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A Comparison Between SCA and ESCA Algorithms in Diagnosis an Erythema to Squamous Disease

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ABSTRACT

Dermatology is considered one of the most challenging medical specialties studied in medical schools due to the considerable similarity among various skin diseases, such as psoriasis, seborrheic dermatitis, chronic dermatitis, lichen planus, pityriasis rubra, and pityriasis rosea. With the rapid advancement of technology, computers have become deeply integrated into medicine, and many decision-support systems have been developed to assist physicians in making accurate diagnoses. Medical data obtained from laboratory analyses can play a decisive role in determining disease type. The application of classification algorithms and feature selection techniques has significantly improved the efficiency of diagnostic systems, particularly through the use of metaheuristic algorithms. In this research, a classification methodology for skin diseases is proposed by introducing a novel hybrid feature selection (FS) technique. The sine cosine algorithm (SCA) was employed within a wrapper model framework to select the optimal subset of features for classification. To enhance exploration and maintain diversity, a mutation factor was incorporated as an internal function, evolving the SCA into the enhanced sine cosine algorithm (ESCA). Consequently, the system generates two outputs for each algorithm. Experimental results demonstrated that the SCA achieved a diagnostic accuracy of 96% with 79% of selected features, whereas the ESCA achieved a remarkable diagnostic accuracy of 98% while reducing the selected features to 63%.

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1. INTRODUCTION

The skin is the outer covering of the body, as it protects the body from external influences and preserves the body's internal organs [1]. Skin diseases are a complex health problem that causes inconvenience and anxiety to humans due to their association with the aesthetic aspect, especially if it appears on the face, hands, or hair. Skin disorders come in a variety of shapes and types [2]. Skin diseases constitute a large percentage compared to other diseases due to the large area of human skin, as every part or area of the skin is exposed to different types of injuries [3]. Skin cancer has been increasing in rates in recent years [4]-[6]. Skin cancer is known as an abnormal growth in skin cells [7][8]. The technical innovations that are emerging in the fields of health, medicine, and remote diagnosis have the potential to make a quantum leap in many countries to help provide medical dermatological advice and reduce financial costs [9], [10].

Artificial Intelligence (AI) has complex mathematical algorithms that implement tasks similar to a human brain, means it can learn and understand the world as human do. Machine Learning (ML) is a technical term that means the use of a set of techniques and tools which help computers and intelligent machines in general to learn and adapt on their own. The basic task of ML is to extract valuable information from data, thus it is very close to data mining (DM) [11]-[12]. Diagnostic classification is based on developed algorithms that provide high accuracy for predicting the disease. AI is increasingly being used in the diagnosis of skin cancer and has achieved promising results. From diagnosis to personalized care, ML can change dermatologists' practices [13].

There are several applications for ML, the most significant of which is DM. DM can optimize decision-making in healthcare organizations by extracting new patterns and information from large amounts of data. Healthcare organizations store a big amount of information in the daily records [14][15]. Information Technology (IT) allows for the automation of DM, which aids in the discovery of hidden patterns that would be interested which eliminate manual works management and speed-up access to information by a direct method through electronic records systems that could minimize the cost of services. Early diagnosis of diseases leads to better treatment for the patient and saves lives [16][17]. Strong optimization algorithms that are independent of the problem are known as metaheuristics. Many metaheuristics, such as ant colony optimization, are derived from natural phenomena [18]. FS basically is a series of operations targeted at identifying which relevant features to include and which irrelevant ones to exclude in predictive modeling. It is an indispensable task since this would help ML classifiers reduce the error rate, computation time, and overfitting while improving the classification accuracy [19]. SCA is the most famous algorithm in field of FS technique. Many researchers resorted to use it since it achieved promising results and especially after merging it with other algorithms [20].

The research employed a binary version of the SCA. A mutation function was incorporated into the experiment, which yielded different results. The main contribution of this study lies in utilizing SCA for feature selection (FS) to achieve higher performance values. This was accomplished by enhancing the algorithm's exploration strategy through the introduction of a new FS approach, which led to the development of ESCA. The performance of both algorithms was evaluated using six criteria: average selection size, classification accuracy, average fitness, standard deviation, worst fitness, and best fitness.

