Artificial Intelligence in Agriculture 3 (2019) 62–68

Contents lists available at ScienceDirect

Artificial Intelligence in Agriculture

journal homepage: http://www.keaipublishing.com/en/journals/artificial-intelligence-in-agriculture/

Sunflower leaf diseases detection using image segmentation based on particle swarm optimization

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ARTICLE INFO

Article history:
Received 16 June 2019
Received in revised form 23 September 2019
Accepted 24 September 2019
Available online 9 November 2019

Keywords:
Image segmentation
Soft computing techniques
Sunflower leaf diseases
Particle swarm optimization

ABSTRACT

Sun flower (*Helianthus annuus* L.) is one of the important oil seed crops and potentially fit in agricultural system and oil production sector of India. Sunflower crop gets damaged by the impact of various diseases, insects and nematodes resulting in wide range of loss in production. Disease detection is possible through naked eye observation, but this method is unsuccessful when one has to monitor the large farms. As a solution to this problem, we developed and present a system for segmentation and classification of Sunflower leaf images. This research paper presents surveys conducted on different diseases classification techniques that can be used for sunflower leaf disease detection. Segmentation of Sunflower leaf images, which is an important aspect for disease classification, is done by using Particle swarm optimization algorithm. Satisfactory results have been given by the experiments done on leaf images. The average accuracy of classification of proposed algorithm is 98.0% compared to 97.6 and 92.7% reported in state-of-the-art methods.

1. Introduction

According to US-based food company Cargill Inc., "The company aims to double its branded consumer business in India by 2020, by doubling its retail reach to about 800,000 outlets and increase market share to become national leader in the sunflower oil category which will help the company be among the top three leading brands in India". Till present day there are >30 diseases, have been identified on sunflower leaf (Gulya et al., 1995). So this research paper proposes an innovative methodology for detection and classification of Sunflower leaf diseases using image processing and Particle Swarm Optimization Algorithm.

Since ancient ages, identification of diseases in plants has been carried out by experts through naked eyes based on their vivid experience. Obtaining expert opinion, diagnosis of disease and contacting practitioners for advice is a long, tedious, tiring, expensive and time consuming practice. It becomes sometimes too late for diseases to be cured. This method is also not practically feasible for large fields. Accurate identification and control of disease in sunflower plant can be precisely acknowledged by automatic detection of the disease symptoms appearing on sunflower plant leaves.

Detection of plant diseases using modern available techniques involves image processing, pattern recognition and some automatic classification tools. These are proving useful for farmers in improving the quality and quantity of crop products.

Diseases easily spread and affect various parts of plants such as stem, leaves and fruits. Diseases can be detected by either or all of the following:

- Identifying the infected object/part
- Extracting the set of features of the infected object/part
- Detecting and classifying the diseases.

In the present work, symptoms of plant leaf have been considered for the detection of disease.

1.1. Image segmentation

Image segmentation partitions an input image into non-overlapping, homogeneous and connected regions (Usinskas and Kirvaitis, 2003) such that "union of any two spatially adjacent regions is not homogenous". Enhancement of image quality is an essential step for image perception and is achieved by noise removal and amplification of image contrast. Evolutionary algorithms have been adopted to achieve faster processing times and better results for image Segmentation (Chang-Shing et al., 2005; Kulkarni and Ashwin Patil, 2012; Muntaenu et al., 2000).

However, Keri Woods (2007) suggested that good image segmentation should meet the following requirements:

1. Every pixel in the image must belong to a region and each region should be homogeneous with respect to a chosen characteristic, which could be syntactic e.g. color, intensity or texture or the characteristic based on semantic interpretation.

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https://doi.org/10.1016/j.aiia.2019.09.002
2589-7217/

2. Every region should be connected and non-overlapping i.e. any two pixels in a particular region should be connected by a line that does not leave the region.
3. It should not be possible to merge two adjacent regions to form a single homogeneous region.

Segmentation in color images is easy when all the objects are having distinct colours and boundaries but becomes a complex problem in following cases:

(i) When images have "many complex objects with less distinct colours" (Woods, 2007)
(ii) Gradual variations are found in color, illumination, shading and textures.

