

For $L * a * b*$

$$\begin{aligned} \Big\{L^* &= \left\{116Y^{\frac{1}{3}}\ if\ Y > k;\ 903.3\ Y\ if\ Y \leq k\right\}\ with\ k = 0.008856 \\ a^* &= 500 f\ (X) - f\ (Y)\ \ with\ f\ (t) \\ &= \left\{t^{\frac{1}{3}}\ if\ t > k;\ 7.787t + 0.1379\ if\ t \leq k\right\} \\ b^* &= 200\left(f\ (Y) - f\ (Z)\right)\Big\} \end{aligned} \quad (3)$$

The image we used consists majorly of green color. The $a*$ channel of the $L * a * b$ space is used to extract the color which is also our region of interest. A gamut of each image is generated, thus creating a chunk of related images.

FIGURE 4. (a) Original image (b) L ∗ a ∗ b∗ color space (c) a∗ channel.

This chunk of related images is concatenated in a single array shown in Fig. 4.

2) TEXTURE FEATURE

For extracting the texture, the LBP is used. Local binary pattern (LBP) is among the most powerful descriptor for representing local structures due to computational power and resistant to the illumination changes. Introduced in 1990, LBP is more frequently used for making a feature set from the texture descriptors extracted from the image. It is acquired by parsing a window across the image and comparing the grayscale pixel value by its neighboring pixel with the center pixel threshold value. The value of the neighboring pixel is assigned to 1 if its value is greater than the center pixel based on the threshold value, otherwise assigned to 0. This process allows 256 possible values and creates 8 digit binary numbers known as Local binary pattern [35]. The central pixel is assigned with the decimal number based on the binary value of the neighboring pixel by using the eq. (4) and eq. (5).

$$LBP = \sum_{p=0}^{P} v(j_p - j_c)2^P \tag{4}$$

$$v(l) = \begin{cases} 1 & if\ l \geq T; \\ 0 & otherwise. \end{cases} \tag{5}$$

where j_p = value of current pixel, j_c = value of center pixel, P = radius of the window for calculation of LBP, p = significance in binary number. When p = 8 then p is known to be the most significant neighbor of i_c with greater value. And when $p = 0$ then p is least significant, T = threshold value for center pixel, $v(l)$ = step function used for calculating LBP.

After the binary operation, the LBP histograms are computed. As given by the eq. (6) the LBP feature set is obtained by calculating the LBP for every channel of RGB as

$$LBP = \left[\left(\sum_{p=0}^{P} v(j_p - j_c)2^P\right)^2 \left(\sum_{p=0}^{P} v(j_p - j_c)2^P\right)^2 \left(\sum_{p=0}^{P} v(j_p - j_c)2^P\right)^2 \right] \tag{6}$$

The textural descriptors obtained by moving a window (a chunk of pixels called cells) across the image. The window to be examined is divided into cells and for each cell, the pixels of its neighbors are compared along with the central pixel as a threshold and assigning the binary values. Subject to the threshold, if the value of the neighboring pixel is greater than the central pixel value, then the value assigned to the neighboring pixel is 1, otherwise 0. The histogram also called the 'feature vector' is computed over the cell, depending on the frequency of each number occurring. The histogram is normalized and concatenation of all cells results in generating a feature vector for the entire window.

D. PARTICLE SWARM OPTIMIZATION ALGORITHM (PSO)

PSO developed by Russell Eberhart and James Kennedy in 1995, is a population-based stochastic optimization method motivated by social behavior of bird flocking or fish schooling. PSO is quite similar to Genetic algorithm or evolutionary computation. A group of individuals known as particles moves in phases all over a region. At every phase, the objective function is being evaluated for each particle. On the basis of this evaluation, the new velocity of particle is decided by the algorithm. And this procedure continues until finding an optimal solution. PSO is simple, easy to implement and has been used in a number of applications. The movement of the particle is given by the eq. (7) and (8):

$$V_s(t+1) = wV_s(t) + C_1 r_1 (P_s - X_s(t)) + C_2 r_2 (G - X_s(t)) \tag{7}$$

$$X_s(t+1) = X_s(t) + V_s(t+1) \tag{8}$$

where $V_s(t)$ = velocity of particle s in t time, $X_s(t)$ = position of vector of particle s in t time, P_s = personal best solution of particle s, G = best solution of the particle found at present, w = inertia weight, $C_1 = C_2$ = acceleration constant known as cognitive and social parameters, $r_1 = r_2$ = random functions in the range [0,1].

