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***Research paper***

# Hybrid feature- selection using group search particle swarm optimizer for plant- leaf classification

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**Abstract**

Plants are considered to be the important sources for food and medicine. They are critical for the protection of the environment as well. The plant leaves carry information on the species of the plant. This kind of work can describe an approach that is optimal for the selection of the feature subset in classifying the leaves on the basis of a Group Search Optimizer (GSO). Owing to the high level of complexity in selecting optimal features, data classification has become now an important task to analyse the data of leaf images. Here for this work, there is a hybrid algorithm known as the Group Search Particle Swarm Optimization (GSPSO) which is based upon Particle Swarm Optimization (PSO) and here the GSO has been proposed wherein a PSO model along with the GSO model is made use of. A GSPSO combines all advantages in both the algorithms, the high speed of computing in the PSO and the good performance in the GSO. The Fuzzy classifier is that form of the many-valued logic which is derived from the theory of a fuzzy set. A Multilayer Perceptron Neural Network (MLPNN) concept is used for classification. Such techniques are selected as they can provide a training that is faster to solve the problems of pattern recognition by making use of the technique of numerical optimization.

***Keywords***: *Plant Leaf Classification; Feature Selection; Artificial Neural Networks (ANN); Multilayer Perceptron Neural Network (MLPNN); Particle Swarm Optimization (PSO) and Group Search Optimizer (GSO).*

## 1. Introduction

Plants are critical to maintaining the ecology system. They give sustenance, fuel, medicines and, shelter and also ensure a breathable and healthy atmosphere. Some plants are getting closer to extinction owing to the incessant de-forestation, and therefore to conserve them, there is a need to efficiently recognise and classify them. To this end, the computer vision, along with the techniques of pattern recognition, is used for cataloguing several species of plants to provide sustainable methods of search for the flora as well as fauna population. Most such techniques are dependent on visual feature extraction like colour, shape, and texture. Even though different parts of the plant like the root, the seed, the bud or the flower may be used to recognise them, the recognition based on the leaf is extremely effective [1].

The classification of plants on the basis of leaves is very easy and quick to complete. Based on the theory of taxonomy, the plants are classified on the basis of the shapes of the texture or shape. A leaf consists of the blade, the petiole and, the stipules. A blade is that part of the leaf that is flat and photosynthetic, the petiole being the stem and the stipules, the formation that is leaf-like on the base of a petiole. The leaves generally are two-dimensional and flowers, three-dimensional. Normally, only a single blade in the leaf is taken into consideration at the time of digital classification of plants and their retrieval. A blade has a particular shape as well as texture. Further, the leaves are collected during any season but flowers are obtained only in their blooming season [2].

The prime work of the system of leaf classification would be the extraction of all common features that are among images which belong to a similar data set and then indexing them. The method is also applied for capturing the visual image content used for the purpose of retrieval [3]. A great amount of variability in the shape and the size of leaves would make this task challenging. The shape, as well as the textures, is extracted either by using the Scale Invariant Feature Transform (SIFT) or the Local Binary Patterns (LBP). The colour features are extracted using the Colour Moments, the Colour Histogram and so on. Several methods of feature extraction are available which are the Principal Component Analysis (PCA), and the Linear Discriminant Analysis (LDA). The methodologies of Feature extraction can analyse the images of the leaf for extracting the prominent features that tend to represent different classes of the objects.

The task of feature selection is very critical and permits the determination of the relevant features used for the purpose of recognizing a pattern. The features that are extracted are normalized and also reduced by means of choosing the appropriate features for improving the accuracy of classification [4]. An ideal feature selection has some specifications. There is a need for better generalization and a training that is faster. The redundant leaf images would have to be removed. The recognition is focused on properties of one small set. It displays only a final outcome which is classified. There may be many different methods of selection which are implemented specifically for reducing the features and their dimensionality. There are many types of researchers that have been focussing on the feature selection. The progress in the innovation of database has enabled a large number of datasets having a large component or variable number being now omnipresent in recognizing the pattern, machine learning and, data mining.

Feature selection may be addressed using three schemes, the filter, the wrapper and the embedded methods [5]. The Filter methods view the problem to be an aspect that is independent of model selection (which means an inductive generalization which does not involve the process of feature selection). Contrastingly, the wrapper method would associate its hypothesis search along with their inductive classifiers for obtaining feedback. Here, several combinations of the subsets get generated and also evaluated for improving the performance of classification. Finally, the embedded methods look out for a subset that is optimal and has been internally designed for the construction of the classifier.

Presently, the feature selection is being used in machine learning as well as in data mining. For the purpose of identifying an optimal set which is an NP problem, researchers have started opting for a feature set that is near optimal. Today, the algorithms that are metaheuristic are gaining momentum which are the Particle Swarm Optimization (PSO), the Ant Colony Optimization (ACO) and the Genetic Algorithm (GA). For these metaheuristic algorithms, a measure to evaluate quality is given and a specific candidate set is improved. Lastly, there are some excellent feature sets that are obtained. These metaheuristic algorithms tend to make some assumptions on optimal feature sets and also find some feature sets in search spaces that are large. This has been found to be well - suited for problems of feature selection [6].

