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Plant species identification using leaf biometrics and swarm optimization: A hybrid PSO, GWO, SVM model

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Abstract. The classification of plants species is a crucial process in some agricultural-based industries. However, different plant species share a very close relationship to human beings. This paper proposes a plant identification model based on leaf biometrics (shape, texture and color) hybrid with two most recent swarm optimization algorithms. For which, particle Swarm Optimization (PSO) is adopted as a pre-processing phase for leaf image segmentation. While, Grey Wolf Optimizer (GWO) is obtained to reduce the dimension of the leaf texture descriptors. Finally, the dual coordinate descent L2-SVM classifier is used to classify the different plant species. The proposed model aims to achieve high identification accuracy using less leaf's descriptors. Several experiments on Flavia dataset and swedish dataset are conducted. The experimental analysis showed that, the proposed model yields to improve the identification rate up to 98.9% and 93.3% for both Flavia and Swedish dataset respectively, which are the improved values over the literature.

Keywords: Plant identification, bio-inspired optimization, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), support vector machine (SVM)

1. Introduction

Plants play an essential role in conserving the earth's ecology and play a major one in medical science. Thus, the research of plant categorization is needed to identify the classes and families of the plants. In general, plant identification is based on the observation of various plant's morphological characteristics such as the structure of flowers, bark,roots, fruits or leaves [1,2].

Plant leaves play a paramount role in plant classification due to its easiness to access, carry and process. For this reasons, plant species identification systems based on plant leaves have been by far the most reported in the literature [3–7].

However, the challenges in automatic plant identification through leaves images arise from the fact that leaves taxonomic have large variability in color and texture within the same species and a very fine differences between the various species. Therefor, interest for the visual classification of plant species have grown recently [8,9].

Several researchers have made an attempt to develop efficient and robust plant identification system by exploiting different image processing techniques and pattern recognition. Kadir et al. presented a plant identification system that integrates leaves shape, color, and textures features. The probabilistic neural network was employed for the classification of plant leaves. Color and lacunary based texture features were taken for consideration to offer better performance. The scheme was tested on the Flavia dataset to perform accuracy of 93.75% [10].

Lee and Hong presented a leaf recognition system using the leaf major main vein and the shape for the classification of plant. The system employs the frequency domain data by using Fast Fourier Transform

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(FFT) methods with distance between contour and centroid on the detected leaf image. For which, 21 leaf features were extracted ten features using FFT magnitude, four basic geometric features, five vein features, and convex hull feature. Their system provided an average recognition rate of 97.19% on the Flavia dataset [11].

Sainin and Alfred presented a leaf plant identification system, where they propose a modified nearest neighbour method called NNDM for leaf classification based on unsupervised and supervised distance matrix. For which, the Euclidean distance method coupled with a distance loss function is used to create the distance matrix. Their system shows classification accuracy of 92.6% on the swedish dataset [12].

Aakif and Khan proposed an algorithm for plant identification based on three distinct stages: preprocessing, feature extraction and artificial neural network (ANN) classification. Different morphological features, Fourier descriptors and a proposed shape-defining feature, are extracted. To verify the effectiveness of their algorithm, it has been tested on Flavia dataset; where the results reported 96% classification accuracy [13].

Nature is consider to be the best teacher and its capabilities are extremely enormous, that researchers are trying to mimic nature designs in technology [14]. Majority of bio-inspired methods are based on some characteristics of biological system; for which, a special class of bio-inspired methods have been developed by drawing inspiration from swarm intelligence behavior.

Thus, in the literature, several works related to plant identification based on bio-inspired methods can be found. Ghasab et al. employed the ant colony optimization (ACO) as a feature decision-making algorithm. The ACO algorithm is used to investigate a set of feasible feature such as shape, texture and color for the recognition of individual species. The selected features are used by support vector machine (SVM) to classify the different species. The results of the ACO-based approach achieved an average accuracy of 95.53%.

Eid in [7] proposed a leaf identification model, which adopts the particle swarm optimization (PSO) for leaf images segmentation. The HOG features vectors are extracted from the PSO-segmented image. Then, two pre-processing phase were consider information gain (IG) as feature selection and discritization. The proposed model was evaluated on the Flavia dataset. Experiments are conducted on different classifiers; where, results reported an improvement of the identification accuracy.

It can be observed that many methods have been proposed for plant species identification based on one or two of the leaf biometrics; shape, texture or color; but, only few methods have been proposed on combining shape, texture and color features. However for bringing up such features combination; a long-time training and fully established financial resources are needed.

This motivates to develop an accurate, fast, and efficient model for an automatic identification of wide range of plant species. In the present study, we propose an automated identification model using leaf biometrics (color, texture and shape) hybrid with two swarm optimization algorithms: Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). The proposed plant identification model aims to achieve high classification accuracy using less leaf's descriptors as training data.

This paper presents three major contributions for leaf plant identification:

1. PSO is adopted as a pre-processing phase to segment the the RGB leaf image, in order to enhance the quality of the shape descriptors extracted from the segmented image.
2. GWO is obtained as a post-processing to reduce the dimension of the texture descriptors vector, to speed up the classification time.
3. We demonstrate that combining different leaf biometrics ;shape, texture and color descriptors; with the dual coordinate descent L2-SVM classifier leads to a performance improvement up to 98.9%.

The rest of this paper is organized as follows: Section 2 gives an overview of bio-Inspired Optimization, where Sections 2.1 and 2.2 give the mathematical concepts of Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). While, Section 3 describes the different modules of the proposed plant identification model. Section 4 presents two leaf plant dataset; the Flavia and swedish dataset. Experimentation and discussion occupy the remainder of the paper in Section 5. Finally, conclusions are draw out in Section 6.

