Plant Leaf Disease Identification using Exponential Spider Monkey Optimization

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Abstract

Agriculture is one of the prime sources of economy and a large community is involved in cropping various plants based on the environmental conditions. However, a number of challenges are faced by the farmers including different diseases of plants. The detection and prevention of plant diseases are the serious concern and should be treated well on time for increasing the productivity. Therefore, an automated plant disease detection system can be more beneficial for monitoring the plants. Generally, the most diseases may be detected and classified from the symptoms appeared on the leaves. For the same, extraction of relevant features plays an important role. A number of methods exists to generate high dimensional features to be used in plant disease classification problem such as SPAM, CHEN, LIU, and many more. However, generated features also include unrelated and inessential features that lead to degradation in performance and computational efficiency of a classification problem. Therefore, the choice of notable features from the high dimensional feature set is required to increase the computational efficiency and accuracy of a classifier. This paper introduces a novel exponential spider monkey optimization which is employed to fix the significant features from high dimensional set of features generated by SPAM. Furthermore, the selected features are fed to support vector machine for classification of plants into diseased plants and healthy plants using some important characteristics of the leaves. The experimental outcomes illustrate that the selected features by Exponential SMO effectively increase the classification reliability of the classifier in comparison to the considered feature selection approaches.

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1. Introduction

Agriculture is one of the important sources of earning for human beings in many countries. A different variety of food plants are harvested as per the need and environmental conditions of land. However, a number of problems are also faced by the farmers such as shortage of water, natural disasters, plant diseases and many more. However, some of the problems may be reduced by providing technical facilities to the farmers. Automated plant disease identification and prevention system is one of such solutions that can aid the farmers. This type of system can overcome from the problems of lack of plants disease knowledge as there are very few experts for the same [1], [2]. Moreover, it may increase the food productivity by performing the on time prevention from the disease and there is no need to search for an expert. Such automated system will also be time and cost efficient. Therefore, this manuscript proposes a novel strategy to recognize the various plant diseases.

Generally, leaves of the plants are first source to detect the most of the plant diseases. Yellow and brown spots, primary and late blister, and other ailments caused by bacteria, virus and fungus can be detected automatically through efficient image processing techniques [3], [4]. Therefore, this paper focuses on the plant disease identification using leaves properties only. However, plant disease identification through image processing is not an easy job because of the huge disparities available in the leaves of different and similar plants for instance size, texture, color, shape, etc. Various image processing strategies have been anticipated to overcome from such problems and normally all methods have two steps [3]. In the first phases prominent features are extracted from the input images of the leaves and in second phase, a particular classifier is used which categorise the images into healthy or diseased images. Major classification techniques that are popularly used for disease identification in plant are k-nearest neighbor (kNN) [5], support vector machine (SVM) [6], fisher linear discriminant (FLD) [7], neural network [8], random forest (RF) [9] and many more.

The performance of a classifier is generally relies on the extraction of important features. As per the contemporary, feature extraction methods for image analysis may be categorized into hand crafted and automatic generated (without human experts) features [10]. Hand crafted features may be shape-based, texture-based, color information-based features. To identify the four classes of

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rice grains, Sakai et al. [11] used geometrical attributes namely maximum length, area, perimeter, and many others. For similar type of leaves such as texture and color, beetle and pepper features were used [12]. In some of the literature, the combined texture and shape features have been used to identify the leaves. Although, hand crafted features shows good results for plant disease identification, however, it requires human expert knowledge and many features may be skipped or redundant features may be selected through this process. Therefore, many researchers proposed different machine learning based feature extraction methods that do not impose such constraint such as intra and inter-block dependencies (CHEN) [13] for Markov features, for spatial domain subtractive pixel adjacency model (SPAM) [14], bag of visual words [15], convolutional neural network [16] and many more. These methods automatically generate the high dimensional features without human experts. However, high dimensionality [17] is a major concern in case of images. An expending order of training data is mandatory to engender the high dimensional features, which increases the classifier's computational complexity. Moreover, the performance of a classifier may degraded due to generation of inappropriate and unnecessary features. Thence, there is a prerequisite for a competent technique for feature selection to solve the problem [18].

Generally an evaluation parameter is used by a feature selection method to obtain the optimal or sub-optimal feature subset. A number of search methods exists for selecting the prominent features. In case of exhaustive search, 2^N feature subsets are compared for N dimensional feature space. It shows a complexity of $O(2^N)$ which is impractical for large N [19]. For that reason, numerous approaches like filters, embedded methods and wrappers[20] have been introduced for feature selection to overcome these issue. The most efficient technique in these methods is filter technique that consider a set of features as class variables. On the other hand, for a specific classifier, it may do weakly [21]. The embedded methods use the information returned by a supervised classifier to pick the features like SVM with recursive feature elimination (SVM-RFE) [22] which eliminate the features, comprising minimum weight acquired from a trained SVM. Furthermore, Wrapper methods uses predictive models to appraise the feature subset and are more preferred than filtering techniques [20]. Greedy hill-climbing search approach is one of the popular wrapper technique and repeatedly eradicates the smallest relevant features is Sequential backward selection (SBS) [23]. Though, both the embedded and wrapper techniques are computationally expensive procedures [24].

To overcome the limitations of above mentioned methods, nature inspired algorithms have widely

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been used in the literature. Large number of methods have been evolved using nature inspired algorithms [25, 26] for feature selection. Spider monkey optimization (SMO) [27], particle swarm optimization (PSO) [28], artificial bee colony (ABC) [29], gravitational search algorithm (GSA) [30], and grey wolf optimization (GWO) [31] are few popular meta-heuristic useful in feature selection.