The tasks such as object recognition & detection, feature extraction and classification are dependent on the quality of segmentation process. Raj Kumar Mohanta and Sethi (n.d.) have reviewed the application of GA in image segmentation and concluded that "the quality of image segmentation can be improved by selecting the parameters in an optimized way".

1.2. Particle swarm optimization (PSO)

Particle swarm optimization algorithms are population-based optimization algorithms which are modeled after the simulation of social behavior of bird flocks (Kennedy and Eberhart, 2001). PSO is an automatic unsupervised algorithm which is used for better feature extraction. In Particle swarm optimizers based optimization, a swarm of individuals (known as particles) fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is updated by the best position visited by it.

The advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO perform better than the GA with respect to computational efficiency.

PSO is initialized with a population of random particles (swarms) and then searches for optimal solution by updating generations. Each particle is being associated with position vector present[ ] and velocity vector v[ ]. The size of these vectors is equal to the dimension of the search space.

In every iteration, each particle is updated by two "best" values. One is "pbest" which store the fitness value of the best fitness solution and other is "gbest" which is a global best or swarm's best fitness value.

After finding the two best values, the particle updates its velocity and positions with the following equations.

$$v[\,] = v[\,] + c1 * \text{rand}(\,) * (\text{pbest}[\,] - \text{present}[\,]) + c2 * \text{rand}(\,) * (\text{gbest}[\,] - \text{present}[\,])$$

$$\text{present}[\,] = \text{present}[\,] + v[\,]$$

where v[ ] is the particle velocity, present[ ] is the current particle (solution). pbest[ ] and gbest[are defined as stated before. rand ( ) is a random number between (0,1). c_1, c_2 are pre-specified constants.

According to empirical studies (Angeline, 1998; Clerc, 2006) for standard PSO the value of parameters (w, c_1 and c_2) are considered as w should be about 0.7 to 0.8, and c_1 and c_2 around 1.5 to 1.7.

According to Jadoun et al. (2014) for the different developed PSO variants, the value of parameters is varied. For basic PSO the value of parameters are considered as follow:

$c_1 + c_2 \leq 4$ and Inertia weight (W) may be linearly varied between 0.9 and 0.4.

But we know that there is no parameter configuration for metaheuristic algorihtms like PSO that performs better for every problem. State-of-the-art studies conclude that for the different developed PSO algorithms and different applications, the value of PSO parameters is varied. We can say that tuning to parameter of the optimization algorithms can be considered as an optimization problem.

In our study an experimental results show that the value of w and (c_1 and c_2) should be 0.9 and 1.2 respectively for image segmentation problem.

2. Literature review

In recent years researchers has proposed vivid techniques, some of them are studied and reviewed as discussed below:

Dheeb Al Bashish et al. (2010) proposed K-means based segmentation and ANN to detect five prevalent diseases in leaves i.e. early scorch, late scorch, Cottony mold, Ashen mold, and tiny whiteness in the images of leaves taken from Al-Ghor area in Jordan. The experimental results show accuracy in identification of diseases of around 93%.

Arun Kumar Beyyala & Beyyala (2012) reviewed few techniques for detection of plant traits or diseases using Image Processing. Piyush Chaudhary et al. (2012) have implemented an algorithm for disease spot segmentation using image processing techniques in plant leaf. A comparison of the effect of CIELAB, HSI and YCbCr color space in the process of disease spot detection has also been carried out.

Sannakki et al. (2011) proposed a system to detect various diseases of pomegranate plant. The proposed system is also able to determine the stages in which the disease is. The methodology uses different machine learning techniques such as ANN, Decision tree learning, Bayesian networks, SVM, Fuzzy Logic etc.

This paper (Xu et al., 2014) states that there are three common diseases, respectively, downy mildew, black spot and bacterial leaf spot. Research targets for sunflower leaf and presents a system to diagnose leaf diseases of sunflowers based on image processing. The proposed system is implemented in MATLAB with GUI tool kit. After several investigations, the proposed method was proved to be able to identify three types of sunflower diseases effectively, respectively, downy mildew, black spot and bacterial leaf spot.

