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Sine Cosine Algorithm for Enhancing Convergence Rates of Artificial Neural Network: A Comparative Study

Maria Ali[1,2], Fatima Pervez[1], Muhammad Nouman Atta[1], Abdullah Khan[1,*] and Asfandyar Khan[1]
[1]*Institute of Computer Science and Information Technology, The University of Agriculture Peshawar, Pakistan.*
[2]*Department of Computer Science, Iqra National University, Pakistan.*
**Corresponding author:* Abdullah_khan@aup.edu.pk, *ORCiD*: 0000-0003-1718-7038
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***Abstract* — Artificial neural networks (ANNs) is widely adopted by researchers for classification tasks due to their simplicity and superior performance. This study offerings the ANN and it variant such as Elman Neural Network (NN) model to address its strengths, although it faces with issues like local minima and slow convergence. This study presents a comprehensive evaluation of four distinct algorithms for classification tasks, focusing on their performance on both training and testing datasets. These algorithms such as Sine Cosine Algorithm is integrated with Artificial Neural Networks (SCA_ANN), Back Propagation Neural Networks (SCA_BP), Elman Neural Networks (SCA_ElmanNN), and Elman Neural Networks (ElmanNN). The evaluation employs two key performance metrics: Accuracy (ACC) and Mean Squared Error (MSE). The training dataset, representing 70% of the data, is used for algorithm training, and the testing dataset, constituting the remaining 30%, assesses the algorithms' ability to generalize to new, unseen data. Results indicate that SCA_ElmanNN in both training and testing datasets, achieving high accuracy and minimal MSE, showcasing its proficiency in classification and prediction precision. SCA_BP and SCA_ANN also demonstrate robust performance. Conversely, ElmanNN, while relatively accurate, exhibits a slightly higher MSE on the testing data, indicating some variability in its predictions. These findings offer valuable insights for researchers in selecting the most appropriate algorithm for specific classification tasks.**

Keywords— Sine Cosine algorithm, Neural network, Back-propagation, Local minima, ElmanNN, Mean square error (MSE).

I. INTRODUCTION

Classification, is the most fundamental machine learning technique, involves categorizing data into predefined groups based on specified similarities and constraints. To accomplish this, researchers have employed a range of regression models and classification methods [1], including Logistic Regression, Linear Regression, Linear Discriminant Analysis, Hidden Markov Models, Support Vector Machine (SVM), Bayesian Algorithms, Decision Trees, K-Nearest Neighbor (KNN), Particle Swarm Optimization (PSO), along with various traditional, statistical, and computational approaches [2]. Optimization is the process of selecting the most suitable parameter values within a vast array of options to maximize or minimize a system's output. This field holds significant importance for scholars as optimization challenges are prevalent across various domains of study. Optimization techniques can be broadly categorized into two main groups: local search techniques and population search techniques, notably recognized as meta-heuristics [3, 4]. Local search techniques, focus on refining a single solution during the optimization process by iteratively exploring its neighborhood [5]. While these methods are best at exploitation searches, their primary limitation lies in their emphasis on local exploration, often overlooking global search possibilities.

In contrast, population search techniques work with multiple solutions (populations) in each iteration, aiming to generate one or more improved solutions [6, 7]. These approaches are effective at exploring broader areas within the search space but may struggle to efficiently exploit certain regions, potentially getting stuck in local optima [8]. To enhance the learning process of ANNs, researchers have employed various optimization models, with several common optimization algorithms [9] being used for different tasks. This study introduces the Sine Cosine Algorithm (SCA), is a population-based optimization approach pioneered by [5, 10]. SCA used trigonometric sine and cosine functions as a basis for generating diverse initial solutions and guiding them towards optimal outcomes. This technique incorporates random and adaptive variables to balance exploration and exploitation of the search space during crucial optimization phases. SCA effectively combines the key strategies of both population search and local search, facilitating global exploration and local exploitation.