The SMO is one the recently anticipated meta-heuristic based on the social activities of spider monkeys and is established by Bansal et al. [27]. As compared to other meta-heuristic algorithms, SMO shows better performance in searching the relevant features from high dimensional feature space. SMO uses the concept of fissionfusion social system (FFSS) of spider monkeys. Initially it explore the feasible search reason and exploits slowly, by the means of social organization of spider monkeys. A number of variants of SMO are also available in literature such as modified position update in SMO [32], modified SMO [33], fitness based position update in [34], SMO for constrained optimization [35], improved SMO [36], hybrid of SMO and GA [37] and many more. Perturbation rate is one of the important parameter of SMO which affects the convergence behavior of SMO. Generally, perturbation rate is a linearly increasing function. However, due to the availability of non-linearity in different applications, a non-linear function may affect the performance of SMO. Therefore, to improve the performance of SMO, this manuscript recommends a novel alternative of SMO, exponential spider monkey optimization (ESMO), with improved perturbation rate and desirable convergence precision, rapid convergence rate, and improved global search capability. The new variant ESMO, used in feature selection for plant disease identification. The SPAM method has been employed for extraction of features from the given database of leaf images. Further, the identified features are given to individual classifiers to categorise the leaves in the category of healthy or diseased leaves. The results of the anticipated technique has been measured with PSO, GSA, DE, and SMO. In addition, SVM, kNN, LDA, and ZeroR classifiers are used to classify the images into their respective categories.

The main contributions of this manuscript are listed here:

1. A novel exponential spider monkey optimization (ESMO) method has been introduced.

2. The extraction of relevant features from the considered leaf images done using SPAM.

3. A new approach for selection of feature subset has been anticipated based on ESMO.

4. For classifying the healthy leaf images and diseased leaf images, kNN, SVM, ZeroR, and LDA classifiers are analyzed.

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The remaining manuscript is structured as follows. The SMO algorithm introduced in Section 2. Section 3 illustrates the anticipated image classification method. Experimental results of ESMO on standard benchmark problems and the proposed classification technique along with statistical analyses has been discussed in Section 4. Lastly the Section 5 conclude this manuscript.

2. Preliminaries

This section describes the basic spider monkey optimization (SMO) algorithm that is used for feature selection.

2.1. Spider Monkey Optimization (SMO)

The SMO is comparatively new algorithm based on the mathematical model of intelligent behavior of spider monkeys that follow the fissionfusion social structure (FFSS). According to FFSS, monkeys distribute themselves from bigger to minor groups and vice versa for foraging. The main characteristics of the FFSS are as follows [27]:

1. Initially, all spider monkeys persist in the groups of $40 - 50$ individuals. **Each initial group has a leader under whom the food sources are explored. It is termed as a global leader of that group.**

2. In case of insignificant quantity of food, the global leader create smaller subgroups from larger group with each subgroup containing three to eight members to forage independently and each subgroup headed by local leader.

3. The decision of searching food in each sub-group is also decided by a leader, known as local leader.

4. The group members maintain social bonds and defensive boundaries by communicating among themselves and with other members of the group using a unique sound.

The mathematical model of foraging behavior of SMO for optimization problem has six different phases discussed in subsequent sections. Initially, SMO randomly generates a population of N spider monkeys. A D-dimensional vector used to denote a spider monkey. Let X_{ij} depicts the jth dimension of ith individual. In SMO, each X_{ij} is initialized as follows:

$$X_{ij} = X_{minj} + U(0, 1) \times (X_{maxj} - X_{minj}) \tag{1}$$

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where X_{minj} and X_{maxj} are lower and upper bounds in j^{th} direction for X_i and $U(0, 1)$ denotes a random number in the range [0, 1]. The next section describe all six phases of SMO in detail.

2.1.1. Local Leader Phase (LLP)

In this phase, new position of an individual is attained on the basis of the knowledge from the local leader and individuals of group using Eq. (2). Quality of solution decided by their fitness value. The solution with higher fitness (the new position is better than the current position) selected for next iteration.

$$Xnew_{ij} = X_{ij} + U(0, 1) \times (LL_{kj} - X_{ij}) + U(-1, 1) \times (X_{rj} - X_{ij}) \tag{2}$$

where, X_{kj} and X_{rj} denote the positions of jth direction of the local group leader and randomly chosen r^{th} spider monkey from k^{th} group respectively. In order to manage the perturbation in the present location, probability pr is used which is known perturbation rate. The steps of LLP are summarized in Algorithm 1.

Algorithm 1 Local Leader Phase (LLP) [27]

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for each member $X_i \in k^{th}$ group **do**
    for each $j \in \{1, \ldots, D\}$ **do**
        if $U(0, 1) \geq pr$ **then**
            $Xnew_{ij} = X_{ij} + U(0, 1) \times (LL_{kj} - X_{ij}) + U(-1, 1) \times (X_{rj} - X_{ij})$
        else
            $Xnew_{ij} = X_{ij}$
        end if
    end for
end for

2.1.2. Global Leader Phase (GLP)

All individual update their position based on information from global leader and all member of group as shown in Eq. (3) during GLP.

$$Xnew_{ij} = X_{ij} + U(0, 1) \times (GL_j - X_{ij}) + U(-1, 1) \times (X_{rj} - X_{ij}) \tag{3}$$

where, GL_j shows the jth direction of the global leader. Furthermore, the probability $prob_i$ is used to select the particular dimension for updating the X_i and is calculated using the fitness values of

each individual as depicted in Eq. (4).

$$prob_i = \frac{fitness_i}{\sum_{i=1}^{N} fitness_i} \tag{4}$$

Similar to LLP, the better solution from the newly generated position and old position of the SM are used for further processing. Algorithm 2 presents the steps of GLP.