TABLE 4. Algorithm k-means.

Algorithm
1. Select K points to start and let these be the initial cluster
2. for every point
Find the Euclidean distance to every cluster center
Note the nearest distance
Assign the point to the cluster that is nearest to it
3. then
for every new cluster
evaluate the new cluster center
4. End
if no points left

E. SEGMENTATION

K-means algorithm is used for the segmentation purpose. It is among the simplest and computationally efficient method for segmentation. This algorithm divides N observations among K clusters by assigning an observation into a cluster using a distance function generally an Euclidean distance function. The algorithm for the k-means algorithm is given in TABLE 4.

F. CLASSIFICATION

Support Vector Machine (SVM) is also called supervised learning algorithms, associated with the learning algorithms that analyze the data used for classification and regression analysis. It was first defined by Cortes and Vapnik in 1995. It is also called the non-probabilistic linear classifier on the basis of how it models and assigns the values to a training set. It is fundamentally a two-class classifier. SVM is a hyperplane i.e., there's a margin separating a set of non-related (negative and positive) data or points into high dimensional space using a nonlinear mapping function, thus constructing an optimal separate hyperplane by the maximum margin between two sets of vectors.

In SVM, the data points (labeled data) are scattered into an n-dimensional space where n represents the features taken into consideration. Each feature is the value of a particular coordinate. The data points are either related or non-related, thus belonging to and forming different classes. So the main aim of SVM is the classification of data on the basis of relation with the other related data sets. Hyperplanes are the boundaries that help classify the data points. The goal is to maximize the margin between the hyperplane and the data points. The decision boundary that exists between the distributed data classes is chosen to be the one for which the margin is maximized. This concept is motivated by computational learning theory also called the statistical learning theory.

For example, consider a case where we have two features x1 and x2. The linear decision surface (hyperplane) is calculated as given by (9):

$$Score = \left(f_1, f_2 f_3, \ldots f_n\right) \begin{matrix} w_1 \\ w_2 \\ w_n \end{matrix} \tag{9}$$

where f_x denotes feature x and w_y denotes weight y.

The working of SVM is divided into different scenarios depending upon the distribution of data and the number of hyperplanes. In this particular example, we have two data classes and three hyperplanes as the scenarios for selecting the right hyperplane. In order to maximize the margin, certain cost functions and gradient updates are employed. The output of the linear functions is taken, and if that output is greater than 1, it is identified with one class whereas if it is -1, it is assigned to another class. Thus the threshold values are set between -1 to $+1$. Therefore the reinforcement range of values $[-1, 1]$ act as margin. The hinge loss function aids to maximize the margin of the hyperplane.

Support vector machine is used for classification of the leaves. The input features are fed into the classifier with a target class, followed by the mapping of training vectors into high dimensional space via a non-linear mapping function and a separated optimal hyperplane constructed by the maximum margin between the two sets of vectors. The vectors generated have class assignments and the classification decision is made by a maximum elect of class assignments.

G. EVALUATION

1) SPECIFICITY

Defines the capability of an algorithm to segment the normal regions existing in the input image. Result near to 1 shows accurate segmentation. Mathematically given by eq. (10)

$$Specificity(SP) = \frac{TrueNegative}{TrueNegative + FalsePositive} \tag{10}$$

where*True Positive* $= TP$, *True Negative* $= TN$, *False Positive* $= FP$, and *False Negative* $= FN$

2) SENSITIVITY

Sensitivity values define the proper segmentation of the input image and also provide the information about an object. The segmented value near to 1 shows accurate segmentation. Sensitivity is mathematically given by eq. (11)

$$Sensitivity(SE) = \frac{TruePositive}{TruePositive + FalseNegative} \tag{11}$$

3) ACCURACY

Is calculated on the basis of pixel classification among *TP*, *TN*, *FP*, and *FN*, lying between 0 and 1. A segmented value near to 1 shows better segmentation, Accuracy is mathematically given by eq. (12), as shown at the bottom of this page.