2. Bio-inspired swarm optimization

Optimization literally means finding the best possible solution. The nature of different optimization algorithms can be divided into two main categories: deterministic and stochastic [15]. Stochastic algorithms are further classified into: heuristic and meta-heuristic method [16]. The former methods discover the best solution based on trial and error. While, the later methods are based on the iterative improvement of either a population of solutions (Evolutionary algorithms) or trajectory solution (Tabu Search). Meta-heuristic methods employ local search and randomization to solve a given optimization problem [17].

To solve real problems, optimization require enormous computational efforts, which tend to fail as the problem size increases. This motivate for employing bio-inspired stochastic optimization algorithms as computationally efficient. The majority of bio-inspired algorithms have been developed by drawing their inspiration from swarm intelligence.

Swarm intelligence refers to the implementation of collective groups of agents that simulate the behavior of real world swarm. For which, the collection of agents interact locally with each other as well as with their environment; whereby, they follow very simple rules without any centralized manipulation of the random local behavior. The main reasons of the growing popularity of swarm intelligence based algorithms are the flexibility and versatility offered by them. As a result, the adaptability and self-learning capability of the swarm intelligence algorithms attracted several application areas.

2.1. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a global optimization technique developed by Kennedy and Eberhart in 1995 [18]. PSO is inspired by the social behavior of bird flocking searching for food. For which, the swarm is initialized with a random population of particles; where each particle of the swarm represents a candidate solution in the search space. In order to find the best solution, each particle changes its searching direction based on two positions: The individual best previous position (pbest), represented by $P_i = (p_{i1}, p_{i2}, ..., p_{id})$; and the global best position of the swarm (gbest) $G_i = (g_{i1}, g_{i2}, ..., g_{id})$ [19].

For a d-dimensional space, the position of the particle i at iteration t can be represented as:

$$x_i^t = x_{i1}^t, x_{i2}^t, ..., x_{id}^t \tag{1}$$

And its velocity is given by:

$$v_i^t = v_{i1}^t, v_{i2}^t, ..., v_{id}^t \tag{2}$$

The particle updates its velocity according to:

$$\begin{aligned} v_{id}^{t+1} = w \times v_{id}^t + c_1 \times r_1(p_{id}^t - x_{id}^t) \\ + c_2 \times r_2(g_{id}^t - x_{id}^t) \end{aligned} \tag{3}$$

Where, w is the inertia weight and $r1$ and $r2$ are random numbers distributed in the range $[0, 1]$. The cognition learning factor and the social learning factor are represent by the positive constant c_1 and c_2 respectively. p_{id}^t denotes the best previous position found so far for the i^{th} particle and g_{id}^t denotes the global best position so far [20].

While, each particle updates its position in the swarm based on the following equation:

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \tag{4}$$

2.2. Grey Wolf Optimizer (GWO)

Grey Wolf Optimizer (GWO) is a meta-heuristic optimization algorithm; inspired by grey wolves swarm [21]. The GWO mimics the social leadership hierarchy and hunting mechanism of grey wolves swarms in nature. The population in GWO algorithm is divided into four types: alpha α, beta β, delta δ and omega ω. For which, the formal three wolves types guide the final wolves type toward the optimum areas in the search space.

During optimization, the wolves update their positions by:

$$\overrightarrow{X}(t+1) = \overrightarrow{X_p}(t) - \overrightarrow{A}.\overrightarrow{D} \tag{5}$$

$$\overrightarrow{D} = |\overrightarrow{C}.\overrightarrow{X_p}(t) - \overrightarrow{X}(t)| \tag{6}$$

where, t indicates the current iteration, $\overrightarrow{A}$ and $\overrightarrow{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is the position vector of the prey, and $\overrightarrow{X}$ is the position vector of a grey wolf.

The coefficient vectors $\overrightarrow{A}$ and $\overrightarrow{C}$ are calculated by:

$$\overrightarrow{A} = 2\overrightarrow{a}.\overrightarrow{r_1}(t) - \overrightarrow{a} \tag{7}$$

$$\overrightarrow{C} = 2\overrightarrow{r_2} \tag{8}$$

where, a decreased linearly from 2 to 0, and r_1, r_2 are random vectors in the range $[0, 1]$.

During GW optimization, α, β and δ are assumed to be the first three best solutions respectively. While, ω update their positions with respect to α, β and δ, as follows:

$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{9}$$

where,

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.(\overrightarrow{D_\alpha}) \tag{10}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.(\overrightarrow{D_\beta}) \tag{11}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.(\overrightarrow{D_\delta}) \tag{12}$$

and

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \overrightarrow{X}| \tag{13}$$