Algorithm 2 Global Leader Phase (GLP) [27]

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counter=0

while group_size > counter **do**

   for $\forall$ X_i ϵ group **do**

      if $U(0,1) < pr$ **then**

         counter=counter+1

         Arbitrarily choose j ϵ {1,...,D}

         Arbitrarily choose X_r ϵ group and i $\neq$ r

         $Xnew_{ij} = X_{ij} + U(0,1) \times (GL_j - X_{ij}) + U(-1,1) \times (X_{rj} - X_{ij})$

      end if

   end for

end while

2.1.3. Global Leader Learning (GLL) phase

The global leader acquire position with overall best fitness in this phase and a global limit counter used to keep the record of change in the position of global leader.

2.1.4. Local Leader Learning (LLL) phase

The position with best fitness within group assigned to local leader. Similar to GLL phase, if local leader's new position is same as the previous position, then the local limit counter updated by one.

2.1.5. Local Leader Decision (LLD) phase

If local limit counter of a local leader reaches to a threshold count, then the all group members re-initialized by using Eq. (5). The steps of LLD phase is presented in Algorithm 3.

$$Xnew_{ij} = X_{ij} + U(0,1) \times (GL_j - X_{ij}) + U(-1,1) \times (X_{rj} - X_{ij}) \tag{5}$$

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Algorithm 3 Local Leader Decision [27]

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if Local_Limit_Count > Local_Leader_Limit **then**
    Local_Limit_Count = 0
    for each j ϵ $\{1, \ldots, D\}$ **do**
        if U(0,1)$\geq$pr **then**
            $Xnew_{ij} = Xmin_j + U(0,1)(Xmax_j - Xmin_j)$
        else
            $Xnew_{ij} = X_{ij} + U(0,1) \times (GL_j - X_{ij}) + U(-1,1) \times (X_{rj} - X_{ij})$
        end if
    end for
end if

2.1.6. Global Leader Decision (GLD) phase

[140]   The global leader creates small size sub groups if her position not updated for a predefined number of iterations. In GLD, the local leaders of each group are elected by LLL process. The global leader merges all subgroups into a single group if its position not updated till pre decided threshold. This way, SMO mimics the FFS structure. Moreover, the complete SMO is presented in Algorithm 4.

Algorithm 4 Spider Monkey Optimization [27]

Initialize Population, pr, $Global\_Leader\_Limit$, and $Local\_Leader\_Limit$.
Calculate fitness.
Identify local and global leaders by employing greedy selection.
while Stopping condition is not contented **do**
    (i) Stimulate the new positions for the whole group by with knowledge of all individuals including themselves, local leader, group members with the help of Algorithm 1.
    (ii) Employ the greedy selection process for the whole group based on their fitness.
    (iii) Compute the probability $prob_i$ of the whole group using Eq. (4).
    (iv) Identify new locations for all the members of group, selected by $prob_i$, by own previous knowledge and experience of global leader and group members using Algorithm 2.
    (v) Local and global leader update their position using greedy selection strategy for all groups.
    (vi) All the members of a specific group redirected for foraging by Algorithm 3 if its Local leader is not able to update her position after a predefined number of times.
    (vii) A group further divided into smaller sub groups, with minimum size of each group four, if Global Leader not able to update her location for a predefined number of times.
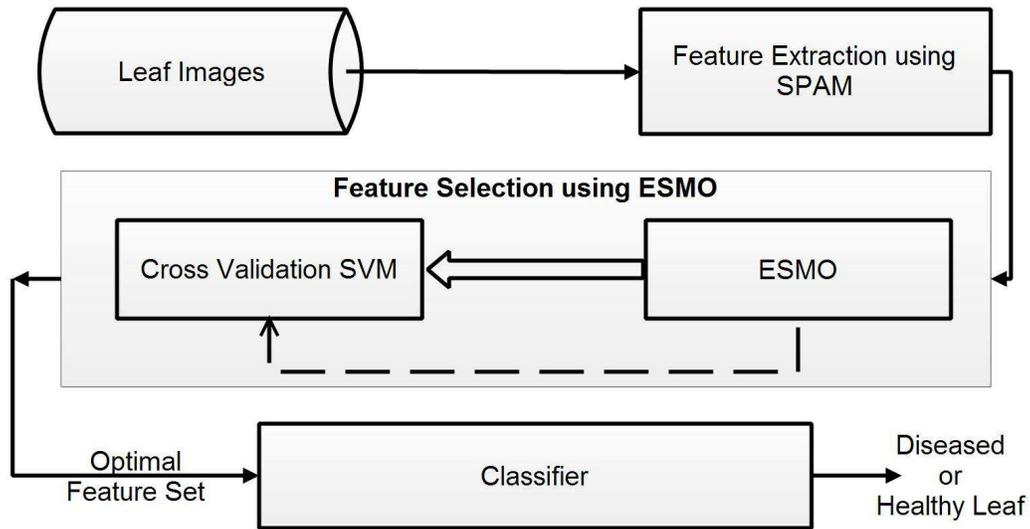**end while**

Figure 1: The proposed leaf image classification method.

3. Proposed Approach

The newly anticipated approach for image classification has three steps as depicted in Fig. 1: (1) 1st step uses SPAM for features extraction from the collection of leaf images, (2) 2nd step selects the distinguished features by the means of newly proposed feature selection algorithm using ESMO, and (3) Ultimately, the classifier is used to categorise the leaf images into diseased and healthy leaf images. Detailed description of these phases given in subsequent sections.

3.1. Feature Extraction

The most important step in image analysis is feature extraction. The extracted features decide the success of a classifier. For an efficient image analysis algorithm, multi-dimension and divergent features must be extracted which can differentiate healthy leaf images from diseased leaf images. For the same, a number of feature extraction methods have been proposed. This paper uses SPAM for feature extraction from considered leaf images, which is discussed in the next sections.