The author (Sowmya et al., 2017) presents a system for early and accurately detection of plant diseases using diverse image processing techniques. According to authors farmers face great difficulties in changing from one disease control method to another. As naked- eye observation to detect and classify diseases is very expensive various plant diseases pose a great threat to the agricultural sector by reducing the life of the plants. There are three steps where first is capturing the images then Filtering and last segmentation using median filtering method. After segmentation features are extracted for classification of diseases (Table 1).

Computer image processing technology is one of the best methods to control and accurately identify the disease of sunflower leaf (Di et al., 2015) in the production. Texture feature extraction is one of the widespread techniques used by researchers. This research paper states that there is a need of in-depth research on sunflower leaf diseases for a more accurate identification of diagnosis.

Further it has been observed while reviewing the literature of research on leaf image Segmentation that proposed methods work well only on leaf images which were captured in a controlled environment. Texture feature extraction is mainly used technique used by researchers and there is a need in depth research on sunflower leaf diseases for a more accurate identification of diagnosis. The proposed algorithms can further be extended by hybridizing with other evolutionary algorithms to increase the clustering accuracy.

Limitation of existing system:

a) More optimization is need as present implementation still lacks in accuracy of result in some cases.
b) Speed of detection needs to be faster.
c) Database extension is needed in order to reach the more accuracy.
d) Very few diseases have been covered and needs to be extended to cover more diseases.

Table 1
Classification results per class for proposed method.

Authors & year	Title	Methodology	Future perspective
Beyyala and Beyyala (2012)	Application For Diagnosis Of Diseases in Crops Using Image Processing	image processing technology based on-farm testing	Better result of detection can be obtained with the specific and sophisticated image patterns understanding
Al Bashish et al. (2010)	A Framework for Detection and Classification of Plant Leaf and Stem Diseases	Image segmentation using the K-Means technique	Selection of better feature extraction and culling classification algorithms.
Chaudhary et al. (2012)	Color Transform Based Approach for Disease Spot Detection on Plant Leaf	Color Transform Based Approach using OTSU Method.	In this paper veins having color similar to the spot is not considered so Further work need to be carried out.
Sannakki et al. (2011)	A Hybrid Intelligent System for Automated Pomgranate Disease detection and Grading	NN and Genetic programming. SVM for classification	Nil
Xu et al. (2014)	Discussion on Sunflower Leaf Disease Diagnosis Based on Imaging Identification	Took G component of image as main object	Needs to be extended to cover more diseases.
Di et al. (2015))	The Research on the Feature Extraction of Sunflower Leaf Rust Characteristics Based on Color and Texture Feature	Color histograms and texture feature extraction	Better result of detection can be obtained with the large database and advance feature of color extraction
Sowmya et al. (2017)	Disease Detection in Pomegranate Leaf Using Image Processing Technique	Image segmentation using the K-Means technique and Classification is based on the Euclidian distance	Better result of detection and accuracy rate can be obtained using different classifier

e) The possible reasons that can lead to misclassifications can be as follows:

➢ disease symptoms varies from one plant to another
➢ features optimization is needed
➢ more training samples are needed in order to cover more cases and to predict the disease more accurately

As such for removing the research gaps a, d and e, a new methodology for classification and automatic detection of diseases in sunflower plant leaf using image segmentation has been proposed.

3. Proposed methodology

Digital camera or similar devices are used to take images of leaves of different types, and then those images are used to identify the affected area in leaves. After image acquisition, different types of techniques for image-processing are applied on them to get different and useful features needed for the purpose for analyzing later.

The step by step algorithm for the proposed image segmentation and classification process is detailed below:

Step 1: Image acquisition is the very first step that requires capturing an image with the help of a digital camera.
Step 2: To improve the quality of image and to remove the undesired distortion from the image preprocessing of input image is done. Median filtering method is carried out to get the enhance image which retains the original lesion useful information. To get the interested image region, clipping of the leaf image is performed.
Step 3: Mostly green colored pixels, in this step, are masked. In this, threshold value is computed for these pixels. Subsequently green pixels are masked, using the following criteria:

"If pixel intensity of the green component is less than the pre-computed threshold value, then zero value is assigned to the components of red, green and blue pixel".