Here, metaheuristic algorithms that are used for feature-selection have been presented for identifying a combination of the GSO and the PSO for the classification of the plant leaf. The rest of the investigation has been organized thus. The related work made in literature has been discussed in Section 2. The methods that have been employed are shown in Section 3. The results of the experiment are duly discussed in Section 4 and the conclusion is made in Section 5.

## 2. Related works

Keerthika et al., [7] introduced another Firefly Algorithm (FA) which was based upon the classification of the biological species. Its research had focused on making use of the digital image processing to classify and recognise the plants. It had five different modules which were 1. Image acquisition, 2. Pre-processing, 3. feature extraction 4) selection of feature and 5) classification. For image acquisition, a module leaf image would be captured with a digital camera. In pre-processing, different techniques were applied. After this, the texture, the shape as well as the leaf perimeter would be extracted from an enhanced image. All optimal features got extracted with the FA. For an image recognition, all leaf images get classified with the MLPNN and Levenberg-Marquardt (LM) Back-Propagation (BP) algorithm.

Eid and Abraham [8] proposed a model of plant identification on the basis of the biometrics of the leaf. To this end, the PSO was adopted to be a phase of pre-processing for the segmentation of leaf images. The Grey Wolf Optimizer (GWO) was obtained for reducing the leaf texture dimensions. Lastly, a dual coordinate descent based L2-Support Vector Machine (SVM) classifier was employed for classifying the various species of the plants. This model was proposed mainly for achieving a high level of accuracy with the descriptors of the leaf.

For solving CNN problems while applying them to the plant leaf system that is diseased like converting it for a classification that is better, a Genetic Algorithm-based Feed Forward Neural Network (GA-FFNN) hybrid technique was presented by Muthukannan and Latha [9]. Apart from this, the segmented hybrid features that are PSO-based were used for analysing the diseased leaf and for classifying the severity of the same. The contribution here was the incorporation of the genetic weight optimization-based Neural Network (NN) systems for the classification of the diseased plant leaves. Here the attributes were combined into a single vector for all the hybrid features.

For this research, on the basis of the techniques of processing and the methods of pattern recognition, a method known as the apple - leaf disease recognition had been proposed by Chuanlei et al., [10]. A structure of colour transformation used for the input that would be Red, Green, and Blue (the RGB) image had been designed and an RGB model had been converted to the Hue, Saturation and the Intensity (HSI), the YUV and the grey models. Thus, the background had been removed on the basis of some threshold values that were specific and the image of the spot with the disease had been segmented using the RGA. About thirty-eight features of classification of the shape, texture and, colour had been extracted. For reducing the feature space dimensionality and for improving the identification of the apple leaf disease, all valuable features had been chosen by means of combining the GA with the Correlation-based Feature Selection (CFS). All diseases are later recognized using the SVM classifier. In this method, the chosen feature subset would be globally optimal.

An approach that was optimal for the selection of feature subset that classified the leaves on the basis of the GA and also the Kernel-Based Principle Component Analysis (KPCA) was described by Valliammal and Geethalakshmi [11]. Owing to its high complexity, this became a critical task. In the initial stages only the shape, colour and texture were extracted. Later they were optimized using a separate functioning of the GA and the KPCA. The approach further performed an operation of intersection on the subjects that had been obtained for the process of optimization. Lastly, the subset that matched got forwarded for training the SVM. The results of the experiment have proved that this application of the GA with the KPCA for the selection of feature subset by using the SVM to be its classifier was effective in terms of computation and also gives an improved accuracy.

Muthevi& Ravi Babu [18] exploited the magnitude component of Local Binary Pattern (LBP) separately from sign component. The Completed Local Binary Pattern (CLBP) was proposed on plant leaf classification by considering a divergent blocks of each texture data set. The proposed method identified the quality leaves for the mechanization of grading procedure in commercial crops like Tobacco etc. Center pixel CLBP (CCLBP) and Signed component of CLBP (SCLBP) were merged and the magnitude part of CLBP (MCLBP) was significantly attained for rotationally invariant texture classification.

Chaki et al [19] proposed a method using Gabor filter and Gray Level Co-occurrence Matrix (GLCM). The shape of the leaf was captured by a Curvelet transform coefficients along with Invariant Moments,by applying a Neuro-Fuzzy Controller (NFC) and a feed-forward back-propagation multi-layered perceptron (MLP)to differentiatethe 31 classes of leaves. The features were applied either separately oras group to examine how recognition accuracies could be enhanced. Experimental results show that the proposed method performed better in identifying leaves with varying texture, shape, size and orientations to an acceptable degree.

