Soft Computing Optimized Models for Plant Leaf Classification Using Small Datasets

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Abstract
Plant leaf classification is an imperative task when their use in real world is considered either for medicinal purposes or in agricultural sector. Accurate identification of plants is, therefore, quite important, since there are numerous poisonous plants which if by mistake consumed or used by humans can prove fatal to their lives. Furthermore, in agriculture, detection of certain kinds of weeds can prove to be quite significant for saving crops against such unwanted plants. In general, Artificial Neural Networks (ANN) are a suitable candidate for classification of images when small datasets are available. However, these suffer from local minima problems which can be effectively resolved using some global optimization techniques. Considering this issue, the present research paper presents an automated plant leaf classification system using optimized soft computing models in which ANNs are optimized using Grasshopper Optimization algorithm (GOA). In addition, the proposed model outperformed the state-of-the-art techniques when compared with simple ANN and particle swarm optimization based ANN. Results show that proposed GOA-ANN based plant leaf classification system is a promising technique for small image datasets.

Keywords:
Plant leaf classification; Artificial Neural Networks; Grasshopper Optimization Algorithm; Particle Swarm Optimization; optimization techniques

1. Introduction

Plants play a vital role in human life, in general, whether as air purifier, as food source, providing countless daily use items, to name a few. Nevertheless, talking about their significance specifically in medical field, they act as a raw material for numerous medicines. Due to their use for treatment of critical diseases, their correct recognition is extremely essential, because, intake of poisonous plants if not recognized properly can be hazardous to human health and may cause prolonged illness or even death. Besides this, agriculture sector also requires accurate weeds recognition that otherwise can hamper the plant growth and hence, crop yield gets badly affected leading to monetary losses. And, if unwanted plants be correctly identified, would assist in timely action thereby controlling the yield damage. Keeping this in context, a large number of researches have been conducted in the past for automatic plant leaf classification using soft computing models.

The past studies show that the task of plant leaf classification requires perceptual power or cognitive capability of human beings which leaves the von Neumann machine far behind. To overcome the limitations of traditional computing paradigm, several novel models of computing have emerged which are collectively known as soft computing (Pal, 1999). To refer the problem in computer science soft computing is a term used in computer science whose solution is not predictable, uncertain and between 0 and 1. In early 1990s soft computing became a formal Computer Science in area of study (Zadeh, 1994). The chief components of soft computing are Artificial Neural Networks (ANN) (McCulloch et al., 1943; Widrow et al., 1964), Fuzzy Logic (FL) (Zadeh, 1965), Evolutionary Algorithms: Genetic Algorithms (GA) (Holland, 1975) and Differential Evolution (DE) (Storn, 1996), Meta-heuristics and Swarm Intelligence (SI) (Dorigo et al., 1996; Kennedy, 1995), Bayesian Networks (Pearl, 1985), Support Vector Machine (), and, Chaos theory (). ANNs have proved their dominance as a remarkable classifier in case of availability of small sized datasets. In spite of their suitability for non-linear and complex real world problems, these sometimes provide local solutions to the problem in hand. This too has been resolved by integrating ANNs with efficient optimization techniques that offers the benefits of global solution at the cost of exact one. Many evidences being available in the literature where ANNs are hybridized with GA, Firefly Algorithm, Cuckoo Search, Predator Prey Optimization, Grey Wolf Optimization, Harmony Search Algorithm (Geem et al., 2001), Particle Swarm Optimization (Kennedy, 1995), Ant Colony Optimization (Dorigo et al., 1996), Whale Optimization Algorithm (Mirjalili and Lewis, 2016), Bio Geographical Optimization, Big Bang Big Crunch Optimization, Teachers Learning based optimization (Rao, 2016), and many more. Of these, GA and PSO are the most successful and widely used global search techniques. These have shown very good results when hybridized with ANN for eliminating its problems and finding the global optimal solution.