Step 4: In the infected clusters, inside the boundaries, the masked cells are removed.
Step 5: Particle swarm optimization is used to obtain the output segments, which are further used to classify the leaf diseases. A color image of size m x n has been considered and every identified pixel has Red, Green and Blue components. A sequence of K cluster centers represents a chromosome. Population is initialized randomly and existing chromosome updated as new chromosome in each round for the next round processing.

Flow chart given below in Fig. 1 illustrates the steps in processing segmentation of leaf images, which is based on the Particle Swarm Optimization.

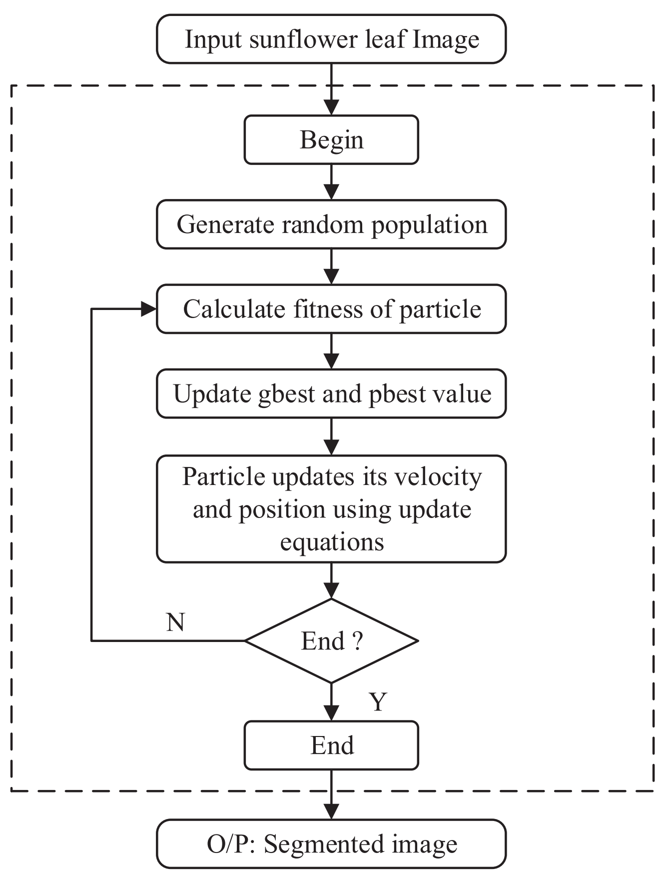

Fig. 1. Image segmentation method based on PSO.

For each iteration of a PSO algorithm, the particle (chromosome) updates its velocity and positions with the following equations.

$$v = 0.9 * v + 1.2 * \text{rand}() * (\text{pbest} - \text{present}) + 1.2 * \text{rand} * (\text{gbest} - \text{present})$$

$$\text{Present} = \text{Present} + v$$

where present = the current particle

pbest = personal best position of the particle

gbest = global best of all particles

rand = uniformly distributed number between 0 and 1

In the first step of fitness computation the dataset of pixel is clustered according to nearest respective cluster centers such that each pixel x_i of color image is put into the respective cluster with cluster center z_j for $j = 1, 2, \ldots, K$ by the following equations.

$$\text{if } \| x_i - z_j \| < \| x_i - z_l \|$$

$$i = 1, 2, \ldots, m \text{ x } n, l = 1, 2, \ldots, K, \text{and } p \neq j$$

In the further step new cluster centres are obtained by calculating the mean of each pixel of the assigned clusters. The new centre of cluster Z_i is given for the cluster Ci as:

$$Z_i(r, g, b) = \frac{1}{n_i} \sum\nolimits_{x_j \in c_i} (x_j(r, g, b)) \quad i = 1, 2, \ldots .k \tag{1}$$

Now the fitness function is computed by calculating Euclidean distance between the pixels and their respective cluster by using the following equations

$$\mathbf{M} = \sum \mathbf{M_i} \tag{2}$$

$$M_i = \sum\nolimits_{x_j \in c_i} | (x_j(r, g, b) - z_i(r, g, b)) | \tag{3}$$

Step 6: Computing the features using color co-occurrence methodology.

For feature extraction, the color co-occurrence method has been used. In this methodology, both color and texture are considered to identify the unique features contained in the image.