V. RESULTS

In this section, experimental results of the proposed algorithm P-SVM are presented. The performance of the P-SVM is quantitatively evaluated on the above mentioned parameters. Furthermore, comparative analysis is performed to demonstrate the effectiveness and robustness of the proposed method.

The proposed model was implemented using MATLAB R2018b on a system with 16GB RAM, i7 processor, and 1TB HDD. For this work, leaf images of seven different plants named Apple, Guava, Grapes, Mango, Jamun, Tomato and Arjun were acquired. All the plants chosen have economical and medicinal importance. Among these seven plants, five are the fruit-bearing plants, one a vegetable plant, and one a non-fruit bearing plant. The images of the leaves were taken in two ways 1) from the plant itself and 2) from the online available database called "crowdAI" [32]. The original database created contains pictures of Jamun, Mango, Guava, and Arjun whereas the images of Apple, Tomato, and

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative} \tag{12}$$

TABLE 5. Segmentation results for sensitivity, specificity, and accuracy.

Segmentation Results	FCM			GA-ANN			SVM			Proposed Method		
	SE	SP	Accuracy	SE	SP	Accuracy	SE	SP	Accuracy	SE	SP	Accuracy
Guava	0.8126	0.8214	0.8122	0.8236	0.8399	0.8256	0.8814	0.8795	0.8826	0.9259	0.9377	0.9435
Jamun	0.8014	0.8311	0.8241	0.8354	0.8324	0.8417	0.8897	0.9145	0.9107	0.9652	0.9797	0.9889
Mango	0.8015	0.8105	0.8340	0.8496	0.8469	0.8355	0.8974	0.9024	0.9188	0.9567	0.9614	0.9722
Grapes	0.7926	0.8025	0.8101	0.8621	0.8544	0.8780	0.9011	0.9214	0.9243	0.9646	0.9785	0.9896
Apple	0.8120	0.8221	0.8327	0.8747	0.8823	0.8891	0.9103	0.9178	0.9245	0.9688	0.9825	0.9846
Tomato	0.8003	0.8115	0.8228	0.8569	0.8647	0.8758	0.8912	0.9210	0.9169	0.9648	0.9578	0.9742
Arjun	0.7969	0.8032	0.8155	0.8390	0.8410	0.8377	0.8856	0.9022	0.8999	0.9610	0.9758	0.9780
Average Results	0.8025	0.8146	0.8216	0.8488	0.8517	0.8548	0.8938	0.9084	0.9111	0.9581	0.9676	0.9759

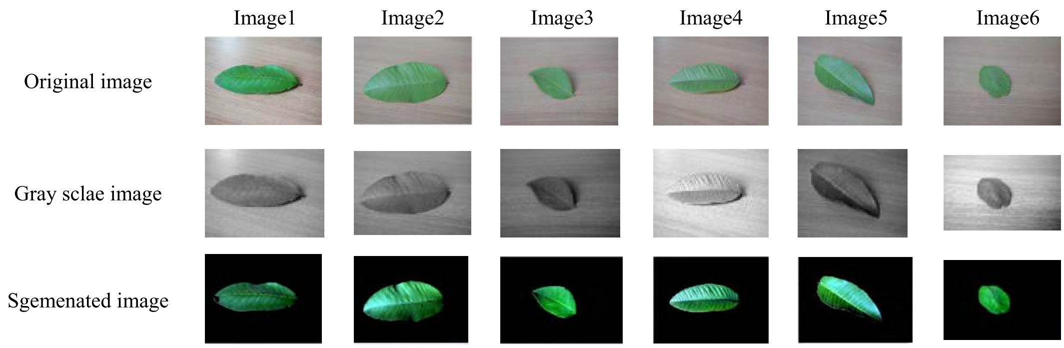

FIGURE 5. Segmentation results for Guava leaves.