Although, efforts have been put by various researchers for developing plant leaf recognition while processing the small and large datasets through suitable image processing and soft computing techniques, however

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very few evidences have been found in the literature that provide an optimal solution to the problem in hand, specifically for improving neural networks efficiency. Thus, there is an immense need of accurate plants leaf classification system in order to classify them based on the features of their leaves. Hence, the motivation of the present work is to propose an optimized neural networks-based model for plant leaf classification which works for smaller datasets as well as has higher classification rates. Rest of the paper is organized as follows: Material and Methods are presented in Section 2, Results and discussions in Section 3; and finally, conclusions are summarized in Section 4.

2. Materials and Methods

The automated plant classification model consists of five chief steps: dataset framing, pre-processing, image segmentation, feature extraction and classification. A general block diagram of the automated plant classification model is shown in Figure 1.

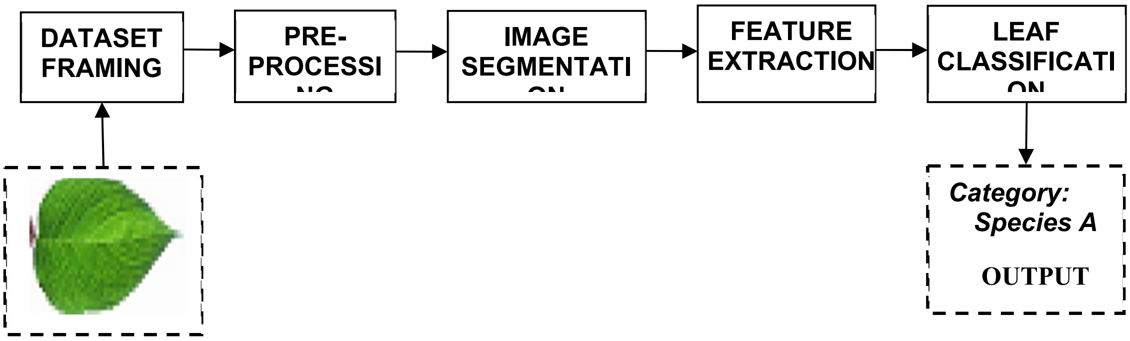

Fig. 1- Block Diagram of Plant Leaf Classification Model

2.1 Dataset Framing

The model initiated with the collection of data task which is also known as dataset framing. A standard dataset "Plant Village" has been chosen for the model with 400 plant leaf images. There are total 20 species considered as leaf samples, each having 20 different images. The details of the plant leaf variants are provided in table 1 with the leaf characteristics. Afterwards, a database was prepared to store the leaf images for further use.

Table 1: Details of plant leaf species used for the proposed model

Sr. no.	Species	Description	Image
1.	Wheat	Wheat leaves form at each node and includes a leaf sheath that wraps around the stem and a leaf. The grain has small atria. These wrap around the stem where the leaf sheath meets the blade. The spike also called the ear or head forms on the top of the plant.	

2.	Wheat weed (Sample 1)		
3.	Wheat weed (Sample 2)		
4.	Wheat weed (Sample 3)	Weeds do enormous damage to the wheat crop. They directly reduce soil moisture and nutrients and compete with cultivated plants for light and space, thereby reducing yields. Indirectly, they cause damage to crops that harbor pests and pathogens. Since its management involves costs, therefore, the reduction of net yields makes harvesting and threshing the crop costly and laborious and decreases the quality and reduces the value of the product. Weeds have been estimated to produce losses of between 10 and 40	

		percent in the grain crop depending on its intensity.	
5.	Spinach	Spinach is rich in Vitamins A, C and K, magnesium, iron. The leaves are green and can be eaten as raw or cooked. The leaves are very nutritious, tasteful and easy to digest	
6.	Spinach Weeds	Weed management in spinach is necessary throughout the season to achieve sufficient commercial yield. Weeds that are present in and around fields during planting sometimes harbor insects, pathogens, nematodes or vertebrates that can invade or spread spinach plants when they emerge. Weed control early in the season is especially important in precisely planted crops such as spinach because, compared to other horticultural crops (sweet corn, tomatoes, and even some cabbage crops), spinach is a relatively poor competitor to weeds. . The loss of spinach seedlings due to weed competition can substantially reduce overall vigor and mass uniformity.	
7.	Spinach		
7.	Turnip	The turnip leaf has high level of nutrients, can enhance health and help to prevent disease. These leaves help to reduce heart disease, stroke and hypertension.	