There are three major mathematical processes in the color co-occurrence method. First, conversion of the RGB images of leaves is done into HIS color space representation. After completion of this process, to generate a color co-occurrence matrix, each pixel mapping is used, which results into three color co-occurrence matrices, one for each of H, S, and I.

Features called as texture features, which include Local homogeneity, contrast, energy and entropy are computed for the H image as given in Eqs. (4) to (7).

$$\text{CONTRAST} = \sum_{i,j=0}^{N-1} (i, j)^2 C(i, j) \tag{4}$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} C(i.j)^2 \tag{5}$$

$$\text{Local Homogeneity} = \sum_{I,j=0}^{N-1} C(i, j) / \left(1 + (i - j)^2\right) \tag{6}$$

$$\text{Entropy} = -\sum_{i,j=0}^{N-1} C(i.j) \log C(i.j) \tag{7}$$

All the features are then combined into one single feature vector for each H image. This feature vector is classified using Minimum distance classifier.

Step 7: Classification of disease.

In this phase of classification, extraction and comparison of the co-occurrence features of the leaves with the corresponding feature values are stored in the feature dataset.

Minimum distance classifier is used to classify unknown image data to classes in multi-feature space. After the training parameter sets are

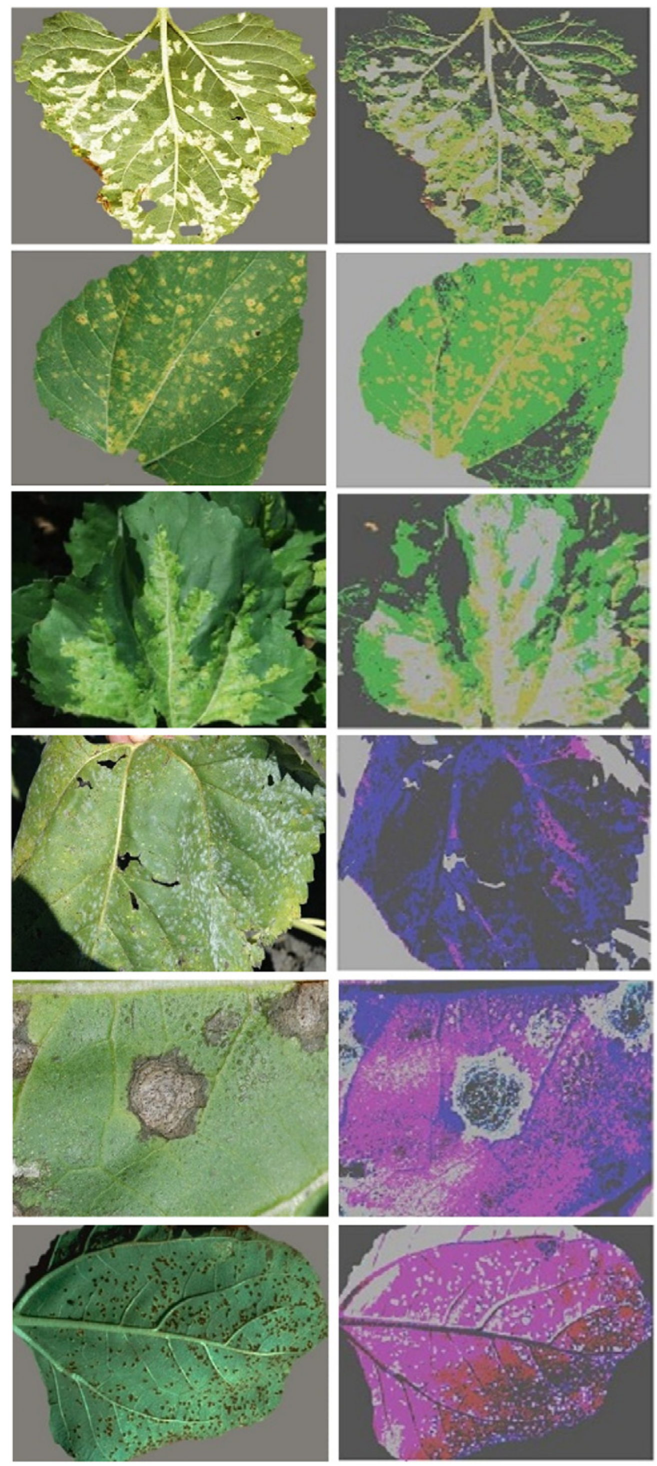

Fig. 2. Original leaf images & its output segmented images using proposed algorithm.