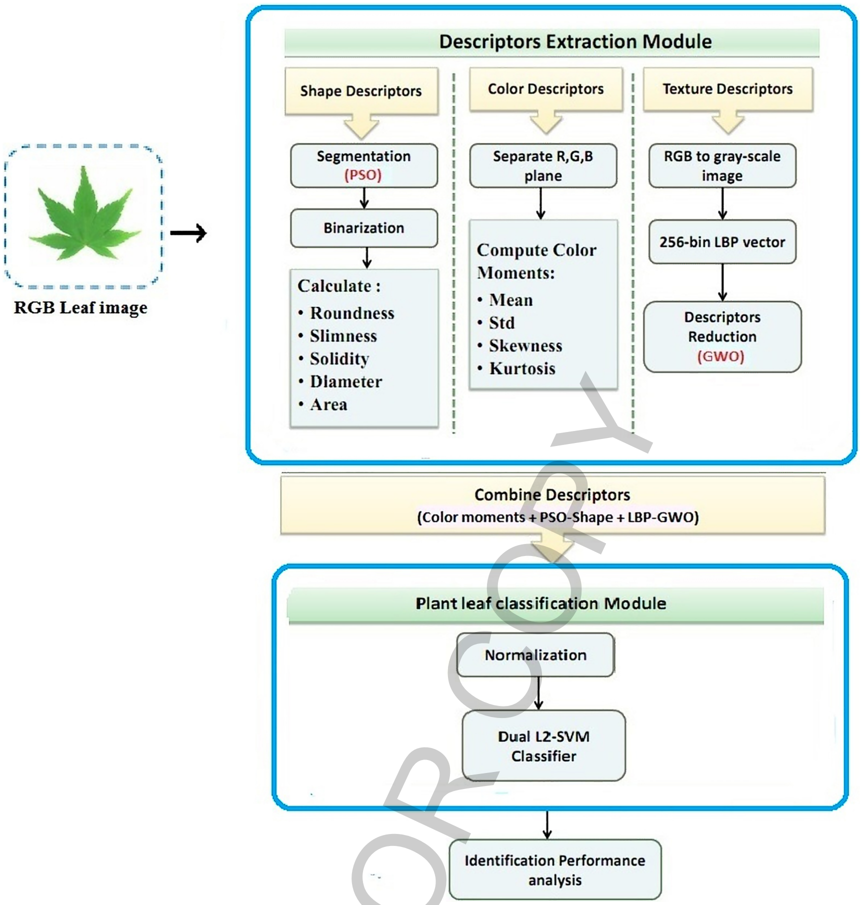

Fig. 1. Proposed plant species identification model.

$$\overrightarrow{D_\beta} = |\overrightarrow{C_2}.\overrightarrow{X_\beta} - \overrightarrow{X}| \quad (14)$$

$$\overrightarrow{D_\delta} = |\overrightarrow{C_3}.\overrightarrow{X_\delta} - \overrightarrow{X}| \quad (15)$$

GW optimization algorithm is able to provide competitive results compared to other meta-heuristics algorithms, as reported in [21]; and is effective in solving challenging real-life problems.

3. Proposed plant species identification model

The architecture of the proposed plant species identification model is shown in Fig. 1. For which, it combines three leaf biometrics descriptors (color, shape and texture) hybrid with two optimization methods: PSO and GWO.

3.1. Shape descriptors extraction module

In the propose model; PSO-segmentation is performed on the RGB leaf image as a pre-processing phase; then, different leaf shape descriptors are obtained from the PSO-segmented image. Particle Swarm Optimization (PSO) is used as optimal thresholding segmentation of the leaf image. For which, a number of particles collectively move in the search space (leaf image pixels) until they reach the global optimum. The global optimum is obtained by maximizing the between-class variance of the distribution of the leaf image intensity levels.

For n-level PSO thresholding, the problem is reduced to an optimization problem to search for the thresholds (t_j^c) that maximizes the fitness function of each R, G, B component of the leaf image. Thus; the fitness function can be defined as the between-class variance σ^{C^2} of the leaf image intensity levels:

$$\varphi^C = max\, \sigma^{C^2}(t_j^C); \quad j = 1, ..., n-1 \quad (16)$$

where, C is the component of the image $C = \{R, G, B\}$

Wherefor, for each leaf image, the PSO particles are evaluated for the fitness function given by Eq. (16).

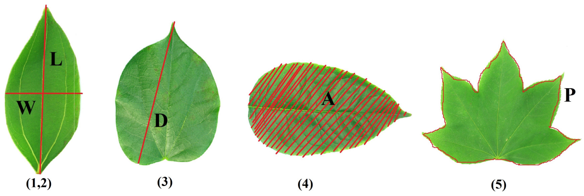

Fig. 2. Leaf shape geometric parameters.

At the initial iteration, the particles' velocities are set to zero and their position are randomly set within the boundaries of the leaf image intensity levels L. Thus, for 8-bit images frames the particles positions will be deployed between 0 and 255.

To extract the leaf shape features; five basic geometric parameters are considered, Fig. 2:

1. Physiological Length (L): Leaf length or major axis refers to the length of the line connecting the two terminal points of the main vein in the leaf.
2. Physiological Width (W): Leaf width or minor axis refers to the length of the longest line segment perpendicular to the physiological leaf length.
3. Diameter (D): Leaf diameter is the longest distance between any two points on the closed contour of the leaf.
4. Area (A): The leaf area is the number of pixels in the leaf region.
5. Perimeter (P): perimeter is the number of pixels comprising the leaf contour.

For the proposed model; a set of five morphological shape descriptors are computed from the PSO-segmented leaf images; the mathematical formulas of the shape descriptors measures are summarized in Table 1.

From Table 1; Roundness measures how a leaf shape is similar to a circle, where a circle's roundness is equal to 1. While, Slimness is the ratio of the length to the width of the leaf. Solidity describes the extent to which the leaf shape is convex or concaves; thus, it expresses the degree of splitting depth in the leaf image.

3.2. Color descriptors extraction module

To generate the color descriptors vector; information about the color distribution of the leaf image is extracted using low order moments. Initially, the leaf image color space is separated to three color planes Red, Green and Blue. Then, for each color plane the four color moments; Mean, Standard deviation, Skewness and Kurtosis; are derived [22]. Finally, the averages of all the color moments of the three color planes are calculated to form a color descriptors vector. Let P_{ij} be the i-th color channel at the j-th leaf image pixel. Then, the four color moments can be defined as summarized in Table 2.