2. Related Work

Many researchers have investigated the diagnosis of skin diseases using artificial intelligence algorithms. In 2016, Maghooli et al. [21], proposed to use the Classification and Regression Tree (CART) to predict the differential diagnosis of the six skin diseases. The proposed method is the Cross-Industry Standard Process for DM (CRISP-DM). The accuracy recorded by the proposed method reached 94.84%. In 2017, Tuba et al. [22], proposed a method for optimizing the Support Vector Machines (SVM) through a modern metaheuristic algorithm to achieve a promising diagnostic result of the six skin diseases. Parameters of the SVM were adjusted by the Elephant Herding Optimization (EHO) algorithm. This method has achieved the highest accuracy with a training/test ratio of 80/20% is 99.07%. In 2018, Idoko et al. [23], proposed a promising manner based on a fuzzy concept. The integrated fuzzy neural network (FNN) utilized the Takagi-Sugeno-Kang (TSK)-type rule as a taxonomy tool. The system merges between the ML abilities of the neural network and the fuzzy concept. The clustering technique was used for feature extraction. The total accuracy for the FNN classifier was 98.37%. In 2020, Soraya Gharavi. [24], were used a hybrid approach to classify the skin diseases by using the FS mechanisms such as Information Gain, Chi-Square, and Principal Component Analysis (PCA). For the evaluation process, the researchers relied on various classifiers, including: KNN, DT, SVM, RF, and MLP. The accuracy obtained was very special. 1n 2022, Obe et al. [25], In the perspective of one versus many classifications' strategy, the proposed ML-based ensemble method classified six categories of each type of skin disease. The results presented here show that stacked ensembles achieved an accuracy of 92.9%, sensitivity of 85.8%, and specificity of 97.4% compared to single and ensemble classifiers.

3. Experimental Methodology

3.1 Data Set Analysis

The data used in the study was downloaded from the famous website (http://archive.ics.uci.edu/ml). The data describes six skin diseases that are similar to each other. These six skin diseases are: seborrheic dermatitis, psoriasis, lichen planus, chronic dermatitis, pityriasis rosea, and pityriasis rubra. The number of features is 34, the number of clinical features is 12 and the number of histopathological features 22. These samples belong to 366 patients. In the main stage of the disease, symptoms of another type of disease may appear, making it more difficult for the doctor to diagnose these disorders. To diagnose these disorders, a biopsy is required. Initially, patients were evaluated based on 12 clinical features, while the remaining features were determined from histological findings. Genetic predisposition was also considered: if a patient had a relative with any of these diseases, the family history was encoded with a value of 1; otherwise, it was assigned a value of 0. Features obtained from tissue analysis were categorized and encoded using four symbols: 0, 1, 2, and 3.

A value of 0 indicated that the feature was absent, values of 1 and 2 represented intermediate levels for comparison, and a value of 3 denoted the highest level of the feature. Table 1 presents the disease categories.

Table 1: Dataset attributes and class distribution

Classes	Number of Patients	Skin Disease Name
Class1	112	Psoriasis
Class2	61	Seborrheic dermatitis
Class3	72	Lichen planus
Class4	49	Pityriasis rosea
Class5	52	Chronic dermatitis
Class6	20	Pityriasis rubra pilaris