8.	Turnip Weeds	Turnip grass grows to about 80 cm tall from a rosette. Difficult to distinguish from other Brassica weeds until its pods form, turnip grass is covered with short, stiff hairs and has yellow flowers. The pods have two segments. The lower one usually contains no seeds. The upper one is round with a conical peak and usually contains only one seed.	

2.2 Pre-processing

The next task after dataset framing is the resizing and cropping of images to a fixed size. All the images have been resized to same dimensions of 100×100. Then the images are enhanced using Wiener filter. The reason for using Wiener filter is that it adjusts itself according to the local intensity variance in the image. For regions of large intensity variance the filter performance was less smoothing and it was more smoothing for regions of small variance values. Therefore, the filter is very well suited for plant leaf classification applications where leaf edges are to be retained while small bruises on the surface are to be smoothed off.

2.3 Image Segmentation

In the proposed model, segmentation is the third and the most important task. Edge based segmentation has been performed used for separating the leaf from the rest of the image. This has been done using Roberts cross gradient operators (Roberts 1965), Prewitt edge detector (Prewitt 1970), Sobel operators (Sobel 1970) and Canny edge operator (Canny 1983). The steps of the algorithm are given in figure 2.
These operators use the approach to locate points in the image where significant gradient changes are occurring. As defined by the masks or kernels, to reduce the effects of noise they use pixel-neighborhood averaging,. In a sense, they transform an input image by boosting the output into an edge image where changes are occurring (edges) and suppressing them where limited or no change exist (background). By differencing, the operators perform their functionality. That is, their output is some function of the difference between the values of its neighbors and a pixel`s intensity value, as defined by the pixel selection and weighting masks used in implementing the function. Basically, of a derivative function this is a discrete form, a computation that derives a measure of rate of change, which is greatest around the edges in the image (Article 1999).

CANNY EDGE DETECTION (Canny 1983)

1. **Smooth the input image with a Gaussian filter.**
2. **Compute the gradient magnitude and angle images.**
3. **Apply non-maxima suppression to the gradient magnitude image.**
4. **Use double thresholding and connectivity analysis to detect and link edges.**

Figure 2: Steps of Canny Edge based

2.4 Feature Extraction

As discussed earlier, to obtain the object of interest from the image Otsu segmentation has been performed. Subsequently, feature extraction has been performed, in which, two different set of features are extracted, namely, color based, shape based and texture based. Six color based features were obtained: mean of R, G and B components and standard deviation of R, G and B components of colored image. Six types of shape based features were extracted like: Area, major axis, minor axis, eccentricity, perimeter-O, and perimeter-S. Two perimeter values were taken. Perimeter denotes perimeter value of object of interest obtained after Otsu segmentation. Finally, Texture, in image processing, is a property of an image that characterizes the spatial variations in it. In order to compute these variations, Grey level co-occurrence matrix (GLCM) method (Haralick et al., 1973) is used. This method is quite simple and effective. Accordingly, the five main textural features used are homogeneity, contrast, correlation, entropy, and energy (uniformity). The details of features are provided in table 2. These texture features provide information regarding the minute textural variations and are quite important when the fact that the most of the leaves have almost same color features and shape features.