Table 1
Measures and formula of the shape descriptors

Shape measure	Formula
Roundness	$Roundness = \frac{4\pi A}{P^2}$
Aspect ratio (Slimness)	$Slimness = \frac{L}{W}$
Solidity	$Solidity = \frac{A}{H}$
Diameter	D
Area	A

H is the convex hull area of the leaf.

Table 2
Measures and formula of the color descriptors

Color moment	Formula
Mean	$\mu = \frac{1}{N}\sum P_{ij}$
Standard Deviation	$\sigma = \sqrt{\frac{1}{N}\sum(\mu - P_{ij})^2}$
Skewness	$Skew = \frac{1}{N}\frac{\sum(P_{ij}-\mu)^3}{\sigma^3}$
Kurtosis	$Kurt = \frac{1}{N}\frac{\sum(P_{ij}-\mu)^4}{\sigma^4} - 3$

The color moments are calculated directly from the original leaf image values. As a result, they do not mull over the relationships with neighborhood pixel.

3.3. Texture descriptors extraction module

In order to create the leaf texture descriptors; the veins distribution of the leaf image is analyzed. For which, the RGB leaf images are converted to grey scale images to capture the spatial distribution of the grey pixel values. Then, local binary pattern (LBP) is considered to extract the leaf texture descriptors vector.

For the proposed identification model; 8-neighbours and a unit radius are used for calculating the local binary pattern of the leaf image. Then, a 256-bin LBP histogram is computed; to form the leaf texture descriptors vector. Finally, the 256-dimensional LBP descriptors vector is reduced by the GWO. A binary grey wolf optimization (bGWO) method proposed by Emary et al. [23] is consider for the dimensionality reduction. bGWO search the feature space for the optimal feature combination; where, the sigmoidal function is used to squash the grey wolf updated position as given in Eq. (17), then these values are stochastically threshold to find the updated binary grey wolf position.

$$x_d^{t+1} = \begin{cases} 1, \text{ if sigmoid}\left(\frac{X_1+X_2+X_3}{3}\right) \geqslant \text{rand}. \\ 0, \text{ otherwise.} \end{cases} \quad (17)$$

where rand is a random number drawn from the uniform distribution $[0, 1]$.

3.4. Combine leaf biometrics descriptors

At this stage, a final descriptors vector characterizing shape, color and texture of a leaf image is constructed. The descriptors vector is constructed based on the combination of the 5-dimensional PSO-shape descriptors + the 4-dimensional color descriptors + the LBP-GWO redacted dimensional texture descriptors. For which, the final descriptors vectors are provided as an input for the plant species classification stage.

3.5. Plant species classification: Dual coordinate descent L2-SVM

Support vector machine (SVM) is a useful tool for data classification proposed by Boser et al. [24]; for which, it is based on the Statistical Learning Theory (SLT) [25].

Given N training data pairs $\{(x_1, y_1), (x_2, y_2), (x_3, y_3), \ldots, (x_N, y_N)\}$, where $x_i \in R^d$ and $y_i \in \{+1, -1\}$. For a hyper plane defined by $(\mathbf{w}, b)$, where $\mathbf{w}$ is a weight vector and b is a bias. A new instance x can be classify by the following function:

$$f(x) = \mathbf{w}^T.x + b \quad (18)$$

Learning the linear SVM classifier can be formulated as an optimization problem:

$$\mathit{min}\ f(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T.\mathbf{w} + C\sum_{i=1}^{N}\xi(\mathbf{w}; x_i, y_i) \quad (19)$$

where $\xi(\mathbf{w}; x_i, y_i)$ is a loss function, and $C \in R$ is a penalty parameter

For L2-SVM the sum of squared losses function is used:

$$\mathit{min}\ f(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T.\mathbf{w} + C\sum_{i=1}^{N} \mathit{max}(0, 1 - y_i f(x))^2 \quad (20)$$

The quadratic optimization problem given by Eq. (20) is the primal form of L2-SVM. However, in practice one often has an easier access of values per instance; by solving the dual optimization problem:

$$\mathit{min}\ f(\alpha) = \frac{1}{2}\alpha^T.\overline{Q}\alpha + e^T\alpha \quad (21)$$

subject to $0 \leqslant \alpha_i \leqslant U, \forall i$ where $U = \infty$ and $\overline{Q} = Q + D$, D is the diagonal matrix and $Q_{ij} = y_i y_j x_i^T x_j$.

Hsieh et al. proposed using coordinate descent methods for solving the dual L2-SVM [26]. Coordinate descent is a popular optimization technique; for which, one variable at a time is updated by minimizing a single-variable sub-problem.

For the plant species identification purpose, a dual coordinate descent L2-SVM classification is used. Whereby, the combined descriptors vectors are normalization as a precaution that descriptors with large values have a stronger influence on the cost function of the classifier. For which, the descriptors vectors are normalized to fall within the range $[-1, 1]$.

Finally, the normalized descriptors vectors are used to train the dual coordinate descent L2-SVM classifier. Then, the learned classifier is used to identify the different plant species. Algorithm 1 shows the steps of training a dual coordinate descent L2-SVM classifier for plant species identification.