The SCA algorithm shares common attributes like simplicity, flexibility, and ease of implementation with other meta-heuristic algorithms, interpreting it a versatile tool for addressing a wide array of optimization challenges, applications include scheduling [11], networking feature selection [12], planning for economic power dispatch, and image processing [13]. In order to improve the learning process of ANNs, the SCA algorithm is used in this study to get around some of the drawbacks of ANNs, including delayed convergence and the problem of local minima. It has been the focus of extensive research to enhance the learning capabilities of both regular ANNs and Elman Neural Networks (ENNs). The balance between exploration and exploitation has been studied using a variety of optimization strategies, each with its own advantages and disadvantages. The Sine Cosine Algorithm is used in this study to propose a novel strategy that is designed to promote more effective decision-making while minimizing resource use. The sine cosine algorithm is a brand-new algorithm that may be used to tackle a wide range of optimization jobs [10, 12]. The sine cosine algorithm (CSA) is specifically used in this research to improve the learning processes of both ANNs and ENNs, providing improved decision-making with less resource usage. Many of the key aspects of this research are covered in this section, including the following:

- The study introduces a pioneering method by suggesting the incorporation of the CSA with ELMAN and ANN models to tackle the problem of local minima and facilitate convergence towards global minima.
- The performance evaluation of this proposed model, in terms of mean square error and accuracy, is compared to ELMAN_NN, the sine cosine algorithm with ANN, and the CSA with back propagation NN.
- The research attains high levels of accuracy and low mean square error when compared to the algorithms utilized in this study.
- By integrating the CSA with ELMAN_NN and artificial NN models, this research effectively addresses the local minima problem inherent in ELMAN_NN.

The subsequent sections of this paper are organized as follows: Section II provides an overview of the related work. In Section III, the proposed model is elaborated upon. Section IV explores into the results from practical scenario-based experiments. Finally, Section V offers the conclusion and outlines future research.

II. RELATED WORK

The author in [5] presents SCA, a population-based optimization method introduced in 2016. SCA employs position updates to optimize solutions, striking a balance between exploration and exploitation. The algorithm's performance was evaluated using various test cases, including uni-model, multi-model, and composite functions, showcasing its ability to navigate local optima and convergence. SCA's performance was assessed through multiple indicators, including search history, trajectory, solution fitness, and optimization efficiency. The algorithm's effectiveness in optimizing a two-dimensional airfoil, representing real-world applications, was also demonstrated. Another paper in [14] used Multi-Orthogonal Sine Cosine Algorithm (MOSCA) combines the (SCA) with a Multi Orthogonal Search Strategy (MOSS) to improve engineering design problem-solving. MOSCA's two-stage approach enhances exploration and exploitation, making it more stable, statistically robust, and efficient, with faster convergence. Evaluation across eighteen benchmark tasks and four engineering design problems shows that MOSCA outperforms other algorithms in most scenarios, demonstrating its promise in optimization.

Further [13] in his paper introduces a modified Sine-Cosine Algorithm (MSCA) for solving the Optimum Power Flow (OPF) problem, aiming to reduce processing time while enhancing accuracy and practicality. MSCA incorporates Levy flights to improve the focus on optimal solutions and avoid local optima, resulting in robust solutions for various objective functions in the OPF problem. Validation on benchmark test systems, including IEEE-30 bus and IEEE-118 bus systems, demonstrates MSCA's effectiveness and compares it to other optimization approaches. In response to the limitations of the SCA, [15] in this study introduces the Multi-Group Multi-Strategy(MMS) with SCA algorithm, which concurrently runs multiple populations, each employing a distinct optimization strategy, with inter-group information sharing. MMSCA's performance surpasses that of the original SCA and demonstrates advantages over other intelligent algorithms across 19 test functions. It is further applied to solve the capacitated vehicle routing problem (CVRP) in transportation, providing superior results and practical feasibility. To address the complexity of concrete property modeling, [16] utilizes a dataset of 1030 concrete samples to accurately simulate compressive strength. A Feed-Forward neural network (FFNN) is employed, to train using the bat algorithm, to predict compressive strength based on eight criteria. Comparative evaluations with other optimization methods and models confirm that the bat algorithm-optimized ANN provides superior accuracy in predicting concrete compressive strength.

III. METHODS

A. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) represent a nonlinear system comprised of artificial neurons, similar to biological neurons in the human brain, designed to process information. ANNs aim to emulate key human brain characteristics like self-adjustment, self-organization, high parallelism, resilience, and fault tolerance. These attributes are crucial for effectively addressing nonlinear problems [17, 18]. Artificial neurons within ANNs can be trained to store, recognize, estimate, and adapt to new patterns without prior knowledge of the functions they handle [6, 19]. This learning and adaptability set ANNs apart from traditional methods [7, 20]. Their capacity to solve complexity issues, time-sensitive problems has made them valuable across engineering disciplines, including biological modeling, financial and weather forecasting, decision-making, control systems, manufacturing and healthcare [21].