3.1.1. Subtractive Pixel Adjacency Matrix (SPAM)

Peny et al. [14] introduced SPAM to extract the features in spatial domain images. SPAM is the most efficient technique for feature extraction as compared to other existing methods and
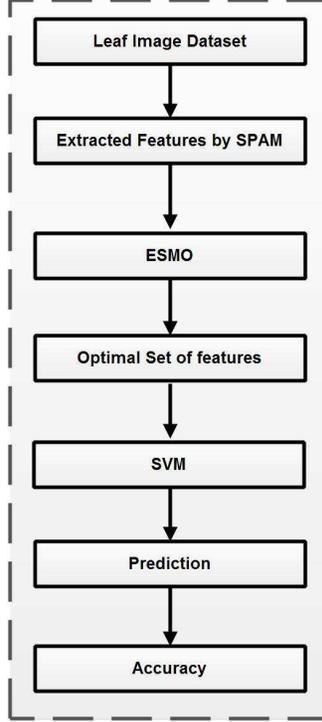
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Figure 2: The proposed ESMO based feature selection method

is based on Markov chain features. It uses the information about the images that in general, an image does not have noise. Furthermore, short-range dependencies amongst noise segments inside an image are used by SPAM to extract the features. It obtains the confined interdependencies between dissimilarity of adjoining face rudiments and used them as a Markov chain to extract the features of images. This paper uses SPAM which extracts 686 features for leaf image data set.

3.2. Feature Selection

SPAM extracts 686 features from image data set which is a high dimensional feature vector and requires high computational cost. These features may have redundant or irrelevant features and sometimes degrade classifier's performance. For that reason, these features are given to the feature selection phase to reduce the unwanted and unrelated features. The overall steps of the ESMO based feature selection are shown in Fig. 2.

The exponential spider monkey optimization (ESMO) lessens the inappropriate and repetitive

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features while selecting feature. The proposed ESMO first initializes randomly the positions of each spider monkey in the population. Each individual has a dimension identical to the quantity of features extracted using SPAM. The ith entity denoted by Eq. (6) if there are total n features extracted and total spider monkeys are N.

$$X_i = \{x_1, x_2, \ldots, x_n\}; \quad i = 1, 2, \ldots, N \tag{6}$$

The value of each x_i, having an arbitrary value in among 0 and 1, is fixed to either 1 or 0 using predefined threshold for computing the fitness. The threshold value is fixed at 0.7 in this manuscript, after empirically analysis. Therefore, the value of x_i is fixed to 1 if it is higher than or equivalent to 0.7 if not then set to 0. Hence, simply the features, having x_i value one, are given to calculate the fitness function. To calculate the fitness value, SVM with ten times counter confirmation is used. In order to select prominent features, the fitness and actual value of spider monkeys are given to succeeding stages of ESMO.

3.2.1. Exponential Spider Monkey Optimization (ESMO)

Perturbation rate is one of the important parameter of SMO which affects the convergence behavior of SMO. Generally, perturbation rate is a linearly increasing function. However, due to the availability of non-linearity in different applications, a non-linear function may affect the performance of SMO. Therefore, to enhance the competency of SMO, this manuscript proposes a novel modification in SMO named as ESMO, with improved perturbation rate that leads to desirable efficiency for convergence, higher rate of convergence, and enhanced global search capability.

For a meta-heuristic algorithm, intensification and diversification are two imperative stages to achieve precise solution and escape from the local optima. In SMO, perturbation rate is one of the prime factors which affect the convergence behavior of SMO. In general, it is a linearly increasing function with the iterations. On the other hand, it has been observed that sometimes poor divergence in SMO leads to entrapping into local optimum. For that reason, in the anticipated optimization algorithm, the value of perturbation rate is customized exponentially in place of linearly.

In ESMO, the parameter, perturbation rate, is increased exponentially as shown in Eq. (7).

$$pr_{new} = (pr_{init})^{\frac{max\_it}{t}} \tag{7}$$

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where, max_it and t symbolize the maximum and the current iteration counter respectively, N stand for the number of spider monkeys and pr_{init} in initial perturbation, initialized randomly in between 0 and 1. Remaining steps of ESMO are similar to basic SMO as depicted in Algorithm 4.

3.3. Classification

Next step after selecting the relevant and non-redundant features is classification of the leaf images into healthy and diseased images and comparison of different classification techniques. For the same, SVM, kNN,LDA, and ZeroR classifiers are used.

4. Experimental Results

The result analysis of newly developed feature selection approach based on ESMO for image classification is given in a couple of phases. 1st phase shows the performance of new approach (ESMO) and second, analyses the effect of feature selection method for plant diseased identification.

4.1. Result Analysis of ESMO

The performance of ESMO has been simulated on 12 standard benchmarks which are represented in Table 1 [38, 39, 40] along with their corresponding optimal value and range of decision variables. Moreover, the proposed ESMO algorithm has been compared with GSA, DE, PSO, and SMO meta-heuristics over the considered benchmark functions. All the algorithms use default parameter settings as mentioned in the corresponding literature except number of iterations (itr) and population size (N) which are taken 50 and 1000 respectively for all the methods. To reduce the inter-dependencies, mean fitness values of 30 runs have been compared.