Algorithm 1 Training the dual coordinate descent L2-SVM classifier

Input:
Normalized extracted leaves descriptors vectors $V = (v_1, v_2, ..., v_i)$.
Leaves classes labels $Y = (y_1, y_2, ..., y_i)$
N number of extracted descriptors.
Output:
Optimized dual coordinate descent l2-SVM classifier.

for all (v_i, y_i) **do**
  while α_i and the corresponding $w = \Sigma_i y_i \alpha_i v_i$ not optimal **do**
    for i=1,...,N **do**
      $G = y_i w^T v_i - 1 + D_{ii}\alpha_i$
      $PG = \begin{cases} \mathit{min}(G, 0), & \text{if } \alpha_i = 0. \\ \mathit{max}(G, 0), & \text{if } \alpha_i = U. \\ G, & \text{if } 0 < \alpha_i < U. \end{cases}$
      if $|PG \neq 0|$ **then**
        $\overline{\alpha}_i \leftarrow \alpha_i$
        $\alpha_i \leftarrow \mathit{min}(\mathit{max}(\alpha_i - G/\overline{Q}_{ii}, 0), U)$
        $w \leftarrow w + (\alpha_i - \overline{\alpha}_i)y_i v_i$
      end if
    end for
  end while
end for
Return only the support vectors $\alpha_i > 0$

Fig. 3. Samples from the swedish dataset.

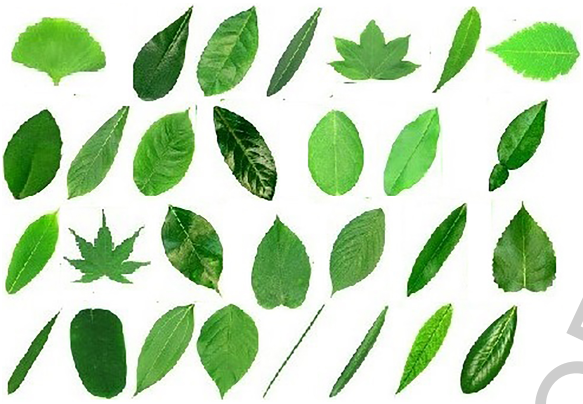

Fig. 4. Samples from the Flavia dataset.

4. Plant leaves datasets

Two challenging leaf datasets from different geographical areas were considered; for the experimentation evaluations purpose.

4.1. Swedish dataset

The Swedish dataset was introduced by Söderkvist [27] for research purposes. It contains 15 different scanned species images of leaves; with 75 images per species. Figure 3 shows sample images of the Swedish dataset.

4.2. Flavia dataset

The Flavia dataset contains 1907 RGB scans images of leaves. It is composed of 32 species; where, each species has 40 to 77 sample leaves. The Flavia dataset was collected by Wu et al. [28]. Samples of the flavia dataset images are given in Fig. 4.

Table 3
Initial parameters setting for experiments

Algorithm	Parameter	Value
PSO	Cognitive constant C_1	0.8
	Social constant C_2	0.8
	Inertia constant w	1.2
	No of iterations	150
	Population size	100
GWO	No of iterations	70
	Population size	8
Dual L2-SVM	penalty parameter C	1
	tolerance of the termination criterion ϵ	0.001
	epsilon insensitive loss function	0.1

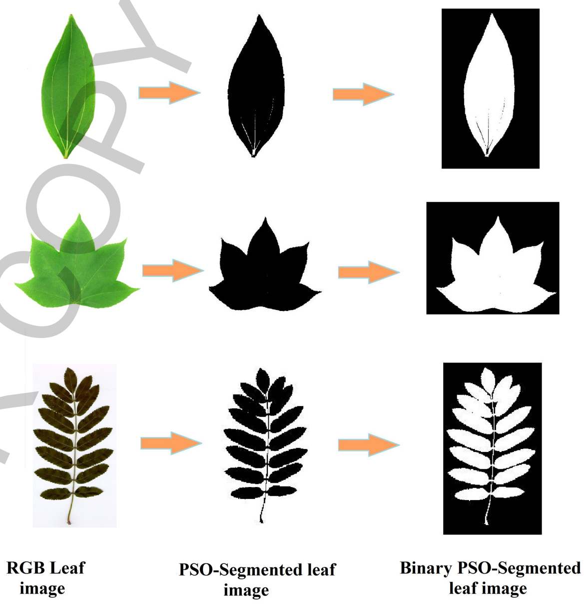

Fig. 5. Leaf images PSO-segmentation and binarization.

5. Experimental settings and analysis

The initial parameters settings of the swarm optimization algorithm PSO and GWO; and for the dual coordinate descent L2-SVM classifier are presented in Table 3.

5.1. Evaluation criteria

To evaluate the proposed hybrid plant identification model, three performance measures are used: (1) *Recall*, (2) *Precision* and (3) *Identification Accuracy* [29]. Recall and Precision are defined mathematically as:

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

$$Precision = \frac{TP}{TP + FP} \tag{23}$$

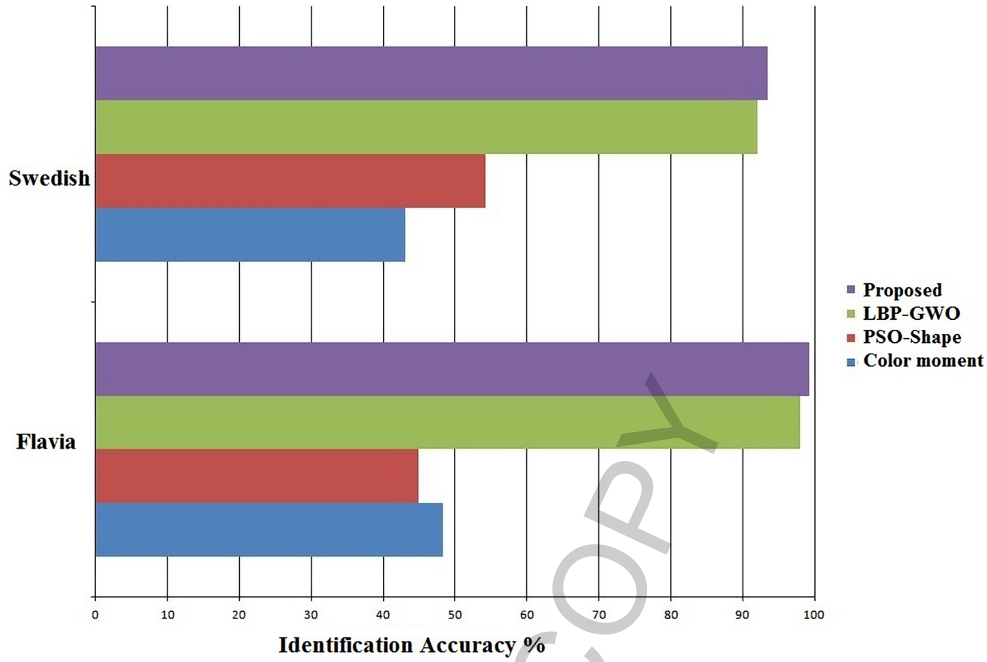

Fig. 6. Performance analysis of the proposed extracted leaf biometrics descriptors.

Table 4
Performance comparison of using GWO algorithm

Dataset	Method	Descriptors#	Accuracy	Time sec.
Flavia	LBP	256	98.0%	11.51
	LBP-GWO	167	98.1%	6.69
Swedish	LBP	256	90.2%	3.43
	LBP-GWO	178	92.0%	1.03

Table 5
Identification accuracy analysis of extracted leaf biometrics combination for Flavia dataset

Combined descriptors	Precision	Recall	Accuracy
Color moments + PSO-shape	62.4%	64.0%	60.7%
Color moments + LBP-GWO	98.8%	98.7%	98.7%
PSO-shape + LBP-GWO	98.7%	98.7%	98.7%
Proposed	99.0%	98.9%	98.9%

Table 6
Identification accuracy analysis of extracted leaf biometrics combination for Swedish dataset

Combined descriptors	Precision	Recall	Accuracy
Color moments + PSO-shape	75.6%	73.3%	71.2%
Color moments + LBP-GWO	92.6%	92.4%	92.4%
PSO-shape + LBP-GWO	92.6%	92.4%	92.4%
Proposed	93.5%	93.3%	93.3%

While, identification accuracy is the proportion of true results, either true positive or true negative. Thus, it measures the probability to correctly identify classes; and is computed by:

$$Identification\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

For which, True positives (TP) and True negatives (TN) refers to classifier correct prediction. While, False positives (FP) and False negatives (FN) correspond to the classifier incorrect prediction.

5.2. Results and analysis

PSO-segmentation is performed on the RGB leaf images of the Flavia and swedish dataset; then, the PSO-segmented images are binarized to extract the leaf shape descriptors vectors. Figure 5 illustrates samples from both Flavia and swedish dataset leaves images after PSO-segmentation and binarization.

The K-nearest neighbor (KNN) was used in the GWO dimension reduction phase. During the training phase, the KNN classification error rate is calculated using 10-fold cross-validation to evaluate the performance of each single feature subset; where, every wolf position represents one feature subset. For which, the training set is used to evaluate the KNN on the validation set throughout the optimization to guide the feature selection process. Then, the selected features are evaluated on the test set to obtain the final evaluation of the selected features.

Table 7
Comparison of identification accuracy on Flavia and Swedish datasets

Publications	Year	Dataset	Method	Features			Identification
				Shape	Texture	Color	accuracy %
Kadir et al. [10]	2011	Flavia	Fourier descriptors+ color moments+ lacunarity+ Probabilistic neural network classifier	✓	✓	✓	93.75
Lee and Hong [11]	2013	Flavia	Fast Fourier Transform (FFT)+ morphological features (4 basic geometric features, 5 vein features) and convex hull feature)	✓	✓	–	97.19
Aakif and Khan [13]	2015	Flavia	Geometrical calculation+ Fourier descriptors+ shape-defining feature (SDF)+ Artificial neural network classifier	✓	–	–	96.00
Hall et al. [30]	2015	Flavia	Hand-crafted features (HCF)+ Deep convolutional neural networks (ConvNet)	✓	–	–	97.30
Ghasab et al. [31]	2015	Flavia	Ant colony optimization (ACO) feature decision-making+ Support vector machine (SVM)	✓	✓	✓	95.53
Naresh and Nagendraswamy [32]	2016	Flavia	Modified LBP+ 1-Nearest Neighbor classification	–	✓	–	97.5
Chaki [33]	2017	Flavia	Shape Feature Selection Template (SFST)+ Neuro-fuzzy controller	✓	–	–	94.00
Eid and Darwish [34]	2017	Swedish	Color moments+ Gray Level Co-occurrence (GLC)+ Gray Level Run Length(GLRL)+	–	✓	✓	
			Naive bays classifier				84.00
			Random forest classifier				78.70
			J48 classifier				94.70
Eid and Darwish [34]	2017	Flavia	Color moments+ Gray Level Co-occurrence (GLC)+ Gray Level Run Length(GLRL)+	–	✓	✓	
			Naive bays classifier				76.40
			Random forest classifier				87.60
			J48 classifier				97.10
proposed method		Flavia	PSO-segmentation+ LBP-GWO+ l2-SVM classifier	✓	✓	✓	98.90
proposed method		Swedish	PSO-segmentation+ LBP-GWO+ l2-SVM classifier	✓	✓	✓	93.30