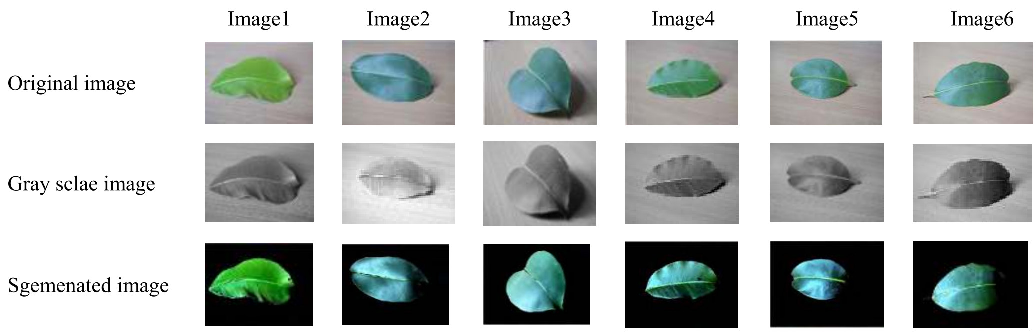

FIGURE 6. Segmentation results for Jamun leaves.

Grapes were taken from crowdAI database. For PSO acceleration constants C_1, C_2 are set as 2 obtaining the optimal fitness solution and inertia weight varies between 0 to 1 for both segmentation and classification process. The results for segmentation and classification are validated separately and are given below.

A. SEGMENTATION

The plant leaves occur in various types depending upon the habitat in which they grow. Segmentation and identification of plant leaves is a complicated task to perform because of similarity in the characteristics among them. In this approach, the $L*a*b$ color space is used to extract the color features, while the LBP is implemented to obtain textural features. PSO due to its foraging nature is employed to optimize the initialization of the segmentation algorithm. For segmentation, the K-means algorithm is applied. The results of segmentation with P-SVM are given in TABLE 5. The results for segmentation are given in Figures 5, 6, 7, 8, 9, 10 and 11.

The performance validation of the proposed system with other existing methods like FCM, GA-ANN, and SVM have been considered. Sensitivity (SE), Specificity (SP), and Accuracy are the three quantitative evaluation parameters selected for this purpose. The proposed method attains the average sensitivity of 0.9581 that proves to be higher when compared with the sensitivity of 0.8025, 0.8488, and 0.8938

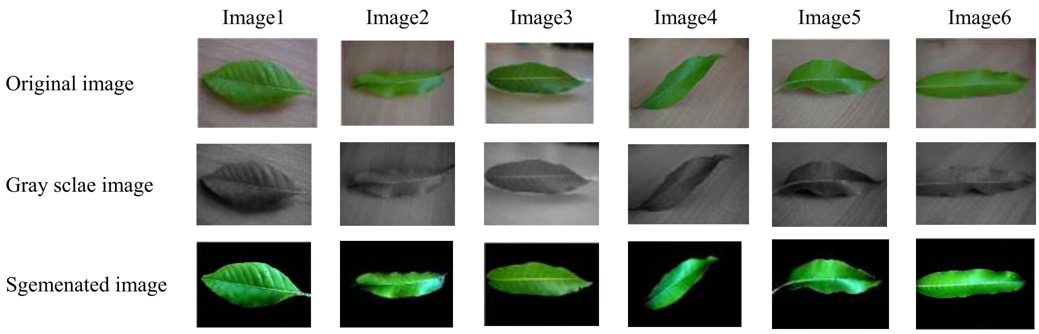

FIGURE 7. Segmentation results for Mango leaves.