## 3. Methodology

In the dataset, around nine species using about 20 samples of 197 leaves having similar structures like Phyllostachys edulis (Carr.) Houz. pubescent bamboo, Aesculuschinensis Chinese horse chestnut, BerberisanhweiensisAhrendt Anhui Barberry, Cercischinensis Chinese redbud, Indigoferatinctoria L. true indigo, Acer Palmatum Japanese maple, Phoebe nanmu Gamble, Kalopanaxseptemlobus castor aralia, CinnamomumjaponicumSieb. Chinese cinnamon, KoelreuteriapaniculataLaxm. goldenrain tree, Ilex macrocarpaOliv. Big-fruited Holly, Pittosporum tobira (Thunb.) Ait. f. Japanese cheesewood, Chimonanthus praecox L. wintersweet, Cinnamomumcamphora (L.) J. Preslcamphortree, Viburnum awabukiK.Koch Japan Arrowwood, OsmanthusfragransLour. sweetOsmanthus, Cedrusdeodara (Roxb.) G. Don deodar, Ginkgo biloba L. ginkgo, maidenhair tree and Lagerstroemia indica (L.)

Pers. Crape myrtle, Crepe myrtle were used. A chain code was put for representing the shape and its periphery. The picture was the object that had a periphery and this would be exemplified by making use of chain codes. For matching one pair of the picture peripheries, the string illustrations would have to be matched by the process of string remoteness. The techniques were then applied for reduction of dimensionality. Here a hybrid GSO optimized along with a PSO - based selection was employed. The subsequent one that is obtained would be used to classify the leaf by making use of the MLPNN and the methods of fuzzy classifiers that have been discussed. The features are extracted using wavelet transforms. The decomposition of horizontal, vertical and diagonal details coefficients and the approximation coefficients were used as feature set. Chain Coded String: this is also known as the Freeman code and the chain code was put into place in order to be able to represent the shape and it periphery. This might also be outlined in a clockwise or the opposite means with the eight codes for the pixels that were allocated with the next pixel relating to its current one. The picture of any object that had a periphery, and this would be exemplified by the chain codes in which the strings would be used for describing the shapes. In order to match any pair of the picture peripheries, the string illustrations had been matched by means of using the string remoteness and their processes.

The Wavelets were the waveforms of the restricted durations that would possess an average value of 0. These were neither regular nor are symmetric and had differing frequencies. An analysis of the wavelets was employed to the 1D data (signals) and the 2D data (images). A primary reason and the benefit of employing the wavelet transform for the detection of the edges in the images would be the potential for the choosing of the size of the details that had been identified, and while processing the 2D images and carried out the wavelet analysis in a distinctly horizontal and a vertical direction the edges needed to be identified in a manner that was separate (Desai 2012). The 2D Discrete Wavelet Transform (DWT) would split the images into various sub images, and details along with approximation. This would be like an inputted image and one-fourth of its original size. The 2D DWT would be an expansion of this 1D DWT for a horizontal and vertical direction and the sub images would be octave and labelled as A, H, V and D, according to the filters that are used for the generation of the sub images. This procedure would be iterated by means of placing the first octave A and its sub image using a set of low and high pass filters. Such iterations helped in the analysis of the multi-resolutions.

The texture would be a significant cue in the analysis of the images and this was used for pointing out to the intrinsic characteristics of the surfaces, more particularly those that did not have any intensities that varied smoothly. The texture had been defined as that set of local neighbourhood traits of the grey levels of the image area and the textural analysis was a task that was problematic and its capacity to classify the segmentation of the images based on textural attributes would be critical to scene analysis, remote sensing and medical image analysis (Livens et al., 1997).

An issue that was significant in the analyses of the wavelets would be the actual quantity of the attributes that had the tendency to be large for that of the decomposition of the wavelet packet. A large set of features, even though might possess a lot of information, would ensure that the classifications and their segmentations were even harder. This phenomenon was quite famous in the pattern recognition and dimensionality. A very basic issue would be that the pre-dominant scales possessing useful data would be different from one texture, and it might be useful to be able to restrict the quantity of such attributes at the generation level in which the attribute nature was considered. Figure 1.4 shows the Pubescent Bamboo used in the investigation.