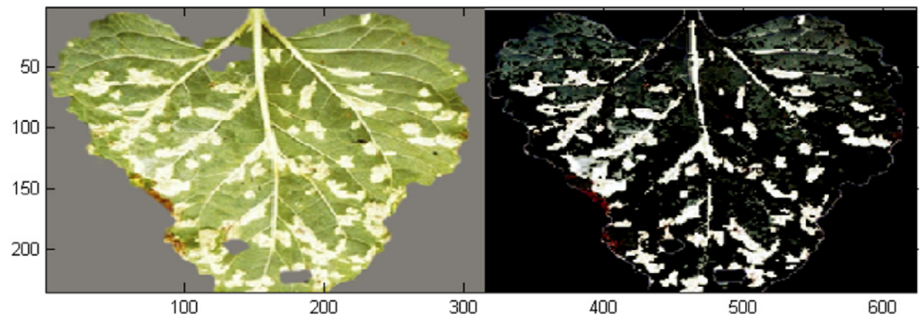

Fig. 3. Input and its output segment image of Sunflower leaf with White rust disease.

obtained, the classifier is evaluated using the test images for each class. The leaf images are divided into training and testing feature set. The classifier is based on the Euclidean distance from the feature vector representing the test image to the parameter sets of the various classes. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity.

The test samples are taken as input and the minimum Euclidean distance between the known feature set and the test sample is calculated. Euclidean distance, Di (x), of a measurement vector, x, from the vector, is given by

$$D_i\ (x) = [(x-z_i)\prime(x-z_i\ )]^{1/2}$$

where $(x - z_i)$ denotes a column vector and $(x\text{-}z_i)'$ denotes the transpose, a row vector test data.

Output is displayed based on the minimum value of Euclidian distance. After the Minimum Distance Criterion has been used for the classification; the successful measurement of classification is caluculated by using the classification gain. Following is used for obtaining the classification gain:

$$\text{Gain}\ (\%) = \text{number of correct classification/Total no of test images} * 100.$$

4. Results

MATLAB is used to conduct all the experiments. Following samples of Sunflower plant were taken as input:

(a) Sunflower leaf with White rust disease
(b) Sunflower leaf with Bacterial leaf spot disease
(c) Sunflower leaf with Downy mildew disease
(d) Sunflower leaf with Powdery mildew disease
(e) Sunflower leaf with Septoria leaf blight
(f) Sunflower leaf with Sun rust disease.

Fig. 2 demonstrates the original images with their respective output segmented images. Feature extraction method is used for classification of segmented image and in identifying different sunflower diseases.

Our proposed method is competent to locate the disease spots and achieve good segmentation results regardless of the complexity of poor illumination. In the same manner classification of diseases of input sunflower leafs are demonstrated in Figs. 3-8.

The co-occurrence features are calculated by using threshold image for mapping with the R, G and B components of the input image to that image. The values of corresponding features are stored in feature library after extraction and comparison of the co-occurrence features for the leaves are done with the corresponding feature.

For performance analysis of the proposed methodology, samples for rust leaf disease images also referred in (Di et al., 2015) have been considered. Two input images and classified output images using proposed algorithm, are shown in Fig. 3 and Fig. 8 respectively. (Di et al., 2015) Shows its efficiency with experiment recognition rate of 66.7%. Whereas the accuracy in detection has improved to 96%, when proposed algorithm has been used. The accuracy in detection of proposed algorithm has been obtained from 2nd and 7th row of Table 2.

The samples for leaf disease that were categorized into five classes of leaf disease using proposed algorithm, are shown in Table 2 and Fig. 9. From the results it can be seen that only few samples from White rust disease, Downy mildew disease and Sun rust disease leaves were misclassified. The average accuracy of classification of proposed algorithm is 98.0% compared to 97.6 and 92.7% reported in (Al-Bashish et al., 2011; Singh and Misra, 2017) respectively.