The distribution of categories in the dataset are shown in Figure 1

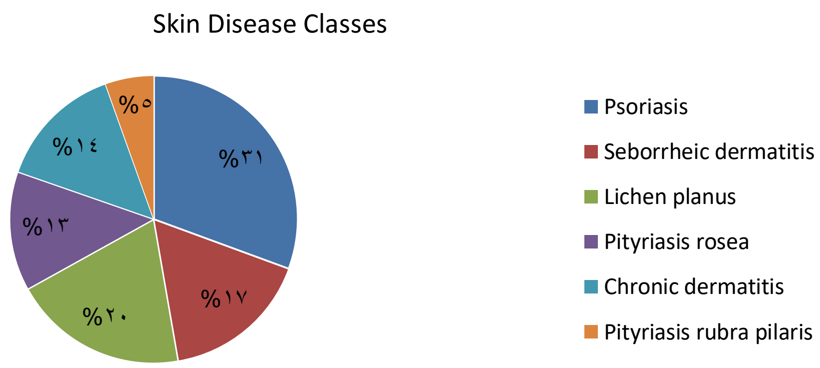


Figure 1: Distribution of categories in the dataset

3.2 Metaheuristic Algorithms for Feature Selection

Features that are unnecessary or superfluous are eliminated by FS. The fitness function yields the best performance with the chosen subset of features. With any kind of categorization strategy, FS is now necessary. To enable further analysis, almost all of the main goals of using FS methods are to prevent data from reaching the over fitting stage. As a result, the proper application of FS techniques for feature selection enhances ways of learning, including training the model in a short time, simpler model debugging, and simpler model understanding. Based on search tactics, FS techniques are classified into three types: wrappers approach, filters approach and embedded approach [26]. Depending on how the solutions are controlled, metaheuristic algorithms can be taken two labels: (population-based), or (single-based). Metaheuristics algorithms can be considered as a subset of ML technology. The fact that the transfer, evaluation, and selection factors are run again until a convincing solution is obtained or compliance a predetermined pause standard is the most prominent feature of metaheuristics [27].

3.3 Sine Cosine Algorithm (SCA)

The most exciting population-based algorithm is the Sine Cosine Algorithm, which was developed by Seyedali Mirjalili in the year 2016. This modern optimization technique focuses on the alteration of sine and cosine positional value and related functions, explained in equations (1) and (2) [28] .

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, \quad r_4 < 0.5 \quad (1)$$

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_{i_i}^t|, \quad r_4 \geq 0.5 \quad (2)$$

These two equations are merged to be utilized as shown in equation (3):

$$X_i^{t+1} \begin{cases} X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 < 0.5 \\ X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_{i_i}^t|, & r_4 \geq 0.5 \end{cases} \quad (3)$$

The parameters used by SCA, *r1, r2,* and *r3* are utilized for the exploration and exploitation of the solutions. *r1* extracts its value by considering the ultimate iterations *T, t* means current iteration, and a means constant value as shown in equation (4).

$$r_1 = a - t\frac{a}{T} \tag{4}$$

r2 determines how far the movement should be towards or away from the destination. *r3* gives random weights to the destination with *r3* > 1 random for the focus or *r3* < 1 for the focus. *r4* varies randomly between the two functions in equation (3). To perform FS using SCA and after conducting various experiments, the wrapper model was chosen. It is used as a guide in implementing the FS process. In order for the FS operation to perform correctly, the algorithm is reversed to the binary version. Thus we obtained the new algorithm called (BSCA). The binary version describes the attributes that are selected or neglected. The value 1 means the attribute was chosen, and when the attribute is neglected, it takes the value 0.

3.4 Enhanced Sine Cosine Algorithm (ESCA)

The initial results of algorithm were not quite stellar. Like most algorithms, it is likely to be a weakness in the SCA's exploration process, so the hybridization process has been tested to ensure an improved solution. In order to increase the efficiency of the algorithm and thus obtain better results, we resorted to hybridization by using the mutation operator as an internal function inside SCA to be the ESCA.

The user can choose the value of the mutation rate, also known as the probability rate, which controls the behavior of the mutation operator. Its range is from one to zero. To ensure satisfactory results, varying ratios were tried in parallel to ensure the stability of the algorithm. The main steps of the ESCA approach are shown in an algorithm 1.

Algorithm (1): main steps of ESCA
Input: Search agent number, dataset, dimension, max iteration, *ub*, *lb*
Output: Vector of 10 best solutions
Step1: For q = 1 to 10
Step2: Divided input skin data set to training Dataset and test Dataset using k cross-validation technique .
Step3: Initialize the set of random solutions
Step4: Convert algorithm domain to binary domain between [0,1]
Step5: Calculate the fitness of the first set and find the best one Eq. (5)
Step6: $t = 2$; % starts at the second iteration.
$while\ t <= Max\_iteration$
Eq. (4)
r1 decreases linearly from *a* to *0.*
Step7: Update the position of solutions concerning the destination
Step8: Update *r2, r3*, and *r4* for Eq. (3)
if $r4 < 0.5$
$Update\ the\ position\ of\ the\ SCA\ by\ Sine\ equation$
else
$Update\ the\ position\ of\ the\ SCA\ by\ Cosine\ equation$
Step9: End if
Step10: Update the algorithm search space using the proposed mutation function.
Step11: for i=1:size(X,1)
Step12: Check if solutions go outside the search space and bring them back.
Step13: Calculate the objective values
Step14: Update the destination if there are better solutions
Step15: End for
Step16: Display iteration and optimum obtained so far
Step17: Increase the iteration counter (t)by one.
Step18: End while
Step19: End for
Step20: Compare the best optimum obtained from the proposed ESCA with BSCA using evaluation criteria.
Step21: Display the iteration and best optimum obtained so far
Step22: End

K-Nearest Neighbors algorithm (KNN) has features that make it one of the most widely used algorithms in the data classification process. The algorithm relies on storing all available data with the corresponding output, so that new data is later classified based on a specific scale based on the output corresponding to the nearest neighbor points, so that K expresses the number of points, and is determined experimentally by comparing the training error with the test error, and the moment at which The two lines become close, that is, in a state of balance, then we have reached the ideal value of K[29].