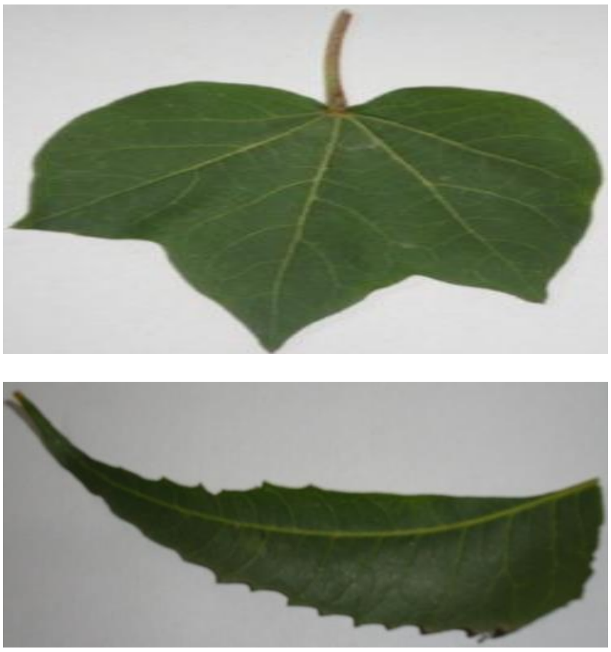

**Fig. 1:** Sample Image of Plant Leaves.

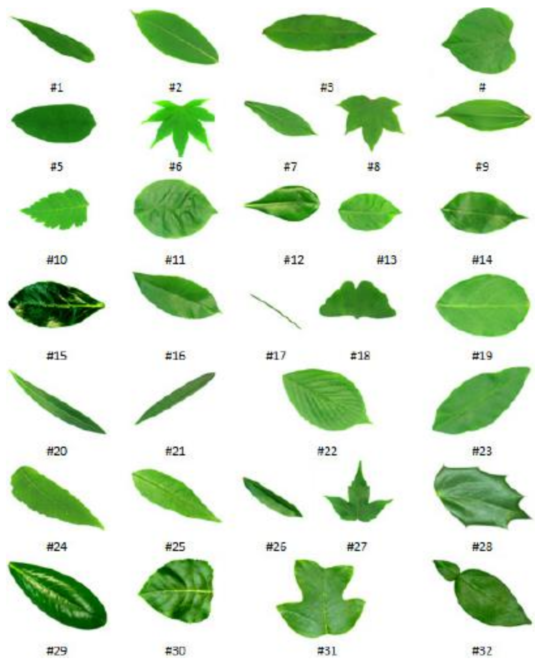


**Fig. 1.2:** Sample of Leaves in Flavia Dataset.

**Fig. 1.3:** Pubescent Bamboo.

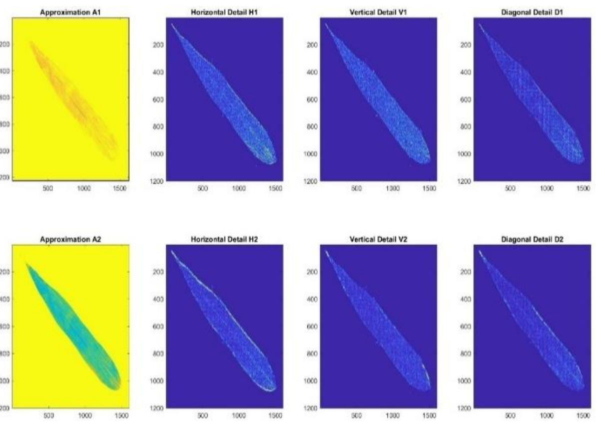


**Fig. 1.4:** Approximation Outputs for Sample Pubescent BambooImage.

### 3.1. GSO based feature selection

The task which analyses the huge datasets for overcoming problems of dimensionality is relevant here and is called feature selection. Here, it makes use of a GSO based methodology of hybrid filter-wrapper for searching for all informative subsets and improving the search. The GSO is that swarm intelligent mechanism that was proposed by S. He, and was based on the animal search and the foraging phenomenon. In GSO based Producer-Scrounger (PS) model, where a population can consist of the producers, the scroungers and the rangers who form the group and every individual in this group is called a member. The producer is a member that makes use of the mechanism of scanning for searching for an optimal solution or any resources that are nearby. Contrastingly, the scrounger tends to follow the policy of joining producers in their search [12].

In case of the artificial GSO optimization-based model, the Rangers have been introduced for performing a walk to make more improvements to the algorithm. The group member can be any solution which has been represented to be the n-dimensional point in a space and would have a head angle that is associated. Ideally, a producer would have the direction of search that is given by that of Cartesian coordinates and their transformations. For the purpose of simplification, the group contains one producer chosen to be the one that has the best value for fitness. Later it scans the environment for searching for resources that are optimal (or the points having better values of fitness). The scanning field of the producer would be taken to be inside that of an n-dimensional space, having properties like the maximum pursuit angle $\theta_{\max} \in R^1$ and also the maximum pursuit distance $l_{\max} \in R^1$. As according to He, a maximum pursuit angle with the distance would be the most characteristic properties in a scanning field vision which is conical. Ideally, the producer can sample three different points that are the zero degrees, a right-hand side hypercube, and a left-hand side hypercube. In case a producer identifies a better value of fitness it may move to this. Else, it can move the head angle. Once a certain number of iterations are complete and the producer is not able to identify better options, it can go back to the zero degrees. For every such iteration, a particular number of members chosen to be scroungers that perform their random walk to the producer will be based on its scrounger movement expression. In addition to this, the GSO further employs a particular number of rangers that can perform another random walk for avoiding problems that are connected to the local minima. The process that generates these new sample points would be repeated till the termination criteria are attained.