B. Back-Propagation (BP)

The Back-Propagation (BP) Neural Network stands as a prominent supervised learning ANN algorithm initially introduced by Rumelhart and Williams in 1986. It is a Multilayer Perceptron (MLP) consisting of three parallel layers: an input layer, a hidden layer, and an output layer, with nodes equipped with nonlinear activation functions [22]. The BP process involves feed-forward and back-propagation stages iteratively, adjusting weights as errors occur, hence its name. Random weight initialization typically starts the process, with subsequent iterations fine-tuning the network until the output closely matches the desired values [23, 24]. BPNN is used in discovering relationships between inputs and outputs and employs the gradient descent method to calculate weights, making it a standard choice for training MLPs [25].

C. Sine Cosine Algorithm (SCA)

The SCA [5] is a recently introduced metaheuristic algorithm. It operates as a population-based probabilistic search technique that adjusts the positions of search agents within the population by leveraging the inherent characteristics of trigonometric functions, namely sine and cosine. SCA draws inspiration from the periodic nature of these functions, which, confined within the range of [-1, 1], endow it with a substantial capability to explore the search space effectively while maintaining a delicate equilibrium between exploration and exploitation. The Sine Cosine optimization process commences by randomly initiating a group of representative solutions or search agents within the search space, collectively forming the population. Each search agent within this population can be proposed as a vector within the d-dimensional search space. These search agents adapt their positions through stochastic equations that incorporate trigonometric sine and cosine functions [10].

D. Proposed Sine Cosine ENN Model

In the proposed Sine Cosine Algorithm and Elman Neural Network (Elman NN) algorithm, each best position within the Sine Cosine Algorithm represents a potential solution, encompassing the initial weight values and corresponding biases for Elman Neural Network (Elman NN). The quality of the solution depends on the population size and weight optimization problem. During the initial epoch, the best weights and biases are set using the Sine Cosine algorithm and subsequently employed in the Elman NN. The weights for the Elman NN are computed. In subsequent cycles, the Sine Cosine Algorithm iteratively updates the weights to find the best solution until the network reaches its final cycle or the desired Mean Square Error (MSE). Here's the revised pseudo code for the proposed Sine Cosine Elman NN algorithm:

i. *Start*
ii. *Initialize the Sine Cosine population size, dimension, and Elman NN structure.*
iii. *Load training and testing data.*
iv. *While MSE is less than the stopping criteria:*
v. *Set Sine Cosine-optimized weights for the network.*
vi. *Perform a feed-forward pass using the weights initialized by the Sine Cosine algorithm.*
vii. *Calculate the error using equation.*
viii. *Minimize the error by adjusting network parameters using the Sine Cosine algorithm.*
ix. *Utilize 70% of the data for training and 30% for testing.*
x. *Continue using the Sine Cosine algorithm to refine the network parameters.*
xi. *Generate new values by transitioning to a different function.*
xii. *If Xj > Xi,*
xiii. *update Xi to Xj;*
xiv. *else,*
xv. *revert Xj to Xi.*
xvi. *End*
xvii. *Repeat this process until the network converges.*
xviii. *End While*
xix. *Perform post-processing on the results and create visualizations.*
xx. End

E. Data Collection

The dataset used in this research is sourced from the UCI website accessible online. The cancer dataset comprises 9 input attributes and 2 classes, Benign and Malignant, with values ranging from 0 to 1 (integer), and a binary output attribute (2 = benign, 4 = malignant). These values are directly employed, scaled to a 0 to 1 range, and represented with two units for the output. Attribute 6 in the dataset has 16 missing values, encoded as 0.3, aligning with its average value of approximately 3.5. the second dataset such as thyroid dataset, the encoding remains consistent with the original data file, employing a 1-of-3 encoding to replace the class number (1, 2, or 3), represented as (1 0 0, 0 1 0, or 0 0 1). In prior studies, the first 3772 thyroid records were designated as training data, while the remaining 3428 records served as test data. Datasets can be obtained from various online sources, including /uciml/datasets and https://archive.ics.uci.edu/ml/index.php.

F. Performance Parameters

The widely favored method for evaluating classifiers and measuring system performance is through accuracy and MSE. This metric is determined by dividing the correctly predicted observations by the total number of observations or real values. A high categorization accuracy signifies improved system performance. This metric assesses how well the model fits the training data. It measures the average squared difference between predicted and actual values in the training data.