Table 2: Details of Features Extracted for Plant Leaf Classification Model

Type	Feature	Description	Formula
1. **Color based features**	Mean_R	Mean of 'R' component	$\mu = \frac{\sum_i^M \sum_j^N x}{M.N}$
	Mean_G	Mean of 'G' component	
	Mean_B	Mean of 'B' component	
	Std_R	Standard deviation of 'R' component	$SD = \sqrt{\frac{1}{n-1}}\sum_i^n (x_i - \bar{X})^2$
	Std_G	Standard deviation of 'G' component	
	Std_B	Standard deviation of 'B' component	
2. **Shape based features**	Area	Number of pixels in the region described by the shape	$Area = \sum_{x,y} I(x,y)$
	Major axis	Largest distance connecting one point to another on the region boundary, going through the center of the region.	---
	Minor axis	Smallest distance connecting one point to another on the region boundary, going through the center of the region.	---
	Eccentricity	Measure of aspect ratio	$Ecc = \frac{major\ axis}{minor\ axis}$
	Perimeter-O	Distance around the boundary of object, calculated from Otsu segmented image. It consisted of leaf boundary only.	$Perimeter = \sum_{x,y} \lvert x_i - x_{i+1} \rvert$
	Perimeter-S	Distance around the boundary of object, calculated from Sobel segmented image. It included defect as well as leaf boundary	$Perimeter = \sum_{x,y} \lvert x_i - x_{i+1} \rvert$
3. **Texture based features**	Homogeneity	It returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.	$Homogeneity = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{1}{1+(i-j)^2} g_{ij}$
	Contrast	It is a measure of the image contrast or the amount of local variations present in an image.	$Contrast = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i-j)^2 g_{ij}$
	Correlation	It returns a measure of corresponding a pixel is to its neighbor over the whole image.	$Correlation = \frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(ij)g_{ij} - \mu_x\mu_y}{\sigma_x\sigma_y}$

	Entropy	It measures the disorder of an image and it achieves its largest value when all elements in P matrix are equal.	$Entropy = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} g_{ij}\, log_2\, g_{ij}$
	Energy	It is also called angular second moment or uniformity. It is a measure of textural uniformity of an image.	$Energy = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} g_{ij}^2$

2.5 **Classification**

Classification is the final step. In consideration of, plant leaf classification is a nonlinear as well as complex problem, it can be resolved using soft computing models. And, the most appropriate candidate to provide solution to such problems is artificial neural networks. Despite, of their extraordinary performance in classifying the objects, these sometimes get trapped in local minima; bring about further slow training and inaccurate results. In order to resolve this problem, some global, random optimization technique is required that when integrated with neural networks provides optimal as well as accurate solution. One related nature inspired swarm optimization technique is Grasshopper Optimization Algorithm (GOA) (Saremi et al., 2017).

For solving optimization problems, the optimization techniques GOA mathematically models and mimics the behavior of grasshopper swarms in nature. Grasshoppers are insects. They are considered a pest, because of their damage to crop production and agriculture,. Slow movement is the main characteristic of the swarm in the larval phase is and small steps of the grasshoppers. Compare to, long-range and immediate movement is the necessary feature of the swarm in adulthood. Seeking food source is another prime characteristic of the swarming of grasshoppers. The mathematical model employed to simulate the swarming behavior of grasshoppers is presented as follows (Topas et al., 2008)

$$Xi = Si + Gi + Ai \qquad ...1$$

where Xi defines the position of the i-th grasshopper, Si is the social interaction, where as Gi is the gravity force on the i-th grasshopper, as well as Ai shows the wind advection. Nevertheless, in order to find an optimal solution to the classification problem of plant leaf, the optimization technique is kept simple by ignoring the force due to gravity and hence Gi component is considered to be zero in equation 1. So, classification is performed by using this simple GOA technique hybridized with ANN. The block diagram of the classification algorithm is shown in figure 3.

In GOA domain, a specific terminology based on natural grasshopper life cycle and food collection way outs. The word ‘swarm’ is used to represent the alternative solution for the problem. In present problem, features extracted from leaf images act as ‘elements’ and set of such elements form the position of a grasshopper (or search agent) in the swarm. Set of grasshopper positions further form the ‘swarm’ of alternative solutions. The term ‘weight’ signifies the importance assigned to inputs, fed to the network. ‘Error’ means difference in the forecasted outputs and the desired ones. In this step the error has not been reciprocated back and the fitness is evaluated for each SA in the considered swarm. The hybrid algorithm is given in figure 4.