The mean fitness values returned by the ESMO and considered methods have been presented in Table 2. The ESMO returns minimum mean values of all the benchmarks among PSO, GSA, and DE except F_4 and F_8 where, DE and GSA returns slightly better results. To confirm the outcome shown in Table 2, wilcoxon rank sum statistical test [41] has been conducted with NULL hypothesis that at 5% significance level, considered two algorithms are similar for respective benchmark. The Table 3 shows wilcoxon rank sum test for proposed and existing methods. For $p < 0.05$, the null hypothesis is considered as discarded and denoted by '+' or '−' otherwise accepted and symbolized as '='. The '+' represents the significantly different result and ESMO returns better result while '−' sign shows significantly different but ESMO gives competitively pitiable results. Table 3 shows

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Table 1: Benchmark functions

Sr. No.	Equation	Dimensions	Range	Optimal Value
1	$F_1(X) = \sum_{i=1}^{d} x_i^2$	30	[-100,100]	0
2	$F_2(X) = \sum_{i=1}^{d} \mid x_i \mid + \prod_{i=1}^{d} \mid x_i \mid$	30	[-10,10]	0
3	$F_3(X) = max_i\{\mid x_i \mid, 1 \leq i \leq d\}$	30	[-100,100]	0
4	$F_4(X) = \sum_{i=1}^{d} ([x_i + 0.5])^2$	30	[-100,100]	0
5	$F_5(X) = \sum_{i=1}^{d} i x_i^4 + random[0,1)$	30	[-1.28,1.28]	0
6	$F_6(X) = -20 exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) -$ $exp\left(\frac{1}{d}\sum_{i=1}^{d} cos(2\pi x_i)\right) + 20 + e$	30	[-32,32]	0
7	$F_7(X) = 0.1\{\sin^2(3\pi x_1) + \sum_{i=1}^{d}(x_i - 1)^2[1 + \sin^2(3\pi x_i + 1)] +$ $(x_d - 1)^2[1 + \sin^2(2\pi x_d)]\} + \sum_{i=1}^{d} u(x_i, 5, 100, 4)$	30	[-50,50]	0
8	$F_8(X) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^2$	4	[-5,5]	0.0003
9	$F_9(X) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4$	2	[-5,5]	-1.0316
10	$F_{10}(X) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1 x_2 + 3x_2^2)] \times$ $[30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1 x_2 + 27x_2^2)]$	2	[-2,2]	3
11	$F_{11}(X) = -\sum_{i=1}^{4} c_i\ exp(-\sum_{j=1}^{3} a_{ij}(x_j - p_{ij})^2)$	3	[1,3]	-3.86
12	$F_{12}(X) = -\sum_{i=1}^{4} c_i\ exp(-\sum_{j=1}^{6} a_{ij}(x_j - p_{ij})^2)$	6	[0,1]	-3.32

that for maximum functions, ESMO returns significantly different and better results except F_4 where DE shows comparatively better results. From the Table 2 and 3, it can be seen that the mean values for F_8 with respect to DE is not significant. Therefore, it can be validated that the ESMO performs better than existing techniques for mean fitness values.

Moreover, the comparison of the computational time, taken by Exponential SMO and other considered methods, have been discussed in Table 4. From the table, it can be visualized that by introducing the exponential k-best in basic SMO does not affect the computational cost of the SMO. An average time taken by ESMO is 2.4385 seconds while SMO takes 2.3989 seconds average computational time. The computational time of DE is also almost similar to ESMO. However, PSO and GSA takes more than 3 seconds for getting the best function values. Furthermore, the convergence behavior of the proposed ESMO has also been compared with the considered state-

Table 2: Comparison of mean fitness values

Function	ESMO	PSO	GSA	DE	SMO
F_1	9.69E-11	2.32E-07	1.12E-05	3.54E+03	1.88E-08
F_2	3.94E-10	3.02E-07	5.27E-04	0.88E+02	3.03E-08
F_3	1.11E-10	5.81E-05	2.47E+00	0.65E+02	2.16E-08
F_4	2.69E-08	1.15E-07	2.811E-05	3.68E+03	9.55E-09
F_5	2.01E-04	2.24E-01	7.13E-02	1.71E+00	2.18E-02
F_6	3.79E-11	1.99E+01	1.40E-04	1.53E+01	4.15E-08
F_7	1.80E-09	1.09E-02	3.39E-05	5.86E+07	1.83E-08
F_8	4.07E-04	2.03E-02	1.68E-03	9.78E-04	3.14E-04
F_9	4.69E-08	4.65E-08	6.23E-08	4.65E-08	4.83E-08
F_{10}	3.00E+00	3.00E+00	3.00E+01	3.00E+00	3.00E+00
F_{11}	-3.86E+00	-3.00E-01	-3.00E-01	-2.50E-11	-3.86E+00
F_{12}	-3.04E+00	-2.98E+00	-3.04E+00	-2.43E+00	-3.04E+00

of-the-art algorithms. For the same, Figures 3-4 depict the convergence graphs for all the considered benchmark functions over 1000 iterations. The best fitness values at every iteration are presented on y-axes in logarithmic scales. From the figures, it can be observed that the proposed ESMO has better convergence behavior as compared to other methods for almost all the benchmark functions. Sufficient iterations for exploration are taken by the proposed method before exploitation phase which help to achieve better objective values. Thus experimentally and statistically, it can be validated that the proposed ESMO returns the optimal solutions along with precise convergence behavior for various benchmark functions.

Table 3: The wilcoxon rank sum test.