IV. RESULTS AND DISCUSSION

A. Thyroid Dataset

In Table I, the performance of four different algorithms is assessed using both training and testing datasets, with a focus on accuracy (ACC) and mean squared error (MSE). In the context of machine learning and algorithm evaluation, the training dataset, which constitutes 70% of the total data, is used to train the algorithms, enabling them to learn patterns and relationships within the data. The testing dataset, representing 30% of the data, serves as an independent measure of how well the algorithms generalize to new, unseen data. In the training dataset, "ACC" indicates the percentage of correctly classified instances, reflecting how well the algorithms fit the data they were trained on. "MSE" quantifies the accuracy of their predictions during training, with lower values signifying closer alignment between predicted and actual values. SCA ElmanNN achieved an accuracy of 99.9587% and an impressively low MSE of 0.0004734. SCA_BP and SCA_ANN also demonstrate high training accuracy and minimal MSE.

Table I. Performance evaluation on thyroid dataset.

Algorithm	SCA_ANN	SCA_BP	SCA_ElmanNN	ElmanNN
30% Testing data				
ACC	99.9380	99.9385	99.9480	94.9792
MSE	0.00058	0.00059	0.00058	0.050208
70% Training dataset				
ACC	99.9378	99.9487	99.9587	89.774
MSE	0.00060	0.00049	0.00047	0.10226

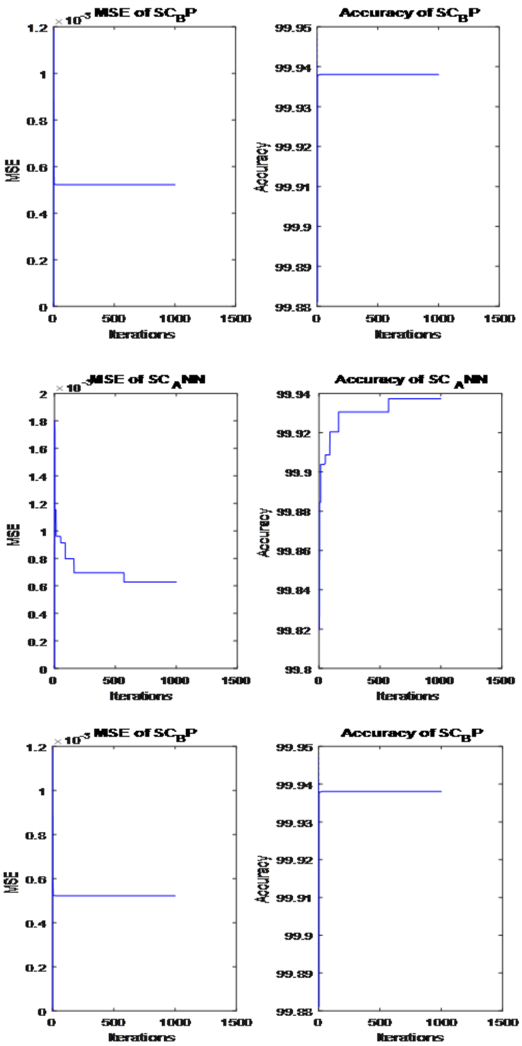

Fig. 1. Result of MSE and accuracy of 30% data of proposed models.

On the other hand, ElmanNN, while still relatively accurate at 89.774%, exhibits a higher MSE, implying some variability in its predictions. In the testing dataset, SCA_ElmanNN maintains its high accuracy, achieving 99.9480%, with an extremely low MSE of 0.000580. SCA_BP and SCA_ANN also deliver impressive accuracy and low MSE. ElmanNN, though relatively accurate at 94.9792%, has a higher MSE, suggesting slightly less precise predictions. These testing values are crucial indicators of how well the algorithms perform in real-world scenarios, further aiding researchers in selecting the most suitable algorithm for their specific classification tasks. Figure 1 give the MSE and ACC convergence of the proposed models in this paper.

B. *Cancer Dataset*

Table II. Performance evaluation on cancer dataset.