The focus was on balancing the recorded accuracy with the number of corresponding features. Equation (5) refers to the fitness function that used in evaluate all the search agents for each algorithm [30]:

$$F = \alpha \times ER(D) + \beta \frac{|L|}{|T|} \quad (5)$$

ER(D), |L|, |T|, α, β refers to the KNN error rate, length of the feature subset, number of features in data set, range between [0,1], (1−α) respectively. The two symbols (α, β) are used to balance accuracy.

3.5 Evaluation Criteria

To measure the efficiency of the model used in this study, a set of dermatological data is tested. The data is randomly divided into two parts, with a percentage of 70% for training the model and 30% for testing the model. Data segmentation is done using a technique K-fold cross-validation. The performance evaluation of the metaheuristic approaches has been performed by considering various evaluation criteria presented in the following.

Accuracy of classification: It tells about the efficiency of the performed FS operations on the given dataset to the classifier. Classification accuracy is obtained from equation 6 [31].

$$Class\ Acc = \frac{1}{M}\sum_{j=1}^{M}\frac{1}{N}\sum_{i=1}^{N} Mach(Ci, Li) \quad (6)$$

Statistical best fitness: refers to the minimal value of the fitness function an optimizer achieved after running different M operations. For an optimization algorithm, the term best refers to the most favorable solution mathematically, which can be given by equation 7 [31].

$$Bst = Min_{i=1 g_*^i}^{M} \quad (7)$$

Let *M* be the frequency of executing an optimization algorithm to determine a feature subset and let g_*^i be an optimal solution obtained from the execution corresponding to the *i-th* iteration.

Statistical worst fitness: refers to the worst solution among the best solutions found after running an optimization algorithm *M* time. Worst represents the pessimistic solution, which can be formulated in equation 8 [31].

$$Wors = Max_{i=1 g_*^i}^{M} \quad (8)$$

Let *M* be the frequency of executing an optimization algorithm to determine a feature subset and let g_*^i be an optimal solution obtained from the execution corresponding to the *i-th* iteration.

Statistical mean: it is the average of solutions obtained from running an optimization algorithm for different *M* runs, the average represents typical behavior for a stochastic optimizer given and can be given by equation 9 [31].

$$Mean = \frac{1}{M}\sum_{i=1}^{M} g_*^i \quad (9)$$

Let *M* be the frequency of executing an optimization algorithm to determine a feature subset and let g_*^i be an optimal solution obtained from the execution corresponding to the *i-th* iteration.

Statistical standard deviation (*Std*): The statistical standard deviation (Std) can be used for measuring the dispersion of the optimal solutions produced in M different runs of a stochastic optimization algorithm. It is formulated in the equation shown by equation 10 [31].

$$Std = \sqrt{\frac{1}{M-1}\sum(g_*^i - Mean)^2} \quad (10)$$

Let *M* be the frequency of executing an optimization algorithm to determine a feature subset and let g_*^i be an optimal solution obtained from the execution corresponding to the *i-th* iteration, and *Mean* is the average defined in equation 9.

Average selected size: represents the average size of the selected features concerning the total number of features. It can be defined as presented in equation 11 [31].

$$AvSeSz = \frac{1}{M}\sum_{i=1}^{M}\frac{siz(g_*^i)}{D} \quad (11)$$

Here, *M* is the number of times the optimization algorithm runs to compute the subset of features; g_*^i represents the optimal solution from the *i-th* run; *siz(x)* counts the number of non-zero elements of the vector *x*; *D* stands for the number of features in the original dataset.

4. Results and Discussion

All results were calculated from the evaluation criteria using the programming language of the Matlab/R2017a. Table 2 summarized the parameter settings and provided an overview of the key parameters.