### 3.2. Particle swarm optimization (PSO)

A PSO [13] is a nature inspired technique that is metaheuristic, and it also simulates the bird and its flocking behaviour according to by Kennedy and Eberhart (1995). This algorithm makes use of a population that is generated randomly and has an associated position and velocity in which every particle would correspond to a solution that is generated randomly. The PSO looks out for optimal solutions by means of changing velocity and also the position on the basis of its own particle's flying experience and also of the group that is towards the gbest as well as the pbest location that is in a successive iteration. The Gbest would correspond to that of the best fitness value of the population achieved by any particle and the pbest is the best value of fitness that has been achieved until now. The velocity and the position for the particle is altered based on the equations (1) and (2) respectively:

$$v_{id} = v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * rand() * (p_{gd} - x_{id}) \tag{1}$$

$$x_{id} = x_{id} + v_{id} \tag{2}$$

The equation (1) has three different parts: 1) the Momentum, 2) the Cognitive and 3) the Social. The momentum would state that the particle's velocity cannot be quickly changed. Every particle would update its best velocity on the basis of its earlier one and the distance it has from its current position from both the gbest and the pbest location. The cognitive part, being $c_1$ describes the learning of the particle from its flying experience and the social part which is $c_2$ indicates the learning of the particle from the group and its flying experience. The stopping criteria for this algorithm would either be a good value for fitness or the maximum iteration number. In the end, either the optimal or the near optimal solution would be obtained.

There have been two versions of the PSO, which are the original continuous PSO and a Binary PSO (BPSO) bbothof which both have been applied in feature selection [14]. Normally, if a continuous algorithm in the PSO has been applied to the problems the search space dimensionality would be n and the total available features within this dataset. Every particle within the sward would be encoded with a vector that makes use of the real numbers n. the particle i and its position that is in the d-th dimension, $x_{id}$, would normally be within the interval [0, 1]. For determining if the feature would get chosen or not, the threshold $0 < \theta < 1$ would be required for comparing them with the real numbers. In case the $x_{id} > \theta$, then its corresponding feature d is chosen and if not abandoned. While making use of the BPSO in solving the problems of feature selection, the particle representation would be the n-bit binary string. The particle and its position would be Boolean, wherein "1" indicates a feature to be chosen and "0" indicates otherwise.

The PSO members keep to one group and do not fly away if they identify any space in the neighborhood. Therefore, it possesses a good ability of globally searching for and seeking a local space. This "local search space" would be a neighborhood of its gbest, and the if the particles get close to this the neighborhood gets smaller.

### 3.3. Proposed hybrid GSO feature selection

In case of a GSO, the members ensure that the search space would be by a producer and the Rangers would only walk around to identify the new clues of the prey. The scroungers, however, move towards the gbest, and if it is in a poor search space other members can tend to come there. The PSO searches for the best search space and then would converge. The GSO also converges at a very high speed. So the hybrid algorithm that is based upon the PSO model along with the GSO model is known as the Group Search Particle Swarm Optimization (GSPSO) [15].

In the GSPSO, this PSO model would be employed to identify the local search space that is good and its GSO model has been used for convergence of all the scroungers and for revising its local space through their rangers. After this, the members make use of the PSO model for finding a smaller but a better local search space for the next model of the GSO. The best point is identified in a step by step method with a mutual correction of this PSO model with the GSO model. The flow chart for this type of a hybrid feature selection of the GSO has been shown as per Figure 5.