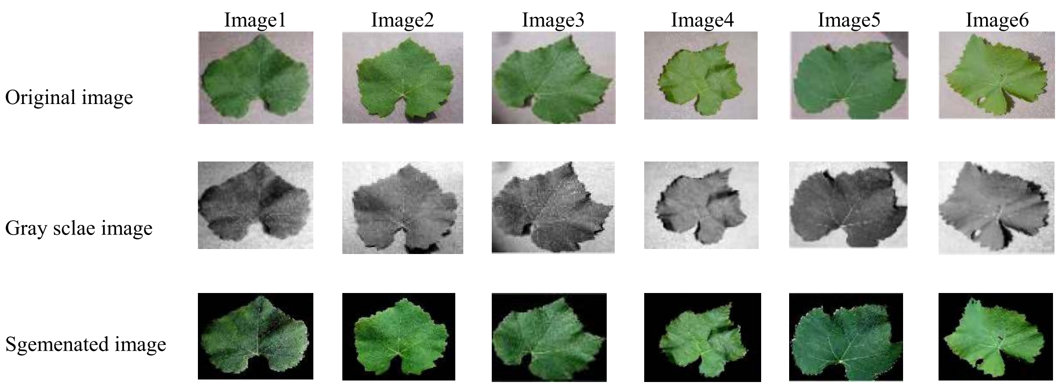

FIGURE 8. Segmentation results for Grapes leaves.

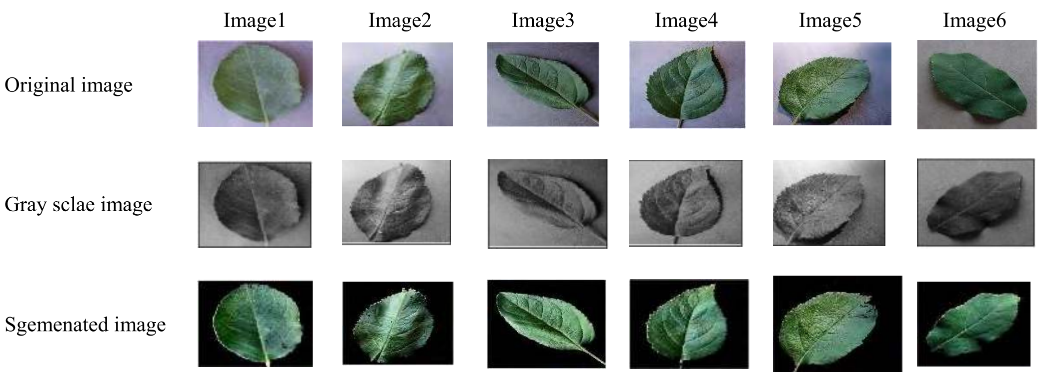

FIGURE 9. Segmentation results for Apple leaves.

respectively for FCM, GA-ANN, and SVM. For sensitivity, the leaf of the apple plant accomplishes higher result with the value of 0.9688 among the different plants for proposed work. The results for sensitivity also validate the performance of the proposed method with 0.9676 over 0.8146 for FCM, 0.8517 for GA-ANN, and 0.9084 for SVM. For this evaluation, also apple leaf segmentation with 0.9825 presents higher specificity value. Finally, the average accuracy value of 0.9759 for the proposed work validates higher performance for segmenting leaves when applied to seven different plant types compared to that of 0.8216 for FCM, 0.8548 for GA-ANN and 0.9111 for SVM. Segmentation of Jamun plant leaf achieves the higher accuracy of 0.9896 when compared with the other plants respectively. The highest segmentation accuracy with a specificity value of 0.9785 is achieved by the proposed system for correctly identifying Grapes. It is seen from the results, that optimizing the initialization of the k-means algorithm improves the probability of identifying the leaves accurately. A graphical representation for the comparative segmentation results is given in Fig. 12.

B. CLASSIFICATION

The classification of the proposed method is done in two ways:

1) Train the machine with training dataset (using 70% of the image data).

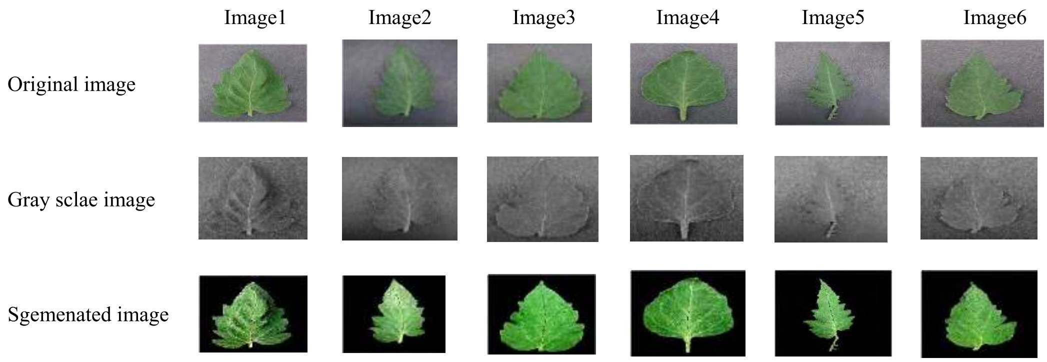

FIGURE 10. Segmentation results for Tomato leaves.