Table 2: Key parameters

Parameter	Value
Search Domain	Binary
The average of runs	10
Dimension	Equal to Attributes number
Probability	0.005
Search agent number	7
The iteration number	100
Lower bound	0
Upper bound	1
α	0.01
β	$1-\alpha$

ESCA was compared with BSCA based on the criteria described in the previous section. After applying the evaluation criteria, the superiority of the ESCA emerged significantly, as shown in Table 3.

Table 3: Evaluation criteria

Skin Data Set	Algorithm	Accuracy	Ava. Selected Size	(*Stadr*)	Mean fitness	Worst fitness	Best fitness
	BSCA	%96	%79	0.021	0.044	0.073	0.017
	ESCA	%98	%63	0.007	0.022	0.032	0.011

High classification accuracy is the most important goal when using a classification algorithm. The ESCA approach had the highest accuracy compared to BSCA. When using FS techniques, the desired goal is to use the smallest number of features. The ESCA approach was less likely to use a number of features compared to BSCA. Figure 2 shows the results of the comparison between ESCA and BSCA in terms of the number of features selected and accuracy.

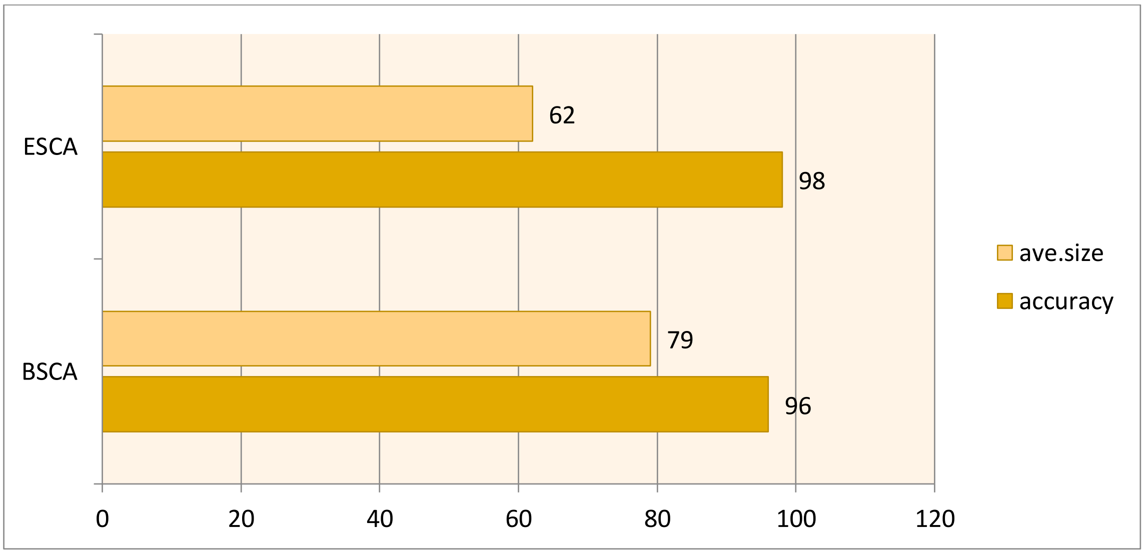
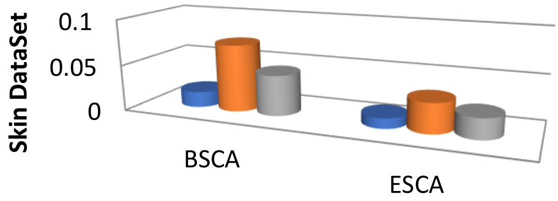


Figure 2: Accuracy and average. size

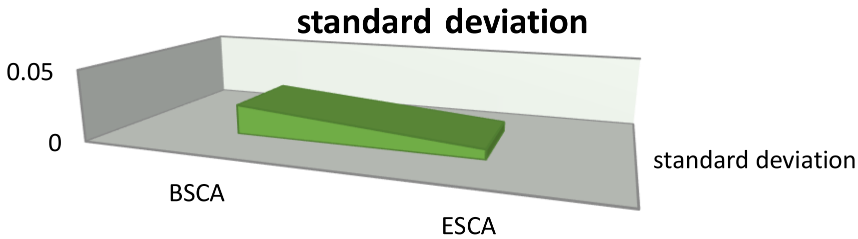
The results that appeared through the application were compared between BSCA and ESCA in terms of statistics (worst, best and mean) in the Figure3.