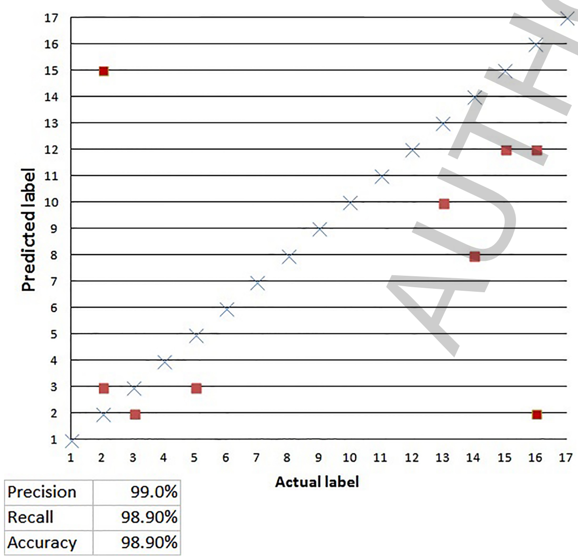

Fig. 7. Dual L2-SVM classification errors of Flavia dataset.

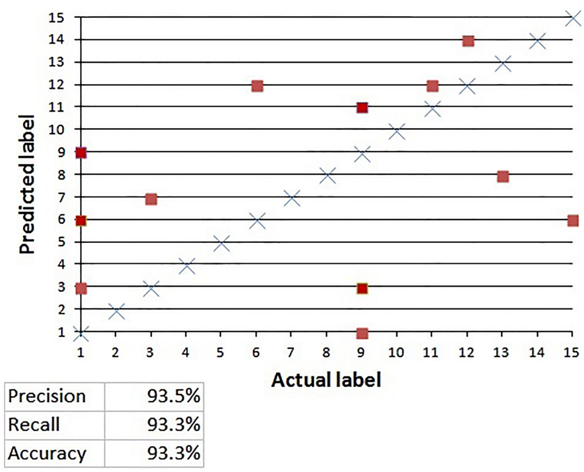

Fig. 8. Dual L2-SVM classification errors of swedish dataset.

To verify the validity of using GWO as a dimension reduction of the leaf's 256-LBP texture descriptors. We compare the performance of the full dimension LBP descriptors vectors with the redacted LBP-GWO descriptors vectors in term of identification accuracy rate and training time consuming, as given in Table 4.

In this study, the efficiency of the three extracted leaf biometrics descriptors vectors (PSO-Shape, color and

LBP-GWO) are evaluated. Performance of the dual L2-SVM accuracy are measured in term of 10-fold cross validation; applied on both Flavia and swedish dataset; as shown in Fig. 6.

Figure 6 illustrates that the proposed leaf biometrics combination gives the best identification accuracy.

In order to evaluate the efficiency of combining different leaf biometrics descriptors, all possible biometrics combinations are examined on both Flavia and swedish dataset, as shown in Table 5.

From Tables 5 and 6, it is observed that using the proposed combination of leaf biometrics descriptors gives the highest identification accuracy of 98.9% for the Flavia dataset and 93.3% for the swedish dataset.

Figures 7 and 8 show the dual coordinate descent L2-SVM classification errors; in term of 10-fold cross validation; for both Flavia and swedish dataset respectively.

Table 7 shows the comparison of different leaf plant identification methods on Flavia and swedish datasets along with the proposed model. As it can be seen from the table, the proposed model compared to all other generated the highest identification accuracy of 98.8%. This high performance of the identification accuracy is under consideration of combining three leaf features (shape, texture and color); hybrid with two swarm optimization algorithms: PSO for leaf segmentation and GWO for texture descriptors reduction.

6. Conclusion

Based on the analysis of previous plant identification models, plant's leaves are regarded as a useful plant organs for the identification of the various species. However, the challenges of developing leaf plant identification models lies in extracting leaves descriptors which achieve high identification accuracy; while taking less execution time. This paper proposed a plant identification model which aims to improve the classification accuracy of plant species using less numbers of descriptors as training data. The proposed identification model take into consideration three leaf biometrics: shape, texture and color. For which, its power lies through the use the leaf biometrics hybrid with two most recent swarm optimization algorithms: particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). To extract the leaf shape descriptors, PSO is adopted as a pre-processing phase for leaf image segmentation. While, the dimension of the leaf texture descriptors is reduced by GWO. Finally, the dual coordinate descent L2-SVM classifier is consider to classify the different plant species. Several experiments on two leaf plant datasets; Flavia dataset and swedish dataset; are conducted. The experimental results showed that, the proposed model yields to improve the identification rate up to 98.9% and 93.3% for both Flavia and Swedish dataset respectively.

References

[1] M.E. Nilsback and A. Zisserman, An automatic visual flora: Segmentation and classification of flower images, Ph.D. thesis, Oxford University, 2009.

[2] S. Fiel and R. Sablatnig, Automated identification of tree species from images of the bark, leaves and needles, in: *Proc. In. 16th Computer Vision Winter Workshop*, Mitterberg, Austria, 2011, pp. 1–6.

[3] X.F. Wang, D.S. Huang, J.X. Du, H. Xu and L. Heutte, Classification of plant leaf images with complicated background, *Applied Mathematics and Computation* **205**(2) (2008), 916–926.

[4] N. Valliammal and S.N. Geethalakshmi, Analysis of the classification techniques for plant identification through leaf recognition, *Int. J. of Data Mining Knowledge Engineering* **1**(5) (2009), 239–243.

[5] J.S. Cope, D.P.A. Corney, J.Y. Clark, P. Remagnino and P. Wilkin, Plant species identification using digital morphometrics: A review, *Expert Syst Appl* **39**(8) (2012), 7562–7573.

