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Optimizing Artificial Neural Networks Using Levy-Chaotic Mapping on Wolf Pack Optimization Algorithm for Detect Driving Sleepiness

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Abstract- *Artificial Neural Networks (ANNs) are utilized to solve a variety of problems in many domains. In this type of network, training and selecting parameters that define networks architecture play an important role in enhancing the accuracy of the network's output; Therefore, Prior to training, those parameters must be optimized. Grey Wolf Optimizer (GWO) has been considered one of the efficient developed approaches in the Swarm Intelligence area that is used to solve real-world optimization problems. However, GWO still faces a problem of the slump in local optimums in some places due to insufficient diversity. This paper proposes a novel algorithm Levy Flight- Chaotic Chen mapping on Wolf Pack Algorithm in Neural Network. It efficiently exploits the search regions to detect driving sleepiness and balance the exploration and exploitation operators, which are considered implied features of any stochastic search algorithm. Due to the lack of dataset availability, a dataset of 15 participants has been collected from scratch to evaluate the proposed algorithm's performance. The results show that the proposed algorithm achieves an accuracy of 99.3%.*

Index Terms— *Electrooculography, drowsiness, neural network (NN), grey wolf optimizer (GWO), levy flight distribution, chaotic Chen map.*

I. INTRODUCTION

An artificial neural network (ANN) is a mathematical model of the biological nervous system. It is made up of neurons that communicate via axons. An artificial neural network is a system that can adapt, learn, and generalize [1]. Multi-layer Perceptron (MLP) has been a commonly used Artificial Neural Networks (ANNs) for many years with at least three layers input, hidden, and output layers. Each layer is composed of sets of neurons and synaptic weights that enable neurons to communicate with the next layer. The MLP layer, though, is just one of many types of ANNs, with varying attributes such as high adaptability, expandable, and self-organization; making them applicable for solving a broad range of types of problems in different application domains such as gaming systems, clustering data, classification data, pattern recognition, and many other applications. In addition, ANNs provide a high accuracy when they solve classification and prediction problems due to the continuous changing of their weight during the learning stage [1-3].

However, Adjusting the optimum setting of ANN's parameters, such as the number of hidden layers, the number of neurons in the hidden layer, and initializing the neurons' weights is considered a difficult and time-consuming process [4]. It is often done by 'trial and error' or 'rules of thumb'. Thus, systems for identifying the optimal parameters used to solve a specific problem have become an attractive area of research.

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Swarm intelligence (SI) is created for the understanding of social organisms or colonies. Swarm-based optimization and clustering algorithms were developed using swarm-based social behavior research. Such as PSO, ACO, GWO, and others. The algorithmic models were designed to solve complicated issues increasingly. Biological and natural intelligence modeling has yielded huge accomplishments, resulting in so-called "intelligent systems." Artificial neural networks, evolutionary computation, swarm intelligence, artificial immune systems, and fuzzy systems are among the examples [5-7].

Driver drowsiness is one of the leading causes of road accidents and has significant consequences for road safety in many countries. According to American National Highway Traffic Safety Administration (NHTSA), about 100,000 accidents in the United States each year are caused by driver drowsiness. While police statistics in the UK show 4% of road crashes lead to death, and 2% of collisions are caused by fatigue. In India, the Ministry of Road transport and highways transport research wing reports 4,49,002 accidents out of this number of data 33.65% was the mortality rate in 2019 [8, 9]. To prevent this type of accident, the driver should be warned on time. Many detection methods have been proposed; They use machine learning techniques and deep learning techniques but still do not provide a good accuracy which is an essential criterion in the work of those techniques [10-12] [13, 14].

This research has the following contributions: 1) enhance the accuracy for the driver drowsiness detection model by optimizing the weights of the ANNs using the GWO algorithm. 2) Solve the problems that face the GWO of poor local searching and slow coverage rate by using Levy Flight-Chaotic algorithm; 3) In addition to providing a new dataset that can be used in the future to train and test proposed algorithms to detect driver drowsiness.

The rest of this research is organized as follows: Section 2 discusses the previous research studies related to ANNs, GWO, and driver drowsiness detection techniques. While section 3 discusses the basics and background divided into Overview of Artificial Neural Networks, Gray Wolf Optimizer, and Levy Flight-Chaotic, while section 4 discusses the proposed method, the following section experimental results, and finally a conclusion.