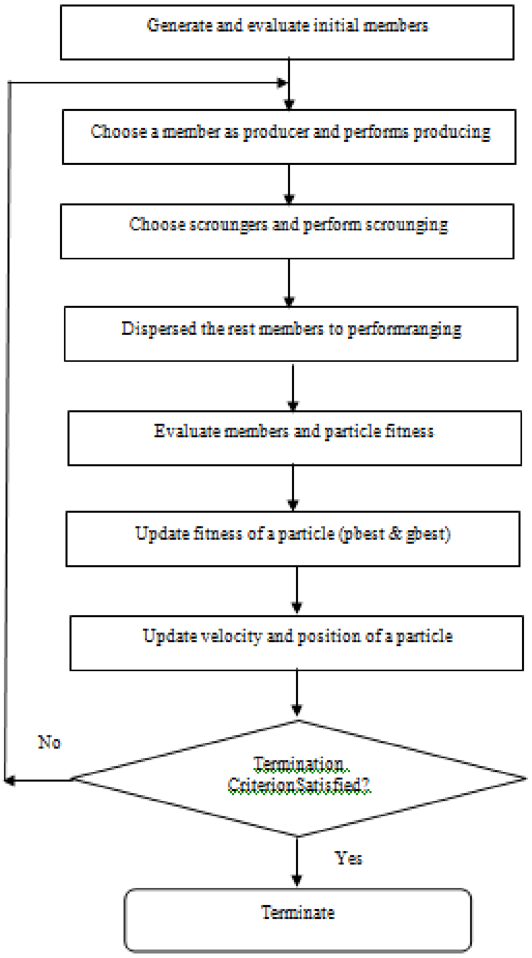


**Fig. 5:** Flowchart for Proposed Hybrid GSO Feature Selection.

The steps that are executed in the GSPSO are :
Step 1: Initializing all the particles in a random manner with the positions and the velocities with head angles, for calculating the particle and its fitness. After this, the one with best fitness value is chosen as the producer.
Step 2: Choosing one member to be the producer, performing producing and choosing scroungers to perform scrounging and the remaining members for performing ranging.
Step 3: Updating of the particles within the GSO model, and also weeding out certain members having poor fitness value within the rate of weed out.
Step 4: Updating of the particles within the PSO model, along with weeding out members having low fitness value within the rate of weed out.
Step 5: Calculating the particle and its fitness and choosing the producer and finally updating the members and their pbest.
Step 6: In case the terminal conditions have not met, then go to Step 2 and if not end the algorithm.

### 3.4. Fuzzy classifier

The Fuzzy logic is applied successfully for solving problems of classification in which the boundaries that are between the classes are not defined properly. There are some fuzzy classifiers that typically contain the interpretable rules which are if-then having some fuzzy antecedents with their class labels falling in their consequent part. These antecedents (the if-parts) of all these rules that divide the input space into various fuzzy regions using the fuzzy sets and the consequents (the then-parts) tend to describe its output classifier within the regions. Generally, the rules, as well as the membership functions, have been formed based on the experience of the experts. The variables being on an increase makes the possible rules to also increase exponentially thus making it challenging for the experts to be able to define a rule set that is complete and also for a good performance [16].

### 3.5. Multi-layer perceptron neural network (MLPNN) classifier

A Multi-Layer Perceptron Neural Network (MLPNN) has been the model that is most commonly used in the applications of the NN that make use of the algorithm of training [17]. A variant of the MLP would be the original Perceptron model that had been proposed in 1950 by Rosenblatt. This has either one or more such hidden layers that are between the input as well as the output layers where the neurons have been organized within these layers with their connections that are directed from the lower to the upper layers. These neurons and their number within their input layer would be equal to the actual number of the measurement for the problem of patterns and the number of neurons in that of the output layer would be equal to the class number. For the purpose of choosing the actual layer number with the neurons in every layer and also their connections, the situation is called the architecture problem that has the objective of optimizing it to a well-suited network having good generalization and sufficient parameters. The learning made for MLP is the adaptation of the connections and their weights for obtaining a marginal difference among the output of the network and the desired output and for this reason, in literature, certain algorithms like the ant colony optimization are used. The one commonly used to be however known as the BP that is based upon the descent gradient techniques. The parameters used are:
Number of input neurons:72
Number of hidden layers:4
Number of neurons in hidden layer:50
Number of output neurons:09
BP parameters:learning rate:0.01, Momentum : 0.1

## 4. Results and discussion

Nine species (Bamboo, Chinese horse chestnut, true indigo, maple, castor aralia, Chinese cinnamon, cheesewood, Don deodar, Ginkgo) with 20 samples are considered for experiments. The algorithms were run using Matlab and Weka softwares. The features extracted were used to train the classification algorithms. Mat lab was used. The features were classified using fuzzy classifier and MLPNN KNN and NB. Equation (3) to (5) shows the formula to measure classification accuracy, precision and recall respectively.

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{3}$$

$$Precision = \frac{T_p}{T_p + F_p} \tag{4}$$

$$Recall = \frac{T_p}{T_p + T_n} \tag{5}$$

Where $T_p$ is the True Positive, $T_n$ is the True Negative, $F_p$ is the False Positive and $F_n$ is the False Negative.
Tables 1 to 4 and figures2 to 5 show the classification accuracy, precision, recall and F measure respectively. Table 5 shows the result comparison table for classification accuracy.

**Table 1:** Classification Accuracy for Hybrid GSO Feature Selection

| | Without GSO FS | Chi Square based FS | MRMR based FS | GSO based FS | Hybrid GSO based FS |
|---|---|---|---|---|---|
| Fuzzy Classi- | 0.7444 | 0.7889 | 0.8167 | 0.8444 | 0.8883 |

| | | | | | |
|---|---|---|---|---|---|
| fier | | | | | |
| MLPNN | 0.7722 | 0.8278 | 0.8556 | 0.9056 | 0.9278 |
| KNN | 0.7111 | 0.7167 | 0.7222 | 0.7389 | 0.7537 |
| NB | 0.7222 | 0.7278 | 0.7389 | 0.7556 | 0.7714 |