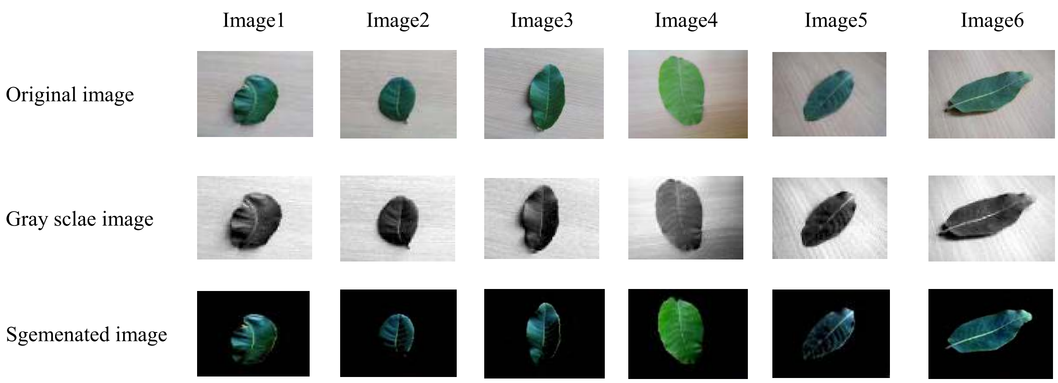

FIGURE 11. Segmentation results for Arjun leaves.

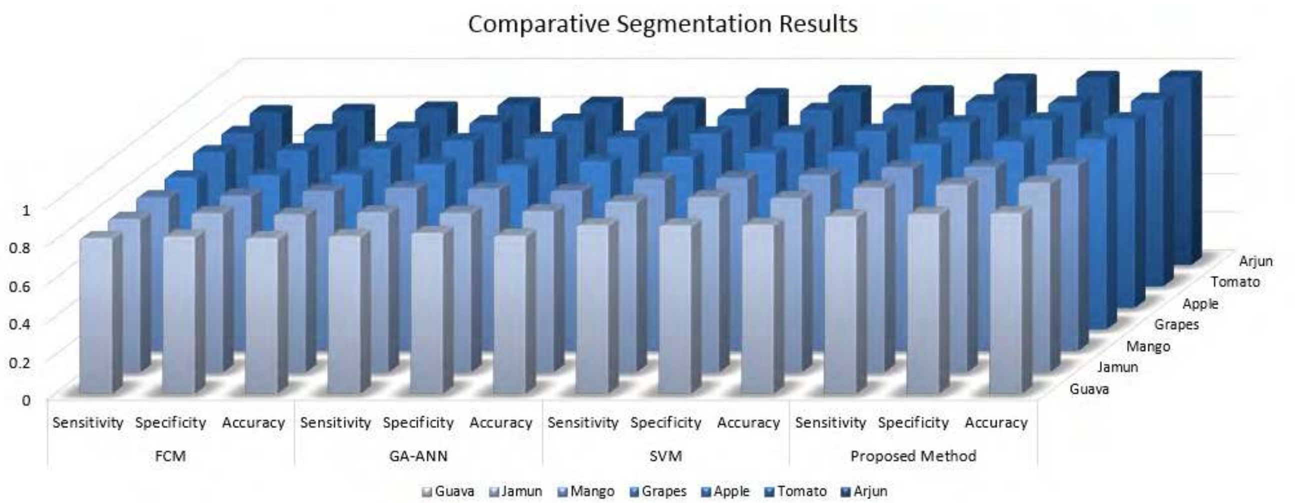

FIGURE 12. Graph for comparative results.