II. RELATED WORK

To train and enhance the accuracy of ANNs output, many research studies have been proposed and focused on optimizing the ANNs parameters: the structure of the ANNs, synaptic weights, and transfer functions using Swarm intelligent algorithms. The work of Conforth and Meng [15] proposed a method that use both Ant Colony Optimization (ACO) and Swarm Intelligent to determine the connection of the ANNs and the synaptic weights. Other work like Da and Xiurun [16] exploits a hybrid of modified Swarm Intelligent and Simulating annealing (SA) to find both synaptic weights and the thresholds of the ANNs. In [17] the Kuok et al. solved the relationship between daily rainfall and runoff by modeling swarm intelligence to adjust the synaptic weights. While Garro et al. [18] solved the classification problems by adjusting the synaptic weights of the ANNs after comparing the back-propagation method and swarm intelligence. Further work by Garro et al. [19] optimized the synaptic weights using swarm intelligence and differential evolution. M. Shariati *et al.* [20] developed a hybrid method that uses a combination of artificial neural networks and swarms intelligence to predict channel connectors' behavior embedded in normal-strength and high-strength concrete. In [21], Zhang and Qui employed swarm intelligence to optimize the hyper-parameters for ANNs for credit scoring. In the paper by Parsian et al. [22], a novel and more efficient method have been developed to identify photos of malignant melanoma. Which exploits the GWO algorithm to optimize the ANNs by minimizing the

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root square error. While in [23], authors focused on the three ANNs parameters at the same time by proposing a new model of swarm intelligent algorithm. However, most of the previous studies showed some limited success, but were far from the best solution or getting the optimal one.

Detecting driver drowsiness to minimize accidents attracts many researchers due to its importance in saving lives. Most of the research studies use machine learning techniques [13, 14, 24, 25]. Studies in [26-30] use ANN to detect drivers' drowsiness, but they didn't focus on tuning the NN parameters that can enhance the accuracy of the model.

Our work focuses on enhancing the accuracy of detecting drivers' drowsiness model by improving the tuning of synaptic weights and other parameters of the ANN through the application of GWO and Levy Flight-Chaotic algorithms.

III. BASIC AND BACKGROUND

A. Overview of Artificial Neural Networks

Many researchers have attempted to develop ANN models for many years. Neural networks help find patterns and spots too complicated for humans or other computer techniques to discover. In addition, neural networks have been trained to model "experts" in specific domains. For example, Wang et al. [31] used data collected from leather subject specialists and Machine-derived parameters for the same example material to produce a model to replicate specialists scores using machine parameters.

The Perceptron and multi-layer perceptron's (MLPs) are the most basic of neural networks. Multi-layer perceptrons extend the perceptron concept, allowing them to be applied to even more complicated problems. Hidden layers make up their structure. Hidden layers add power and allow the network to extract extra features from the input. The standard method for training a multi-layer perceptron is error back-propagation, which involves two passes through each network layer: forward and backward passes [1] [32].

B. Gray Wolf Optimizer

Gray Wolf Optimizer (GWO) is a recent meta-heuristic algorithm developed by Mirjalili et al. (2014) [33]. The GWO algorithm is inspired by the leadership behavior of Grey Wolves and their swarm-hunting ability. It is designed to solve many complex problems based on models derived from wolf pack behavior where GWO has proved to have better results than other current optimization algorithms when identifying the right global solutions. The algorithm has a pack of wolves in which sub-groups of wolves each have a different role in the hunting process. For the GWO algorithm to work, the wolves' social intelligence, alpha wolf leadership, and the pack's three powerful wolves (beta-delta-omega) together with their varied mechanism of searching, approaching, and finally hunting their prey are three key motivating variables. Alpha is responsible for decision-making and can be considered as an optimal solution. The mathematical model of the algorithm incorporates 1) Tracking, Chasing, and approaching the prey. 2) Pursuing, encircling, and harassing the prey until it stops moving. 3) Attacking the prey [6, 7, 34]. The following equations are used to determine the fitness of each possible solution.

$$X(t+1) = X(t) - A.D \qquad (4)$$

Here $X(t+1)$ is a new wolf role. $X(t)$ is wolf's present location, A is a coefficient matrix, and D is a vector with a position of prey Xp as a parameter and determined as follows:

$$D = \left|C.X_p(t) - X(t)\right| \qquad (5)$$

Where, $= 2.r_2$, r_2 is a random vector in the interval [0,1], this can be applied to any number of dimensions as vectors are being used.

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$$A = 2a.r_1 - a \qquad (6)$$

And here, 'a' is the vector with a linear decrease from 2 to 0. 'r1' is random ranges between 0 and 1.