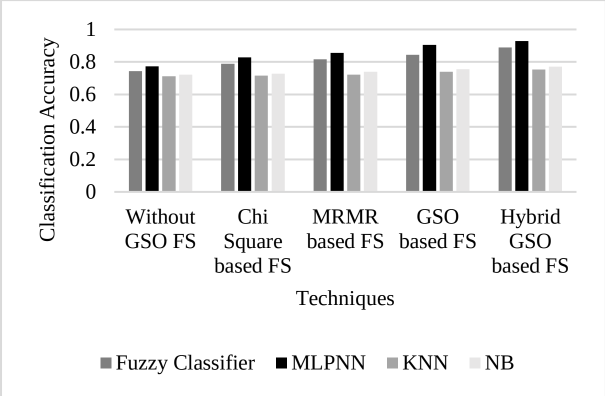


**Fig. 1:** Classification Accuracy for Hybrid GSO Feature Selection.

From the figure 2, it can be observed that the hybrid GSO based feature selection has higher classification accuracy by 17.63%, by 11.85%, by 8.39% & 5.07% for without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for fuzzy classifier. The hybrid GSO based feature selection has higher classification accuracy by 18.31%, by 11.39%, by 8.09% & 2.42% for without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for MLPNN. The hybrid GSO based feature selection has higher classification accuracy by 5.81%, by 5.03%, by 4.26% & 1.98% for without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for KNN. Similarly it can be observed that the hybrid GSO based feature selection has higher classification accuracy by 6.58%, by 5.81%, by 4.3% & 2.06% for without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for NB.

**Table 2:** Precision for Hybrid GSO Feature Selection

| | Without GSO FS | Chi Square based FS | MRMR based FS | GSO based FS | Hybrid GSO based FS |
|---|---|---|---|---|---|
| Fuzzy Classifier | 0.7434 | 0.794344 | 0.8195 | 0.844 | 0.889 |
| MLPNN | 0.7709 | 0.830511 | 0.8568 | 0.9072 | 0.928 |
| KNN | 0.723313 | 0.725717 | 0.8235 | 0.748 | 0.75 |
| NB | 0.7344 | 0.7370 | 0.7475 | 0.761 | 0.77 |

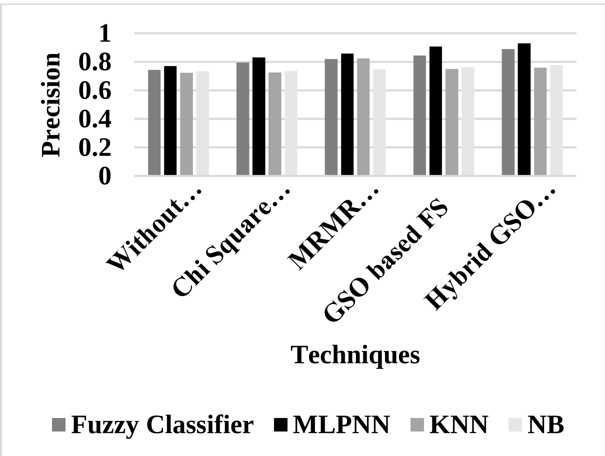


**Fig. 2:** Precision for Hybrid GSO Feature Selection.

From the figure 3, it can be observed that the hybrid GSO based feature selection has higher precision by 17.84%, by 11.25%, by 8.13% & 5.19% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for Fuzzy classifier. The hybrid GSO based feature selection has higher precision by 18.57%, by 11.17%, by 8.06% & 2.35% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for MLPNN. The hybrid GSO based feature selection has higher precision by 4.73%, by 4.4%, by 8.23% & 1.25% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for KNN. Similarly it can be observed that the hybrid GSO based feature selection has higher precision by 5.6%, by 5.25%, by 3.83% & 1.92% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for NB.

**Table 3:** Recall for Hybrid GSO Feature Selection

| | Without GSO FS | Chi Square based FS | MRMR based FS | GSO based FS | Hybrid GSO based FS |
|---|---|---|---|---|---|
| Fuzzy Classifier | 0.7444 | 0.7888 | 0.8166 | 0.8444 | 0.888 |
| MLPNN | 0.7722 | 0.8277 | 0.85555 | 0.9 | 0.9278 |
| KNN | 0.711111 | 0.71666 | 0.7 | 0.738889 | 0.7566 |
| NB | 0.7222 | 0.727 | 0.7388 | 0.7555 | 0.775 |