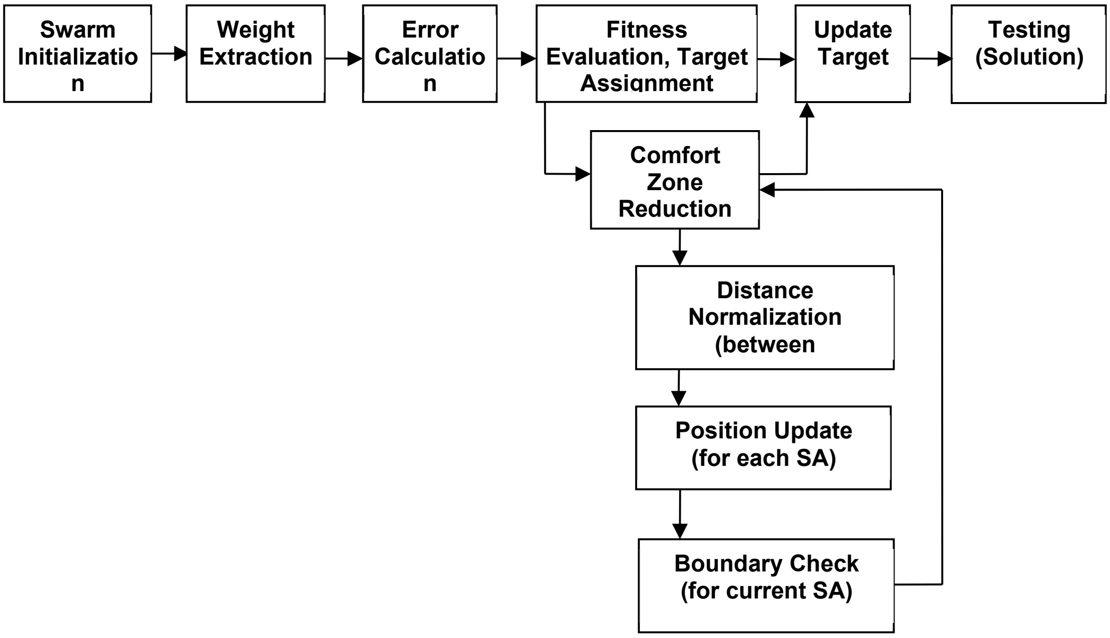

Figure 3: The block diagram of GOA/ANN based Hybrid

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The GOA/ANN algorithm works as follows:

I. TRAINING PHASE:

Step 1: Generate random swarm of 'i' number of position X_i of grasshoppers (suitable solutions for the problem).

Step 2: Extract weights for input-hidden-output (l-m-n) layers from each grasshopper position.

Step 3: Evaluate the fitness f(X) of each grasshopper position X in the swarm by reciprocating the cumulative error values obtained for each input set (plant leaf dataset). Assign any search agent as Target.

Step 4: Update the target by repeating following steps until the finite number of iterations:

4.1 Comfort zone: Reduce the forces applied to each grasshopper for or against reaching the optimal position.

4.1.1 Position Normalization: Keep the position in the finite range of [1,4].

4.1.2 Position Update: Update the new position of each grasshopper in the swarm.

4.1.3 Boundary Check: Restrict the position of each grasshopper within the region of exploration to avoid infinite loop trapping or slower training.

Step 5: Target Update: Update the target when a better SA is found, and ultimately the global solution is found when no more SA is better in the swarm.

Step 6: Loop: Repeat steps 3 to 6 until stopping condition is met.

II. TESTING PHASE:

Step 7: Testing: Feed inputs for unknown sample to get the network tested and provide the output as class.