[6] T. Suk, J. Flusser and P. Novotny, Comparison of leaf recognition by moments and fourier descriptors, *Computer Analysis of Images and Patterns Lecture Notes in Computer Science* **8047** (2013), 221–228.

[7] H.F. Eid, Performance improvement of plant identification model based on pso segmentation, *Int. J Intelligent Systems and Applications* **8** (2016), 53–58.

[8] P.N. Belhumeur, D. Chen and S. Feiner, Searching the world's herbaria:a system for visual identification of plant species, In: *Computer Vision, ECCV , Part IV, LNCS* **5305** (2008), 116–129.

[9] Z. Wang, Y. Li, H. Zhu and T. Xu, Review of plant identification based on image processing, *Archives of Computational Methods in Engineering* **1** (2016), 1–18.

[10] A. Kadir, L.E. Nugroho and P. Santosa, Leaf classification using shape, color, and texture, *Int J. of Computer Trends & Technology* **1** (2011), 306–311.

[11] K.B. Lee and K.S. Hong, An implementation of leaf recognition system using leaf vein and shape, *Int. J. Bio-Sci. Bio-Technol* **5** (2013), 57–66.

[12] M. Sainin and R. Alfred, Nearest neighbour distance matrix classification, in: *Pro. In. 6th Conference on Advanced Data Mining and Applications: Part I*, Chongqing, China, Springer-Verlag, 2010, pp. 114–124.

[13] A. Aakif and M.F. Khan, Automatic classification of plants based on their leaves, *Biosystems Engineering* **139** (2015), 66–75.

[14] A.K. Kar, Bio inspired computing – a review of algorithms and scope of applications, *Expert Systems with Applications* **59** (2016), 20–32.

[15] X. Yang, Nature-inspired metaheuristic algorithms, Luniver Press, U.K., 2010.

[16] A.H. Gandomi, X. Yang, S. Talatahari and A.H. Alavi, Metaheuristic Algorithms in Modeling and Optimization, Metaheuristic Application in Structures and Infrastructures, 2013.
[17] S. Binitha and S.S. Sathya, A survey of bio inspired optimization algorithms, *International Journal of Soft Computing and Engineering (IJSCE)*, ISSN: 2.
[18] R. Eberhart and J. Kennedy, A new optimizer using particle swarm theory, in: *Proc. of the Sixth International Symposium on Micro Machine and Human Science*, Nagoya, Japan, 1995, pp. 39–43.
[19] G. Venter and J.S. Sobieski, Particle swarm optimization, *AIAA Journal* **41** (2003), 1583–1589.
[20] Y. Liu, G. Wang, H. Chen and H. Dong, An improved particle swarm optimization for feature selection, *Journal of Bionic Engineering* **8** (2011), 191–200.
[21] S. Mirjalili and A. Lewis, Grey wolf optimizer, *Advances in Engineering Software* **69** (2014), 46–61.
[22] A.H. Kulkarni, H.M. Rai, K.A. Jahagirdar and P.S. Upparamani, Leaf recognition technique for plant classification using rbpnn and zernike moments, *Int, J. of Advanced Research in Computer and Communication Engineering* **2**(1) (2013), 984–988.
[23] E. Emary, H.M. Zawbaam and A. Hassanien, Binary gray wolf optimization approaches for feature selection, *Neurocomputing* **172** (2016), 371–38.
[24] B.E. Boser, I. Guyon and V. Vapnik, A training algorithm for opti-mal margin classifiers, in: *Proceedings of the Fifth Annual Workshop on Computational Learning Theory*, ACM Press, 1992, pp. 144–152.
[25] V. Vapnik, Statistical learning theory, Wiley, New York, 1998.
[26] C. Hsieh, K. Chang, C. Lin, S.S. Keerthi and S. Sundararajan, A dual coordinate descent method for large-scale linear svm, in: *Proceedings of the Twenty Fifth International Conference on Machine Learning (ICML)*, 2008.
[27] O. Söderkvist, Computer vision classification of leaves from swedish trees, Master's thesis, Linköping University, 2001.
[28] E. Wu, F.X.Q.L. Wang and X. Chang, A leaf recognition algorithm for plant classification using probabilistic neural network, in: *The 7th IEEE International Symposium on Signal Processing and Information Technology, IEEE*, Cairo, Egypt, 2007, pp. 1–7.
[29] R.O. Duda, P.E. Hart and D.G. Stork, Pattern Classification, 2nd Edition, JohnWiley & Sons, USA, 2001.
[30] D. Hall, C. McCool, F. Dayoub, N. Sunderhauf and B. Upcroft, Evaluation of features for leaf classification in challenging conditions, in: *IEEE Winter Conference on Applications of Computer Vision*, 2015, pp. 797–804.
[31] M.A. Ghasab, S. Khamis, F. Mohammad and H.J. Fariman, Feature decision-making ant colony optimization system for an automated recognition of plant species, *Expert System Application* **42** (2015), 2361–2370.
[32] Y. Naresh and H. Nagendraswamy, Classification of medicinal plants: an approach using modified lbp with symbolic representation, *Neurocomputing* **173** (2016), 1789–1797.
[33] J. Chaki, Template based shape feature selection for plant leaf classification, *International Journal of Engineering and Technology (IJET)* (2017) DOI: 10.21817/ijet/2017/v9i3/1709030122.
[34] H.F. Eid and A. Darwish, Variant-order statistics based model for real-time plant species recognition, *International Journal of Information Technology and Computer Science* **9** (2017), 77–84.