5. Conclusions

The proposed method of image segmentation, based on PSO for detection of diseases in sunflower plant leaf has been successful in recognizing and classifying the diseases. It requires no prior information regarding number of segments as the case is with other existing methods. With very less computational efforts, the optimum results were obtained. It effectively shows the efficiency of proposed algorithm in recognition and classification sunflower leaf diseases. Experimentation results reveal that only few samples were misclassified. The average accuracy of classification of proposed algorithm is 98.0% compared to 97.6 and

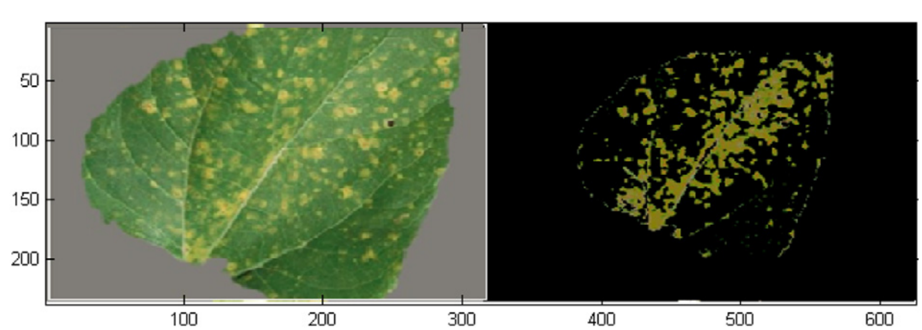

Fig. 4. Input and its output segment image of Sunflower leaf with Bacterial leaf spot disease.

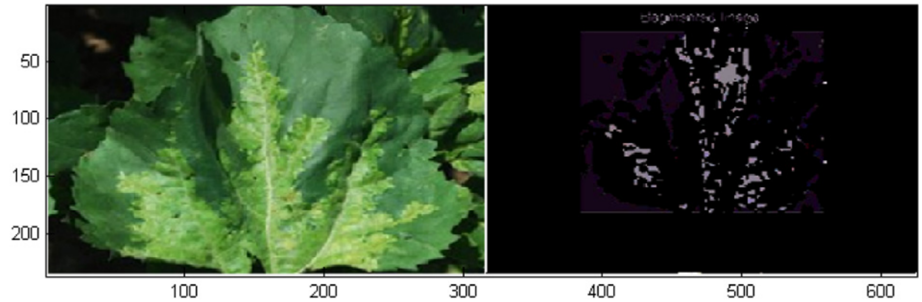

Fig. 5. Input and its output segment image of Sunflower leaf with Downy mildew disease.

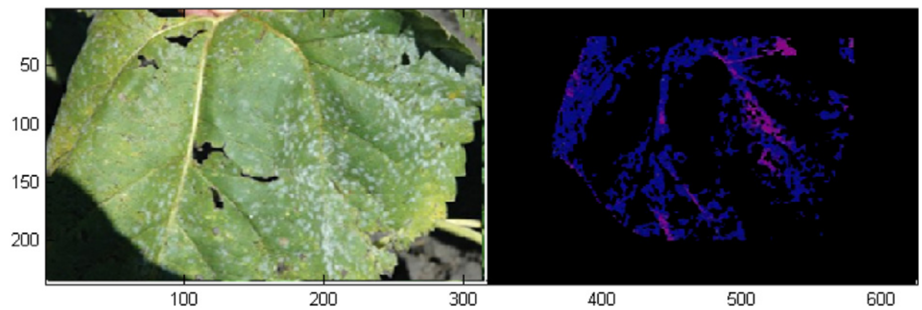

Fig. 6. Input and its output segment image of Sunflower leaf with Powdery mildew disease.

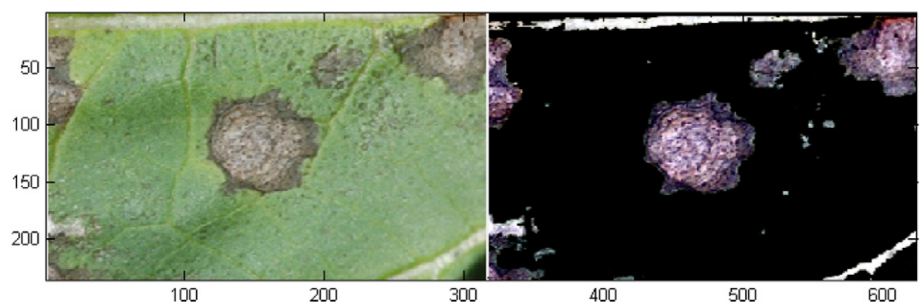

Fig. 7. Input and its output segment image of Sunflower leaf with Septoria leaf blight.