Algorithm	SCA_ANN	SCA_BP	SCA_ElmanNN	ElmanNN
30% Testing data				
ACC	99.9330	99.7910	99.9430	90.3120
MSE	0.00066	0.00200	0.000564	0.09687
70% Training dataset				
ACC	99.9373	99.7870	99.9465	96.7499
MSE	0.00062	0.00210	0.000534	0.03250

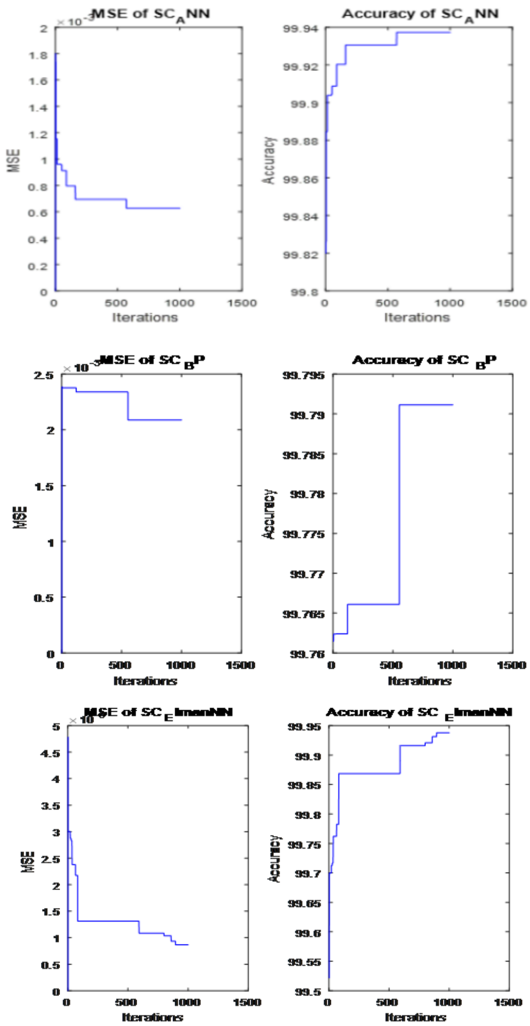

Fig. 2. Result of MSE and accuracy of 30% data of proposed models.

Table II provided compares the performance of four different algorithms on both training and testing datasets, using accuracy (ACC) and mean squared error (MSE) as performance metrics. The training dataset, comprising 70% of the total data, SCA_ElmanNN stands out with the highest training accuracy of 99.9465% and a remarkably low MSE of 0.000534852, showcasing its excellent training performance. In contrast, the testing dataset, representing the remaining 30% of the data, evaluates how well these algorithms generalize to new, unseen data. Notably, SCA_ElmanNN maintains its high accuracy with 99.943% and a very low MSE of 0.0005645, underlining its excellence in classification and prediction precision. SCA_BP and SCA_ANN also exhibit robust performance in the testing dataset. However, ElmanNN, while relatively accurate at 90.3125%, demonstrates a slightly higher MSE, indicating some variability in its predictions on new, unseen data. These values provide valuable insights for researchers, helping them select the most suitable algorithm for specific classification tasks based on its performance on both training and testing datasets. Figure 2 give the MSE and ACC convergence of the proposed models in this paper.

V. CONCLUSION

A comprehensive assessment of four distinct classification algorithms provides valuable insights into their performance on both training and testing datasets. Among the algorithms under consideration, the Sine Cosine Algorithm integrated with Elman Neural Networks (SCA_ElmanNN) emerges as the top performer, demonstrating exceptional accuracy and minimal Mean Squared Error (MSE) in both the training and testing datasets. This show the significant proficiency of SCA_ElmanNN in classification and the precision of its predictions. Furthermore, the Sine Cosine Algorithm integrated with Back Propagation Neural Networks (SCA_BP) and Sine Cosine Algorithm integrated with Artificial Neural Networks (SCA_ANN) also yield commendable results, underscoring their robust capabilities in classification tasks. These algorithms consistently maintain high accuracy levels and relatively low MSE values in both the training and testing datasets. However, Elman Neural Networks (ElmanNN) exhibit a somewhat higher MSE on the test data, albeit still being very accurate. This implies some variation in its forecasts, particularly when working with fresh, previously undiscovered data. Practically speaking, the study's findings give researchers the knowledge they need to select the best categorization method for a given assignment. SCA_ElmanNN stands out as a viable option for a variety of real-world applications thanks to its consistently high accuracy and low MSE, while SCA_BP and SCA_ANN provide reliable alternatives. These findings enhance machine learning's categorization procedures and emphasize the value of thorough algorithm evaluation in both theoretical analysis and real-world application. In future the SCA algorithm will integrate with different algorithms to use for various applications.

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