It is believed that Alpha, beta, and delta are the three optimum solutions in GWO, as they are aware of the correct location. Thus, the other wolves should place themselves as follows:

$$X(t+1) = \frac{(X1 + X2 + X3)}{3} \qquad (7)$$

And modify A, C,& a is calculated as the fitness for all search agents (modify $X\alpha$, $X\beta$, & $X\delta$) such that: ($X\alpha$, $is\ the\ first\ finest\ search\ \ agent$), (X$\beta$, $is\ the\ second\ finest\ search\ \ agent$), and ($X\delta$, $is\ the\ third\ finest\ search\ \ agent$). The pack's main tasks are searching and hunting. The algorithm calls them exploration and exploitation. These activities must be performed to avoid local solution stagnation [34], [35].

C. Levy Flight-Chaotic

Chaos is recently defined as a universal nonlinear phenomenon and one of the optimized search algorithms because changes in initial conditions may lead to nonlinear alterations in future behavior. The primary role of the chaos is to transform parameters/variables to the solution space. Some of the chaotic properties in nonlinear systems follow limited laws because they applied the same formal properties (initial conditions of sensitive, ergodic, stochastically); such Ergodicity refers to the chaotic serial's ability to explore all possible states in a given range without repeating itself. However, this technique is sensitive to the beginning values and performs poorly in global search [36-38]

Lévy flights are Markovian stochastic processes in which the lengths of the individual jumps are dispersed according to the probability density function (PDF). In other words, a particle moving in a Lévy-flight manner takes just a few large steps in between many smaller ones. An example of a typical motion pattern is as follows: the particle first moves locally, taking a series of small steps, before taking a large step, and then moving locally once more after that. Thus, a simple version of Lévy distribution can be defined as:

$$L(\delta,\gamma,\mu) = \sqrt{\frac{\gamma}{2\pi}\, exp\left(-\frac{\gamma}{2(\delta-\mu)}\right)}.\frac{1}{(\delta-\mu)^{3/2}}\ , 0 < \mu < \delta, \quad or = 0, otherwise, \dots\dots\dots (8)$$

Where μ shows a shifting parameter and $\mu > 0$ is a minimum step, and γ is a scale parameter [37-40].

Fractional Order Chaotic Chen Oscillator the Chen oscillator is a continuous nonlinear and autonomous dynamical system, and it is an initial value problem, either an integer or fractional order. Guanrong Chen and Tetsushi Ueta proposed the oscillator, and its fractional-order version is modeled by Caputo's fractional derivative [41, 42], as follows:

$$\bar{x} = a\,(y - x) \dots\dots\dots\dots (9)$$
$$\bar{y} = (c - a)x - xz - cy \dots\dots\dots\dots (10)$$
$$\bar{z} = xy - bz \dots\dots\dots\dots (11)$$

where ($\bar{x}$, $\bar{y}$, $\bar{z}$) is the Caputo's differential operator of order excellent than of 0 and least or equal than of 1; x, y, and z are the system-dependent variables; and, a, b, and c are the system parameters with traditional values of 35, 3, and 28, respectively [41, 43], and these values will be changed in experiments.

IV. PROPOSED METHOD

This section briefly illustrates the main steps for the proposed Levy Flight- Chaotic Chen mapping on Wolf Pack Algorithm in Neural Network, as shown in *Fig. 1*. This study proposes a novel

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way to improve the grey wolf algorithm's performance. First, levy Flight-Chaotic is employed to achieve better results. Then, when the grey wolf algorithm cannot obtain the optimal outcomes after a specified number of iterations, this method uses Levy Flight-Chaotic to avoid becoming stuck in the local optimum. Thus, levy Flight-Chaotic improves global and local search capabilities.