Function	ESMO-PSO			ESMO-GSA			ESMO-DE			ESMO-SMO		
	p-value	h-value	SGFNT	p-value	h-value	SGFNT	p-value	h-value	SGFNT	p-value	h-value	SGFNT
F_1	1.2E- 10	1	+	1.2E- 10	1	+	1.2E- 10	1	+	1.2E- 10	1	+
F_2	1.2E- 09	1	+	1.2E- 10	1	+	1.6E- 05	1	+	4.2E- 07	1	+
F_3	1.1E-08	1	+	1.2E- 10	1	+	1.2E- 10	1	+	1.9E- 07	1	+
F_4	1	0	=	2.4E- 10	1	+	1.3E- 10	1	+	1.1E- 08	1	-
F_5	2.2E- 07	1	+	6.5E- 07	1	+	8.3E- 08	1	+	2.4E- 10	1	+
F_6	1.2E- 10	1	+	1.2E- 10	1	+	1.2E- 10	1	+	1.2E- 10	1	+
F_7	1.7E- 08	1	+	2.4E- 12	1	+	2.3E- 06	1	+	8.3E- 08	1	+
F_8	1.4E- 06	1	+	1	0	=	1	0	=	1	0	=
F_9	1	0	=	1	0	=	1	0	=	1	0	=
F_{10}	1	0	=	1.3E-11	1	+	1	0	=	1	0	=
F_{11}	1.5E- 08	1	+	1.2E- 11	1	+	2.3E- 06	1	+	1	0	=
F_{12}	2.4E- 12	1	+	1	0	=	4.7E- 09	1	+	1	0	=

Table 4: Comparison of computational time in seconds

| Function	ESMO	PSO	GSA	DE	SMO
F_1	2.6828	4.8514	3.7373	2.5380	2.3048
F_2	2.3369	4.0179	4.1698	2.7056	2.3397
F_3	2.2932	4.7995	5.6281	2.3437	2.3291
F_4	2.4616	4.4041	2.9849	2.3770	2.4155
F_5	2.7494	3.2745	2.9529	2.9738	2.7474
F_6	2.4834	3.2092	4.1470	2.4736	2.5012
F_7	2.4275	4.7740	2.9563	2.7722	2.4045
F_8	2.3595	3.6840	2.6673	2.4534	2.3460
F_9	2.3661	3.3271	2.1040	2.3065	2.3288
F_{10}	2.2383	3.4384	2.1209	2.3694	2.2408
F_{11}	2.4322	3.1568	2.2077	2.0033	2.3858
F_{12}	2.4321	3.6273	2.4316	2.0026	2.4432
Average	2.4385	3.8804	3.1757	2.4433	2.3989
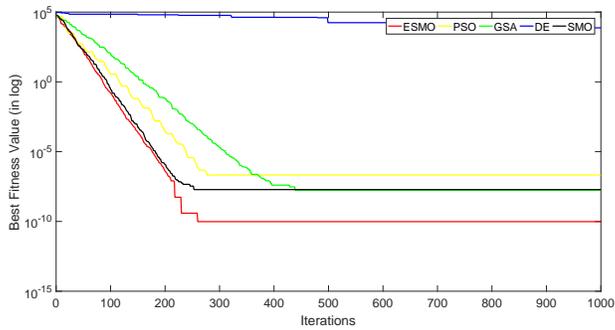
(a) Benchmark Function F1
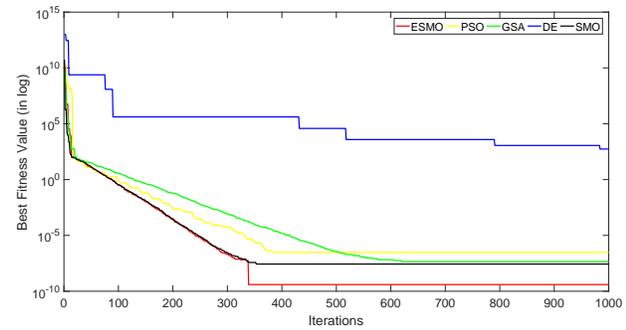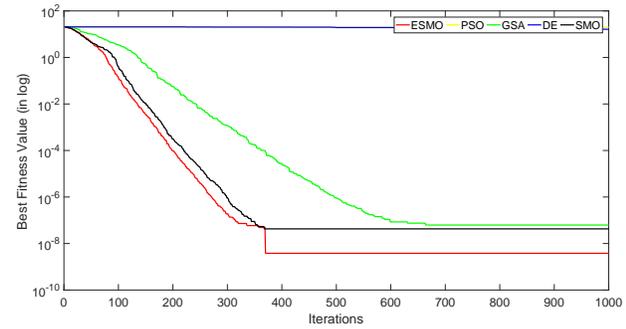
(b) Benchmark Function F2
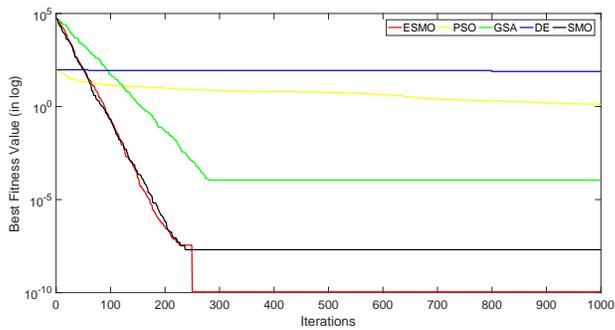
(c) Benchmark Function F3
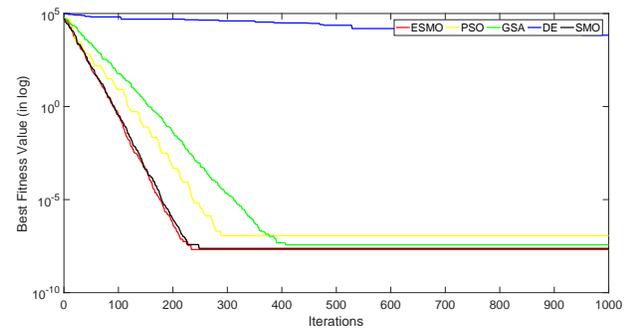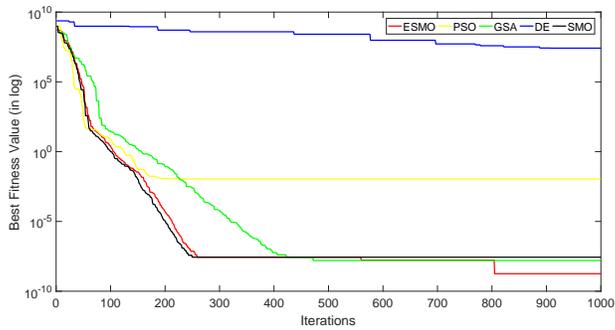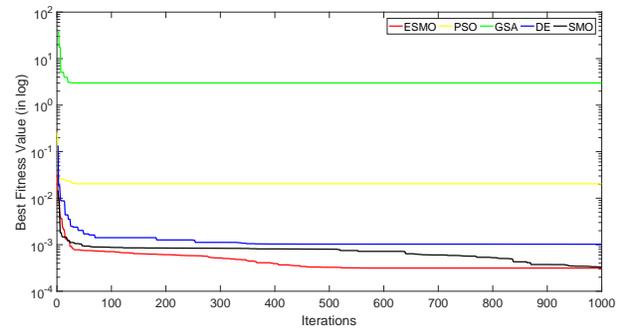
(d) Benchmark Function F4
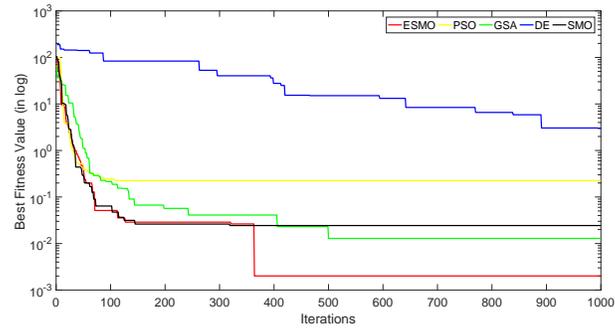
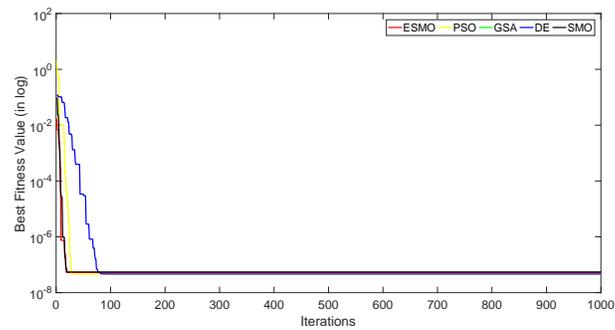(e) Benchmark Function F5