	BSCA	ESCA
Best fitness	0.017	0.011
Worst fitness	0.073	0.032
Mean fitness	0.044	0.022

Figure 3: statistics (worst, best and mean)

comparison of results obtained between the BSCA and ESCA in terms of standard deviation as shows the Figure 4.



	BSCA	ESCA
standard deviation	0.021	0.007

Figure 4: Results BSCA and ESCA in standard deviation term

A comparison was performed between SCA & ESCA in objective space using a benchmark test function that different in dimensions and bound domain to measure the strength of the enhanced approach with the original algorithm. The number of search agents is 30 & the maximum number of iterations is 1000. Details of the selected benchmark function shown below:

1. Dimension=30, Lower bound= -100, Upper bound=100

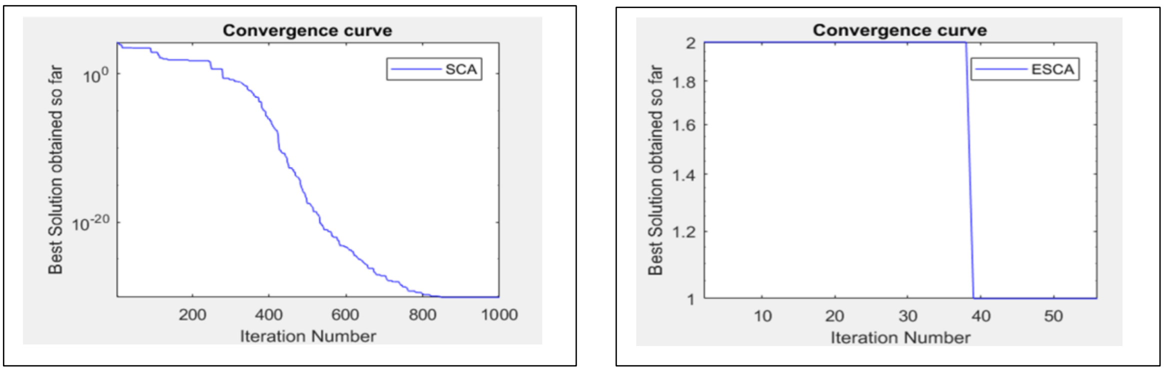


Figure 5: Convergence curve of SCA & ESCA with D=30, Lb= -100, and Ub=100.

Observed through Figure 5 that the SCA came up with the best solution after 800 iterations while ESCA came up with the best solution after 40 iterations.

2. Dimension=10, Lower bound= -10, Upper bound=10

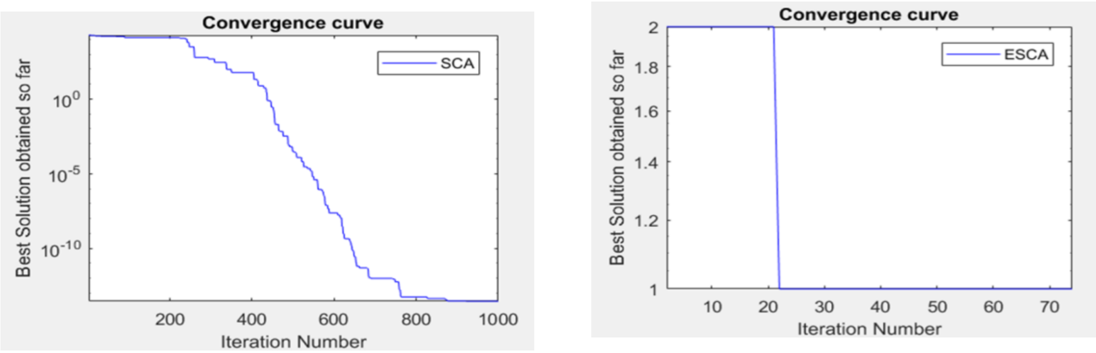


Figure 6: Convergence curve of SCA & ESCA with D=10, Lb= -10, and Ub=10.

Observed through Figure 6 that the SCA came up with the best solution after 800 iterations while ESCA came up with the best solution after 20 iterations.