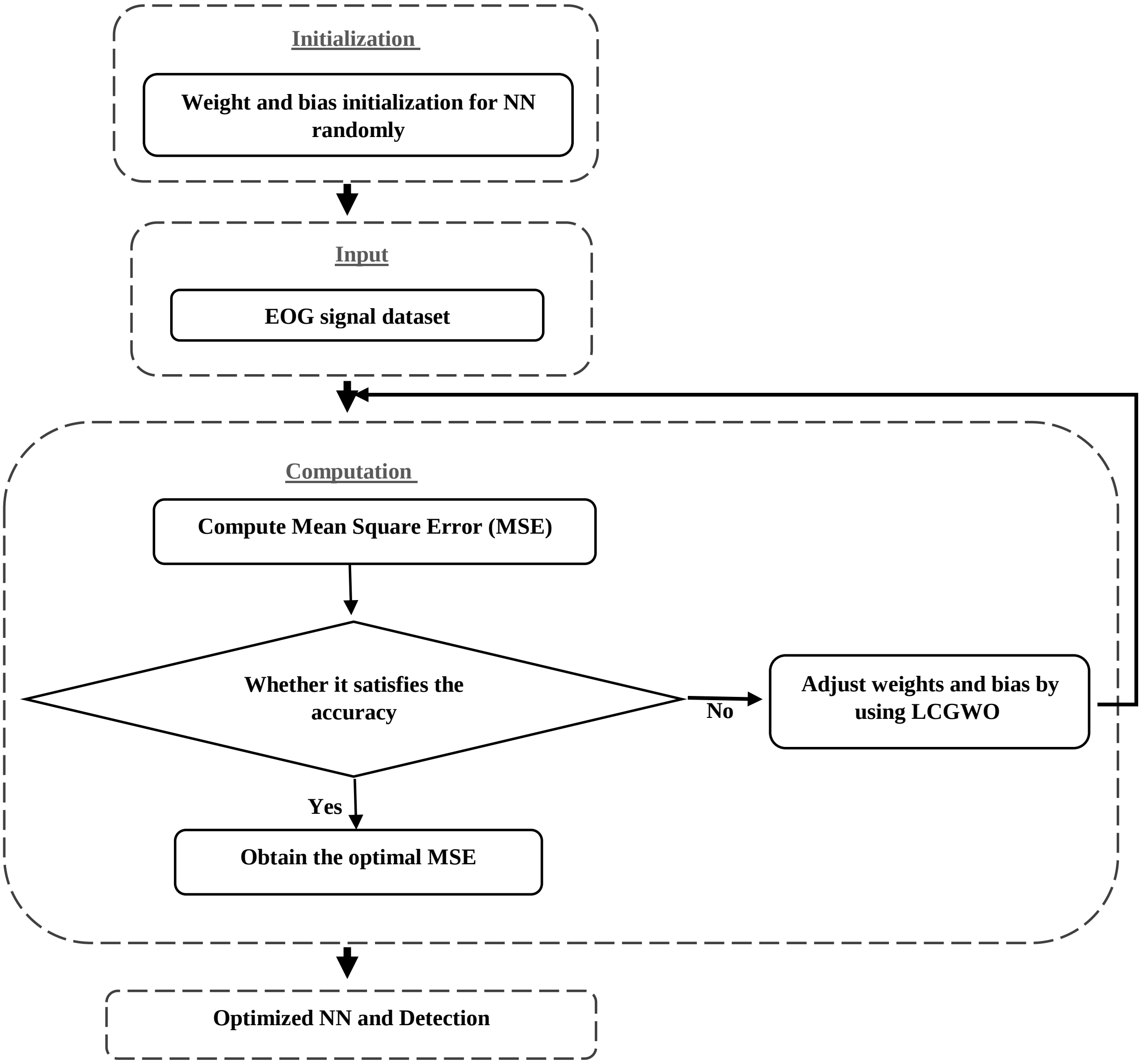

FIG. 1. THE FLOWCHART OF THE PROPOSED METHOD.

A. Initialization

In this step, weights and bias for NN are initialized randomly and will be updated continually by the LCGWO until getting the optimal weights.

B. Input

Electrooculography (EOG) dataset is a physiological metric that our system would employ to determine the driver's safety. Usually, when the driver is drowsy, the eye movement becomes slower than when the driver is awake. Weights and bias are fed into the NN to train it. An ANN trained under a back-propagation algorithm will be constructed to detect drivers' drowsiness.

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C. Compute

This step represents the core work to train the NN. The LCGWO algorithm is used to update the weights of the trained NN to detect the driver's drowsiness. The Root Mean Square Error (RMS error) is calculated in every iteration, and the LCGWO algorithm updates weights. This step is repeated until we get the optimized NN.

V. EXPERIMENTAL RESULTS

A. Dataset

In this experiment, a group of 15 healthy (defined as no know health conditions that would exclude them from the study and legally driving) volunteer participants (8 men and 7 women) were involved. All own their driver's licenses, and their ages are between 26-45 years old. As part of the test parameters, all participants were asked not to drink coffee or tea; they must have had a restful sleep the night before. To gain an accurate result, it is was also recommended that participants drive a vehicle in the real world for 20 minutes. Each experiment has two driving tasks, which are referred to as process 1 and process 2. Process 1 is the initial scenario in which each participant must drive in a grouped fashion. Other cars on the congested highways must keep a close check on them and always remain attentive; that means the driver is not drowsy. Process 2 requires each participant to drive while tired on a busy road in a city, which means the driver is drowsy. Moreover, Process 1 is half an hour before Process 2 for the rest of the Participants. The 7 minutes' maximum EOG signal was recorded for each process. Using the atmage256 Arduino board with the AD8232 biological signal sensor and the Arduino system programming IDE, this step collects eye movement signals. The software is computer access and can collect data.