(f) Benchmark Function F6

Figure 3: The convergence behavior of proposed and existing methods for benchmark functions
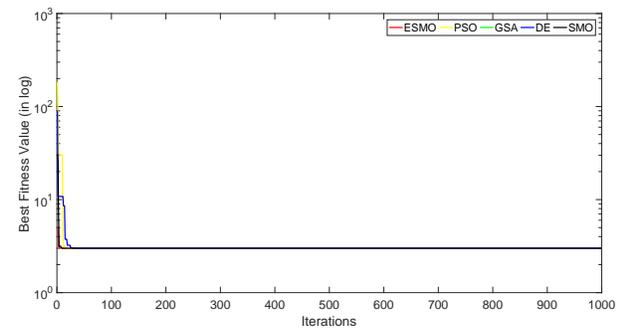
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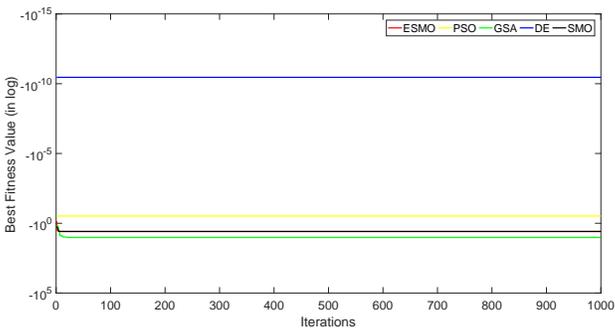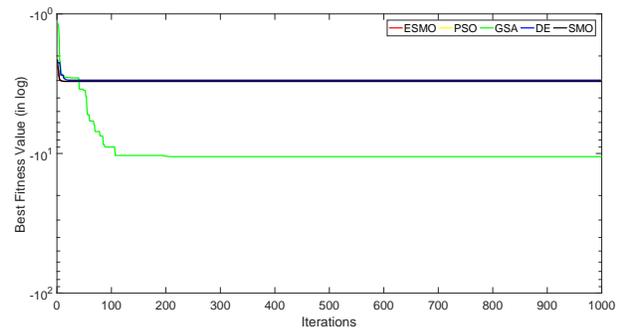(a) Benchmark Function F7

(b) Benchmark Function F8

(c) Benchmark Function F9

(d) Benchmark Function F10

(e) Benchmark Function F11

(f) Benchmark Function F12

Figure 4: The convergence behavior of proposed and existing methods for benchmark functions
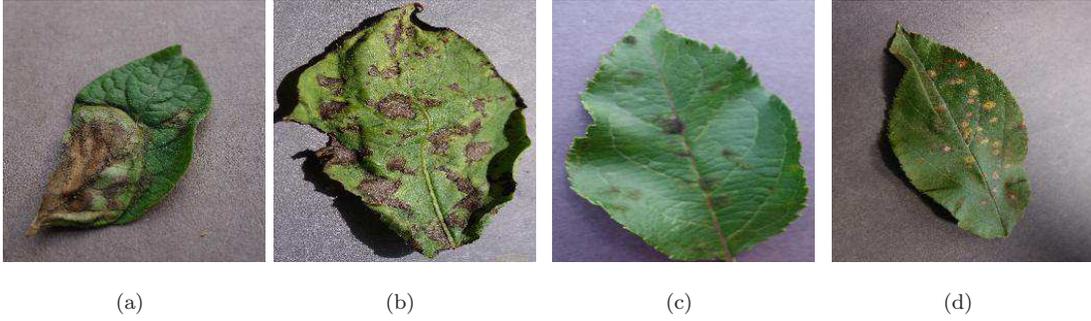
(a) (b) (c) (d)