'Fitness' is how close a grasshopper (alternative solution) to the desired solution. More the fitness of the grasshopper position, more suitable candidate it is for the target. Inversely proportional to the error value is fitness. In addition to this, target assignment is performed. The target is randomly assigned as any grasshopper position, generally the first search agent (SA) in the swarm. 'Comfort zone' indicates the forces applied to each grasshopper for or against reaching the optimal position and these must be reduced. 'Position normalization' implies bringing in the grasshoppers in a uniform range to attain easy convergence. 'Position update' is performed for current SA. 'Boundary check' is performed to bring the grasshopper in the convergent region and if current SA not found in there then is brought back to keep the search going on but in the finite zone. This also assists in finding optimal solution and that too by faster convergence. Afterwards, the target is updated if a better alternative is found.

The output of classification step is in the form of text that specifies the type to which the leaf belonged to. Based on these types, further recognition has been performed. This is the training phase algorithm.

3 3. Results and Discussions

For simulation of artificial neural networks as depicted in figure 5, an l-m-n architecture of 17-9-1 was used .According to the number of feature extracted from the image, the number of input neurons depends, while the number of output neurons depend on the final values to be forecasted. For this framework, the number of neurons was 17 as the features extracted were 17 in count.

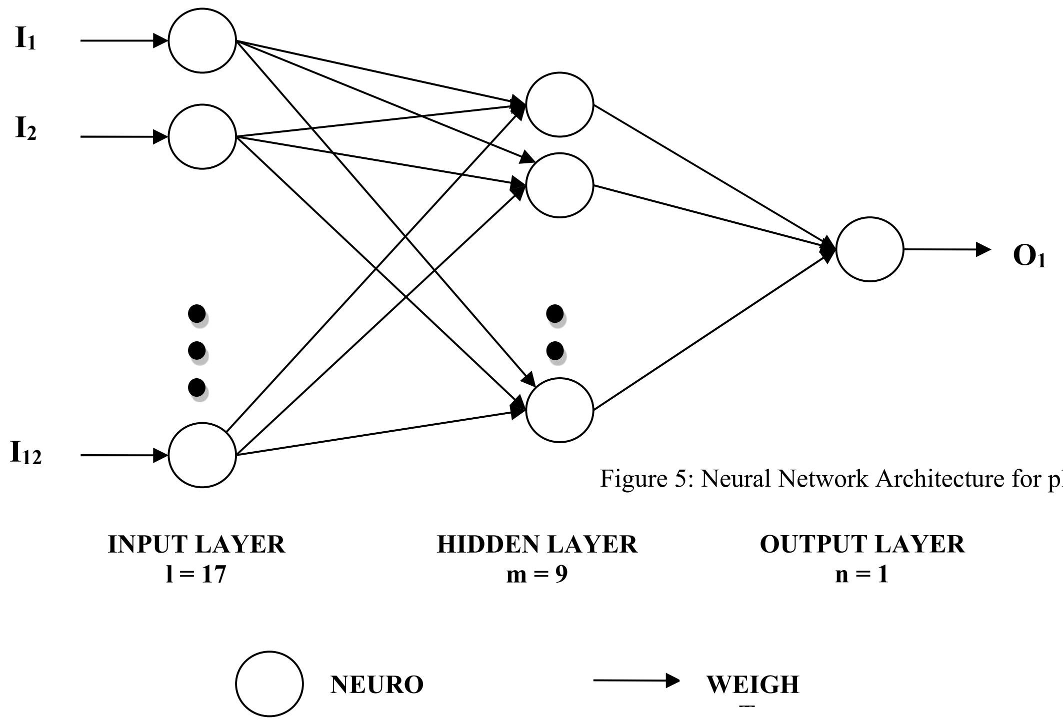


Figure 5: Neural Network Architecture for plant leaf

Figure 5: Neural Network Architecture for plant leaf

Since, the network had shown minimum error values when number of hidden neurons were 9, so, m=9. Finally, as output class the number of output neurons was taken as 1, because, there is one class to which the plant leaf be recognized and will be forecasted.