B. Parameter Settings

Many parameters have been used in this experiment. Some are related to GWO, while others are related to ANN. Tables I and II briefly illustrate the initialized parameters that are used for each algorithm.

TABLE I. PARAMETERS BASED FOR GWO AND ANN

Parameters based for GWO	
Parameters	Value
Iteration NO.	200
Population size	20

TABLE II. PARAMETERS BASED FOR TRADITIONAL ANN MODEL

Parameters	**Value**
Max iteration	1000
Number of (neurons in I/P Layer)	12
Number of (Hidden Layer)	3
Number of (neurons in each Hidden Layer)	7
Number of (neurons in O/P Layer)	2

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C. Experimental Setup and Performance Evaluation

we apply the dataset that has been described in section 5.1 on a traditional Multiplayer Perceptron ANN and then on our proposed LCGWO-NN method. Due to the small, collected dataset, we divided our dataset into 90% training and 10% testing. An accuracy metric has been counted on to evaluate the performance of the proposed method.

Table III shows the results of applying a traditional ANN classifier. It can be noticed that the ANN classifier achieved the best accuracy in run 7.

TABLE III. THE RESULTS PROVIDED BY TRADITIONAL ANN

Run number	**Accuracy (90%-10%)**
1	81.4%
2	77.2%
3	77.4%
4	77.0%
5	79.8%
6	80.2%
7	89.0%
8	85.4%
9	75.6%
10	76.0%

While Table IV shows the results of applying the proposed hybrid method (LCGWO -ANN) using (90%-10%) training test ratios. It can be seen that the LCGWO-ANN method achieved a balanced accuracy in all percentages of the training test, and also it was observed that the value of the input parameters to the chaotic Chen function in which a and c is decreasing, b is increasing that gave good results for the proposed algorithm, while when decreasing a value of the input parameters to the Levy flight distribution ($\bar{x}, \bar{y}$ and $\bar{z}$) leads to accurate results.

TABLE IV. PARAMETERS USED IN THE PROPOSED METHOD

parameter	**Run1**	**Run2**	**Run3**	**Run4**	**Run5**	**Run6**	**Run7**	**Run8**	**Run9**	**Run10**
a	35	30	35	35	25	25	25	25	15	35
b	3	3	10	5	5	5	5	5	9	5
c	28	25	20	7	20	20	20	20	10	7
$\bar{x}$	0.01777	0.01777	9.1	0.092355	0.01555	0.1555	0.9	1.1	2.1	0.9355
$\bar{y}$	1.0177	1.0177	9.9	1.09735	1.0155	1.155	1.9	2.9	3.9	1.935
$\bar{z}$	0.0177	0.0177	9.1	0.09135	0.0155	0.155	0.9	1.1	2.1	0.935
hv	0.077777	0.077777	9.1	0.1993555	0.055555	0.55555	0.9	1.1	2.1	0.93555
Acc. in LCGWO-NN	95.5%	95.9%	96 %	96.7%	98.5%	98.9%	98.5%	98.2%	98.7%	99.3%

Table V shows the values of (best, worst, mean, and standard deviation) of applying two classifiers using (90%-10%) training-testing percentages. Compared to the classifiers of traditional ANN, it can be observed that the value of STD in the proposed method achieved the lowest value, and it achieved the highest value in (best, worst, and mean). Thus, we conclude that the proposed method (LCGWO-ANN) is steady and provides accurate results.

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TABLE V. THE RESULTS OF CLASSIFIERS MODELS

Classifier	Best Acc.	Worst Acc.	Mean	STD.
ANN	89.0%	75.6%	79.9%	0.0414
LCGWO-ANN	99.3%	95.5%	97.6%	0.0136

VI. CONCLUSIONS

In conclusion, a framework focused on optimizing ANN by using one of the swarm algorithms GWO and Levy Flight-Chaotic Chen so-called LCGWO to detect the driver drowsiness. Using the EOG analysis, the dataset in this paper was built from scratch because each researcher used a dataset that was not publicly available. Based on a low misclassification rate, the LCGWO algorithm was able to train artificial neural networks with low error and high classification accuracy. As a result, the LCGWO is an efficient training procedure for artificial neural networks that perform well when used with a variety of datasets. The proposed method provides 99. 3% accuracy and the traditional ANN algorithm provides 89.0% accuracy.

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