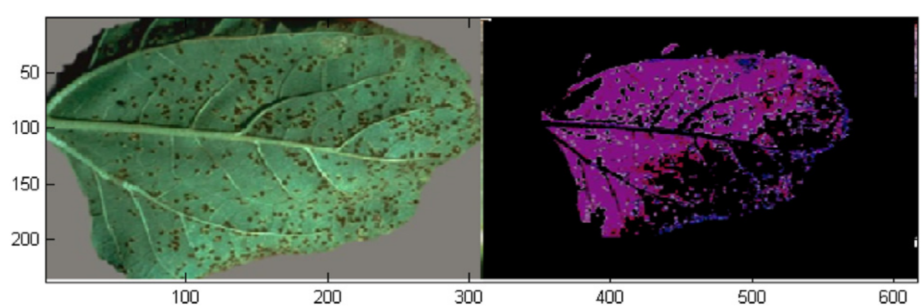

Fig. 8. Input and its output segment image of Sunflower leaf with Sun rust disease.

Table 2
Classification results per class for proposed method.

Leaf disease	White rust disease	Bacterial leaf spot disease	Downy mildew disease	Powdery mildew disease	Septoria leaf blight	Sun rust disease	Accuracy
White rust disease	23	1	0	0	0	0	96
Bacterial leaf spot disease	0	25	0	0	0	0	100
Downy mildew disease	0	0	24	1	0	0	96
Powdery mildew disease	0	0	0	25	0	0	100
Septoria leaf blight	0	0	0	0	25	0	100
Sun rust disease	1	0	0	0	0	24	96
Average							98.0

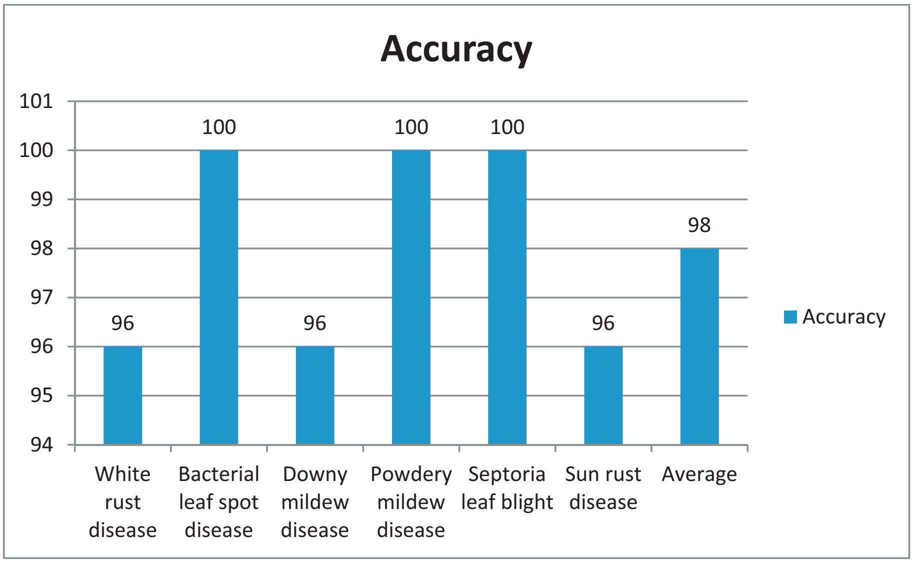

Fig. 9. Accuracy chart showing classification results per class for proposed method.

92.7% reported in (Al-Bashish et al., 2011; Singh and Misra, 2017) respectively.

6. Limitation & scope

Requirement of faster speed to reduce the search time is the major limitation of image segmentation technique. Combination/ hybridization of PSO with other methods like gradient search method may yield faster speed. Further research could involve the investigation of Artificial Neural Network, Bayes classifier and other hybrid algorithms for classification of segmented images to improve the recognition rate.

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