Figure 5: The represented diseased leaf images of (a) potato, (b) potato, (c) apple, and (d) apple leaves taken from [42].
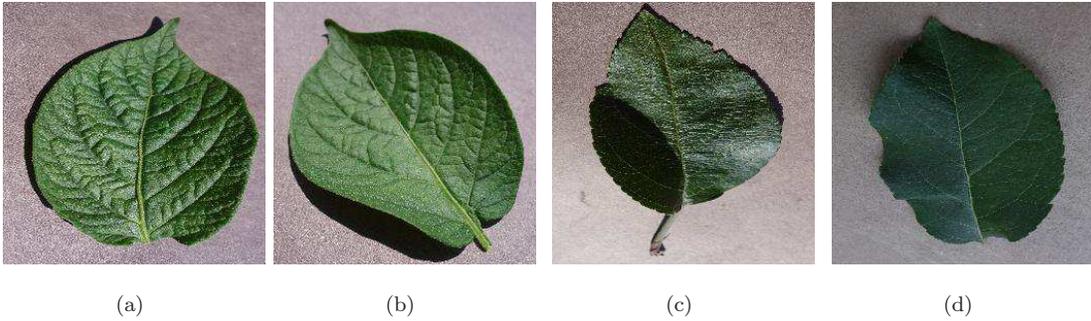

(a) (b) (c) (d)

Figure 6: The represented healthy leaf images of (a) potato, (b) potato, (c) apple, and (d) apple leaves taken from [42].

4.2. Result Analysis of Feature Selection technique

The performance of the anticipated diseased leaf identification system has been tested on 1000 images from PlantVillage dataset [42]. The dataset consists of 500 healthy leaf images and 500 diseased leaf images. Some of the representative images from diseased and healthy categories are delineated in Fig. 5 and 6 accordingly. For each image, 686 features are extracted using SPAM. Furthermore, ESMO is employed for feature selection. The outcomes of ESMO for feature selection have been compared with PSO, GSA, DE, and SMO using the number of selected features and classification precision. Table 5 illustrate the outcome of both the feature selection technique and classifiers.

ESMO based feature selection technique returns 82 features which is the least number of selected features as compared to other feature selection techniques. From Table

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5, it can be observed that approximately 88% features are reduced by ESMO from the 686 extracted features. This reduction of features is highest with respective to PSO, GSA, DE, and SMO which reduce 85%, 87%, 86%, and 87% respectively. From the feature reduction rates, it can be stated that all the considered algorithms along with ESMO eliminate almost same amount of features. However, relevancies of the selected features are tested by feeding them to a classifier for plant leaf disease identification.

For the same, SVM, kNN, LDA, and ZeroR classifiers are used for comparative analysis of accuracies. The results of ZeroR classifier is measured as a reference line for all the feature selection techniques. From Table 5, it can be obtained that without feature selection method all the classifiers give lowest accuracies which validates the presence of redundant and irrelevant features in the set of extracted features from SPAM. After the applicability of feature selection method before identification of diseased leaves, the accuracy of each classifier increases. However, all the considered classifiers shows the best accuracies for the features identified by the anticipated ESMO. Among all the classifiers for ESMO based feature selection method, SVM gives the best classification accuracy of 92.12% . Consequently, it can be specified that the anticipated ESMO based feature selection approach returns minimum number of optimal features which gives better classification accuracy.

5. Conclusion

This paper anticipated a feature selection approach using novel exponential spider monkey optimization (ESMO) for plant disease identification. For the same, diseased and healthy leaf images have been used from plant village dataset. Furthermore, 686 features extracted using SPAM method from the considered image dataset. The performance of ESMO has been compared with PSO, GSA, DE, and SMO methods in terms of mean fitness values. The investigational and numerical outcome authenticate that the anticipated ESMO outperforms the considered approaches. Additional, the performance of newly anticipated feature selection process using ESMO has been contrasted with PSO, GSA, DE, and SMO based feature selection techniques. The anticipated technique extracts the minimum 82 features. The classification results have been analyzed over SVM, kNN, LDA, and ZeroR classifiers. In the midst of all the classifiers, SVM outperforms to classify the plant leaf images into diseased or healthy leaf images. Thus it can be validated that the anticipated feature

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Table 5: Comparative analysis of classifiers and feature selection methods.

Feature Selection Method	Number of Features Selected	Classification Method	Accuracy
None	686	SVM	80.26
		LDA	72.37
		kNN	76.34
		ZeroR	42.29
PSO	97	SVM	89.54
		LDA	78.20
		kNN	82.13
		ZeroR	47.31
GSA	87	SVM	87.54
		LDA	77.66
		kNN	83.82
		ZeroR	46.54
DE	91	SVM	87.45
		LDA	78.77
		kNN	83.79
		ZeroR	47.54
SMO	84	SVM	89.55
		LDA	79.67
		kNN	77.87
		ZeroR	46.44
ESMO	82	SVM	92.12
		LDA	80.79
		kNN	84.76
		ZeroR	49.32

selection technique minimizes the unrelated and superfluous features while, maintains the elevated classification precision. In future, the anticipated technique can be used for multi-class problem where, the different plant disease categories can be identified.

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