3. Dimension=10, Lower bound= -1.28, Upper bound=1.28

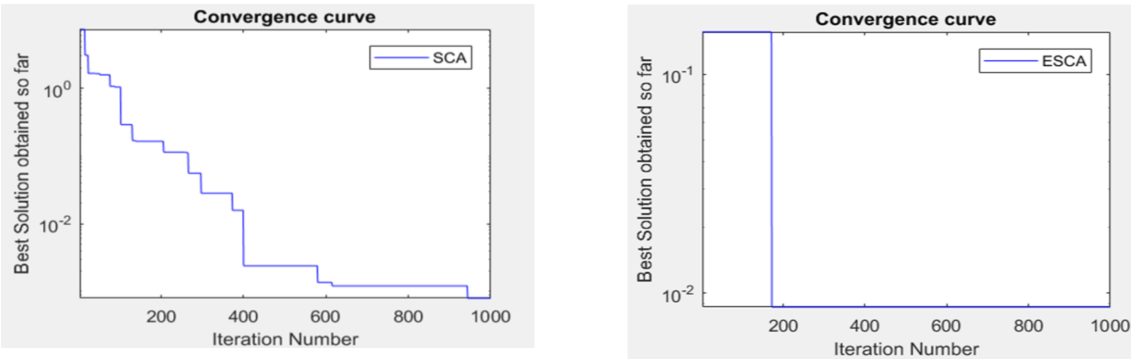


Figure 7: Convergence curve of SCA & ESCA with D= 10, Lb=-1.28, and Ub=1.28

Observed through Figure 7 that the SCA came up with the best solution after 950 iterations while ESCA came up with the best solution after 190 iterations.

4. Dimension=10, Lower bound= -23, Upper bound=23

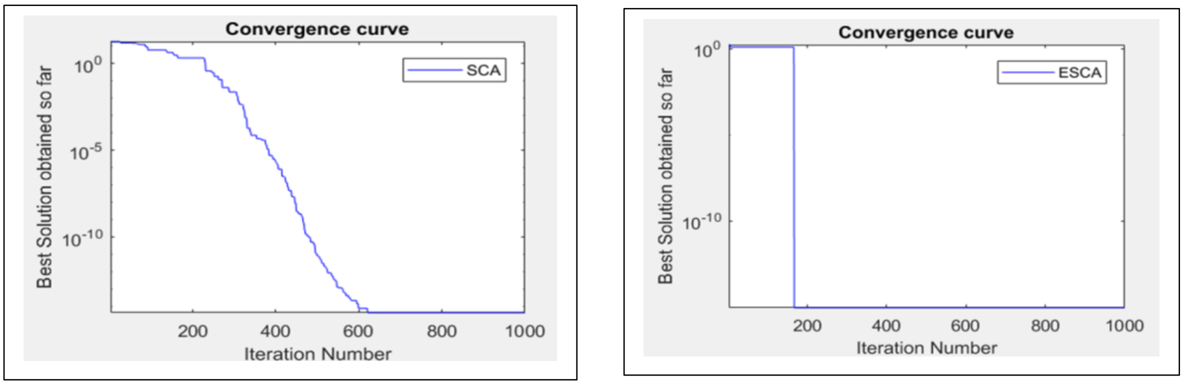


Figure 8: Convergence curve of SCA & ESCA with D=10, Lb= -23, and Ub=23.

Observed through Figure 8 that the SCA came up with the best solution after 620 iterations while ESCA came up with the best solution after 160 iterations.

5. Conclusion

This section summarizes the conclusions of the research. The aim of the research is to take advantage of the SCA in skin disease classification The proposed approach is enhancing the SCA by hybridized with the mutation operator and compared with the BSCA. Feature selection using a wrapper method has been employed to select the most significant features. By nature, this wrapper method is bound to one particular machine learning algorithm. A machine learning algorithm is used for determining the measure of performance. ESCA is the enhanced version of the Sine Cosine Algorithm (SCA) that is based on the utilization of the mutation operator of the Genetic Algorithm to enhance the solution by improving the exploration of the SCA for feature selection in wrapper method. ESCA allows a more extensive search to prevent falling in local optima and then find the enhanced best solutions through the results where it achieved two contradictory goals, maximal accuracy of classification with minimal size of features. The results achieved by the two approaches used (BSCA, ESCA) in terms of classification accuracy were as follows (96%, 98%) respectively. Suggestions for future works summarize as follows Data can be used from Iraqi hospitals and specialized clinics for dermatology. Other data sets can be used for other diseases of different sizes. It is better to use different metaheuristics algorithms, for example the gray wolf optimizer (GWO), Salp Swarm Algorithm (SS), Whale Optimization Algorithm (WOA), Cuckoo Search Algorithm (CS), etc. It is possible to hybridize the SCA with other algorithms of the type single-based.

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