2) Validate the model (using 15% of the image data).
3) Testing phase: The overall classification accuracy for the proposed method is found to be 95.23% with misclassification of 4.77% shows the higher performance when compared with other state of the art methods. The comparative classification accuracy of the proposed method with the existing methods is given in TABLE 6.

C. TIME EFFICIENCY

The comparative time efficiency is given in TABLE 7. The computational accuracy in seconds for correctly segmenting leaves for the proposed system is about 19.24s and the classification is about 18.11s, also showing the higher convergence speed of the proposed work over other methods respectively.

Though the proposed system achieves higher results for both segmentation and classification of the leaves, a number

TABLE 6. Classification accuracy.

Methods	FCM	GA-ANN	SVM	Proposed Method
Accuracy	81.26	85.42	90.14	95.23
Misclassification	18.74	14.58	9.86	4.77

TABLE 7. Time efficiency in seconds.

Methods	FCM	GA-ANN	SVM	Proposed Method
Segmentation	25.33	23.62	22.14	19.24
Classification	22.1	21.35	21.09	18.11

of problems encountered for accomplishing this task. Initially, the collection of images in a real-time environment emerged with a lot of problems like overlapping or clustering of leaves, the structure of the tree branches inhibit in taking images, the problem of shadowing, background details, climatic conditions are some of them. So, to overcome the issues, the images in this work were collected and captured in a laboratory. Due to the similar characteristics and features of plant leaves i.e. color, texture, shape, and size, classifying them is also a major task to perform as well as another major problem associated with images. But the proposed work proves to be more efficient among all the methods when results are compared. The future work is to extend and enhance the capabilities of the proposed system to handle the above mentioned challenges while working in a real-time environment.

VI. CONCLUSION AND FUTURE WORK

The purpose of this work is to offer an automatic vision-based method that can locate different spices of the plants by examining the leaf images, so that conservation of them can be offered in sustaining the forest and fulfilling the need of living organisms. Converging towards the plants with high economic importance seven different plants have been selected for this study. The gathered images are preprocessed and features have been extracted using color channel a$*$ and LBP. Segmentation is performed using the k-means algorithm. Finally, the support vector machine is used for the classification of the leaves. The segmentation and classification algorithm are optimized with the help of Particle swarm optimization method for selecting the initial parameters. This hybridization helps our system in achieving higher performance both in terms of accuracy and time when compared with the other methods. For future work, we are planning to include the plants with medicinal and scientific significance. We also plan to include some real-time images based on underlying concepts of wireless sensor network or internet of things.

APPENDIX

See Table 8.

TABLE 8. Glossary.

Acronym	
AI	Artificial Intelligence
BBP	Bin Binary Pattern
CBP	Cumulative Biogas Production
CLAHE	Contrast Limited Adaptive Histogram
CNN	Convolutional Neural network
DT	Decision Tree
DL	Deep Learning
DSR	Disease Sequence Region
DSI	Damage Structure Index
DI	Damage Index
ESMO	Exponential Spider Monkey Optimization
ENVI	Environment for Visualizing Images
FCM	Fuzzy C- Means
FN	False Negative
FN	False Positive
GA	Genetic Algorithms
GLCM	Gray Level Coherence Matrix
HOG	Histogram of Gradients
HIC	Histogram Information Content
HATSIS	Harmonic Analysis of TS Invariant Spectrum
HARS	Harmonic Analysis of Radialized Spectrum
IoT	Internet of Things
K-NN	K- Nearest Neighbor
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
LS-SVM	Least Squares Support Vector Machine
ML	Machine Learning
MFNN	Multi Scale Fusion Neural Network
MVSM	Multi Vector Support Machine
OED	Orthogonal Experimental Design
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
SPAM	Subtractive Pixel Adjacency Matrix
SLIC	Simple Linear Iterative Cluster
SOS	Symbiotic Organism Search
SIFT	Scale Invariant Feature Transform
SE	Sensitivity
SP	Specificity
SVM	Support Vector Machine
TP	True Positive
TN	True Negative
WSN	Wireless Sensor Network

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