The GOA/BP plant leaf classification model worked in both fractions: Training as well as Testing. In the training phase, for inputs the 17-9-1 network was trained as well as outputs (supervised learning) to obtain weights. Along with different input values these weights were then fed to the network for testing. In this study, the plant leaf classification images were used as inputs and outputs were categories: wheat and its weeds images, spinach and its weeds images, and turnip and its weeds. From the total 60 images, 45 images were used for training purposes while 15 images were used for testing.

A summary of various techniques applied at each step of the plant leaf classification grading model are provided in table 3. Corresponding to five phases, outputs of three samples are depicted in the last three columns of the table. During the time of analyzing the outputs, the images acquired from normal scene are converted to gray scale images and then enhanced by Wiener filter in pre-processing phase. Afterwards, to obtain the plant leaf object from images using edge based segmentation background is separated. The output is binary images. Edge segmentation is well suited for leaf veins distinction. Figure 6 shows the results of four edge operators, namely, Roberts, Prewitt, Sobel and Canny Edge operator. It is clearly visible that 'Canny' edge operator outperformed rest of the edge operators in showing the results and hence for feature extraction and classification purposes, all the images have been segmented using canny edge operator to train the artificial neural networks.

Then, the color, shape and texture based features were obtained in the feature extraction phase. In the classification phase using these features, the GOA/ANN was trained for 45 different images. Weights were extracted after training phase, which were further fed along with new 15 images so as to test them according to the rule discussed earlier. In the table, labels to all the sample images are being provided, for instance turnip is the label.

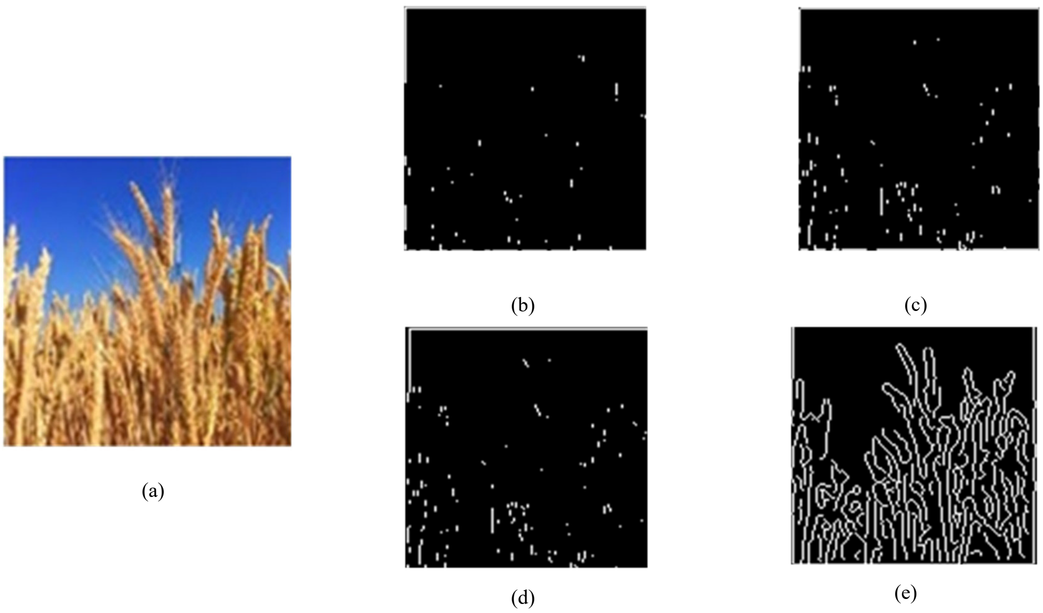
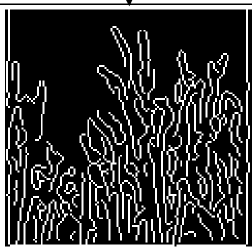


Figure 6: Comparison of Segmentation Techniques (a) Original Image of Wheat (b) Roberts edge segmentation (c) Prewitt edge segmentation (d) Sobel edge segmentation (e) Canny edge