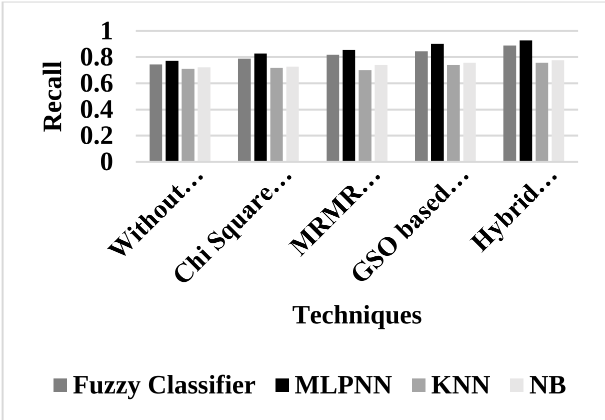


**Fig. 3:** Recall for Hybrid GSO Feature Selection.

From the figure 4, it can be observed that the hybrid GSO based feature selection has higher recall by 17.7%, by 11.9%, by 8.44% & 5.1% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for Fuzzy classifier. The hybrid GSO based feature selection has higher recall by 18.31%, by 11.4%, by 8.1% & 3.04% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for MLPNN. The hybrid GSO based feature selection has higher recall by 6.19%, by 5.42%, by 7.77% & 2.36% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for KNN. Similarly it can be observed that the hybrid GSO based feature selection has higher recall by 7.1%, by 6.33%, by 4.82% & 2.59% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for NB.

**Table 4:** F Measure for Hybrid GSO Feature Selection

| | Without GSO FS | Chi Square based FS | MRMR based FS | GSO based FS | Hybrid GSO based FS |
|---|---|---|---|---|---|
| Fuzzy Classifier | 0.741 | 0.787 | 0.816 | 0.843 | 0.887 |
| MLPNN | 0.769 | 0.827 | 0.855 | 0.902 | 0.928 |
| KNN | 0.711 | 0.718 | 0.756 | 0.737 | 0.757 |
| NB | 0.721 | 0.728 | 0.739 | 0.756 | 0.776 |

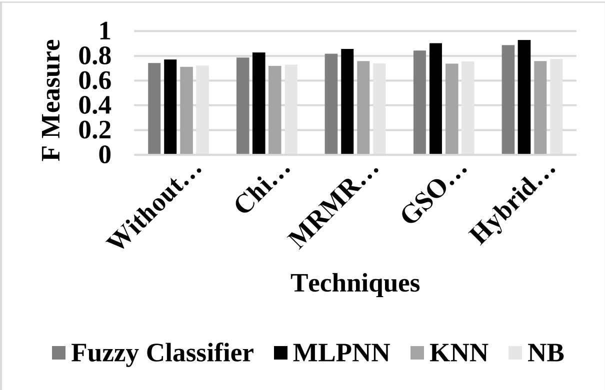


**Fig. 4:** F Measure for Hybrid GSO Feature Selection.

From figure 5, it can be observed that the hybrid GSO based feature selection has higher F Measure by 18.01%, by 11.99%, by 8.33% & 5.15% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for Fuzzy classifier. The hybrid GSO based feature selection has higher F Measure by 18.65%, by 11.44%, by 8.12% & 2.75% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for MLPNN. The hybrid GSO based feature selection has higher f measure by 6.29%, by 5.34%, by 0.09% & 2.68% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for KNN. Similarly it can be observed that the hybrid GSO based feature selection has higher f measure by 7.29%, by 6.31%, by 4.78% & 2.6% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for NB.

**Table 5:** Results Comparison for Classification Accuracy

| | Muthevi& Ravi [18] | Chaki et al [19] | Proposed Hybrid GSO Feature Selection |
|---|---|---|---|
| Classification Accuracy | 84.78% | 87.1% | 92.88% |

Table 5 shows that the classification accuracy of proposed hybrid GSO Feature Selection performs better than Muthevi& Ravi (2017) Babu [18] and Chaki et al [19] respectively.

## 5. Conclusion

The plants are found to be a very critical part of our ecosystem. To identify and classify them has been an interesting matter for laymen and botanists. The feature selection is perhaps the biggest tasks in the problems of classification, and most of them are partially or sometimes even completely redundant or irrelevant. For this work, an optimal and deterministic feature subset has been chosen using a technique of a hybrid GSO. This has been inspired by the social search behaviour of the animals the global performance of which has been now proved to be very competitive. In case of the GSPSO, any PSO model can be used for identifying one good search space where a point of global optimization has been contained having a very high degree of probability. For this, the GSO is used to make a search within its local search space and rangers used for revising the space simultaneously. Results show that the hybrid GSO based feature selection has higher classification accuracy by 17.63%, by 11.85%, by 8.39% & 5.07% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for fuzzy classifier. The hybrid GSO based feature selection has higher classification accuracy by 18.31%, by 11.39%, by 8.09% & 2.42% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for MLPNN. The hybrid GSO based feature selection has higher classification accuracy by 5.81%, by 5.03%, by 4.26% & 1.98% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for KNN. Similarly it can be observed that the hybrid GSO based feature selection has higher classification accuracy by 6.58%, by 5.81%, by 4.3% & 2.06% without GSO feature selection, Chi Square based FS, MRMR based FS and GSO based FS respectively for NB.

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