Table 3: Step-wise Outputs for Plant Leaf Classification Model

Sr. no.	Phase	Technique Applied	Output of Phase		
			Sample 1	Sample 2	Sample 3
1.	Dataset collection	Framing dataset			
2.	Pre-processing	Resizing			
3.	Pre-processing	Gray Scale imaging			
4.	Segmentation	Canny edge based method			
5.	Feature Extraction	Color based Features	Shape based Features		Texture based Features
		Mean_R	Area		Homogeneity
		Mean_G	Major axis		Contrast
		Mean_B	Minor axis		Correlation
		Std_R	Eccentricity		Entropy
		Std_G	Perimeter		Energy
		Std_B			
6.	Classification	GOA/Neural Networks	Wheat	Spinach	Turnip

The error versus iteration graph for back propagation neural networks (BP-ANN) and GOA/ANN is shown in figure 5 and 6, respectively. It is quite evident from the graph that GOA/ANN converged to solution earlier than BP-ANN. It took less than 190 iterations for GOA/ANN to converge while BP-ANN took more than 200 iterations for the same but never got converged. Probable reason for late convergence of BP-ANN might be that it got trapped into local minima. This further led to slow training. The constant line after 80th iteration, in figure 7, undoubtedly supported the fact that BPNN suffers from local minima problem. Also, it is evident from figure 8 that GOA/ANN had eliminated this problem for plant leaf classification model.

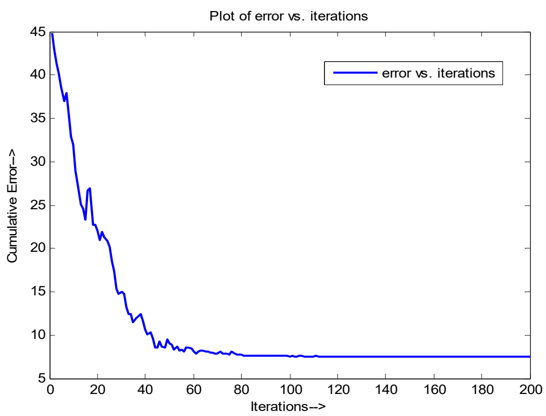


Figure 7: Error vs. Iteration graph for BP-ANN Approach

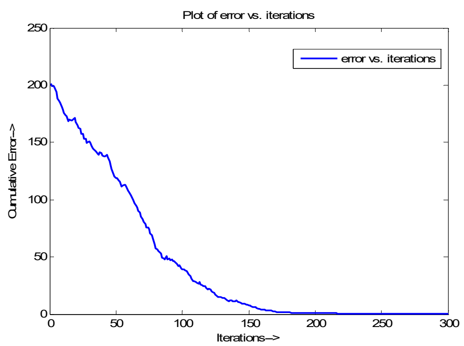


Figure 8: Error vs. Iteration graph for GOA/ANN Approach

4. Conclusion

Accurate classification of plants is of utmost importance both for medical sector as well as in agriculture. In this research article, an optimized neural networks based plant leaf classification model has been proposed. The model works in four main steps: Dataset framing, Image preprocessing, Image segmentation, feature extraction and classification. A total of 60 plant leaf images of mainly wheat, turnip, spinach and their weeds have been used to frame the dataset. The images are firstly resized and then changed to gray scale for better results. Afterwards, edge based segmentation has been performed so that leaf veins can be clearly separated from the background. Thereafter, features have been extracted from the images. For this three types of features namely, color based, shape based and texture based features were extracted to feed to the neural networks. For better performance of ANN that is avoiding local minima problem and slow training rate, some kind of global efficient optimization is required and for this purpose, a global, stochastic swarm based Grasshopper Optimization algorithm (GOA) has been hybridized with ANN. This plant classification model gives remarkable results when classification is performed. Besides, the proposed model when compared with simple ANN outperformed in terms of minimizing the error value in less than 190 iterations which was not possible with ANN alone. Hence, the proposed GOA-ANN classifier can be utilized for other peer applications in future too.

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