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Prediction of Electroencephalogram Time Series With Electro-Search Optimization Algorithm Trained Adaptive Neuro-Fuzzy Inference System

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ABSTRACT Nowadays, artificial intelligence is widely used in many biomedical-oriented problems. Because of obtained effective and efficient results, the use of intelligent solution mechanisms by artificial intelligence techniques is mainly focused on healthcare applications. Moving from the explanations, the objective of this paper is to provide an adaptive neuro-fuzzy inference system (ANFIS) trained by a recent optimization algorithm: electro-search optimization (ESO) for predicting the electroencephalogram (EEG) time series. In detail, the research was directed to the EEG time series showing chaotic characteristics so that an effective hybrid system can be designed for having an idea about future states of human brain activity in the case of possible diseases. The developed ANFIS-ESO system was evaluated with five different EEG time series and the obtained findings were reported accordingly. In addition, the ANFIS-ESO system was compared with alternative techniques-systems in order to see the performances according to different systems. In the end, it is possible to mention that the ANFIS-ESO system provides well-enough results in terms of predicting EEG time series. As a result of encouraging results, ANFIS-ESO is currently used actively for real cases.

INDEX TERMS Adaptive neuro-fuzzy inference system, biomedical, electroencephalogram, electro-search optimization algorithm, time series prediction.

I. INTRODUCTION

In today's modern world, advanced technologies supporting the humankind take an important role to create a sustainable future. Especially, computer oriented solutions, which can be used for solving real-world problems have already transformed the society into a new form dominated by the digital world. At this point, the field of artificial intelligence is a great star among all technological fields, thanks to its flexible solutions methods, and techniques that can be applied in almost all real-world based problems. Today, there is not any field in which artificial intelligence based approaches, methods, or techniques cannot be used effectively. It is possible to see applications of artificial intelligence by considering solution mechanisms such as control, optimization, prediction, recognition…etc. [1]–[4]. In terms of especially prediction, developed intelligent systems use real-world oriented data to predict future states, which can then be used to understand possible future or explain the past by looking at both present and the future [5]–[10]. Because of that, the prediction problem has been attracting researchers' interests too much for a remarkable long time period.

Prediction with artificial intelligence can be done for solving problems of many different fields like medical, engineering, chemistry, or even education [11]–[20]. Artificial intelligence has several methods and techniques to solve that prediction issue and machine learning is known as one of them. Thanks to learning from known samples or given feedback (experiences), machine learning techniques can be effective for solving even advanced prediction problems [21]–[26]. Considering prediction with artificial intelligence, time series is one of the most widely used data because of their mechanism to have some signs for future predictions.

As a series of data stored over a time past (i.e. weekly, monthly, yearly) [27]–[30], a typical time series can be used to explain many facts affecting the humankind, nature, world, even the universe. In this context, intelligent systems formed specifically by machine learning techniques of artificial intelligence can be used to predict future states of time series by using some samples from their past. Even they are chaotic or not, or from natural sciences or social sciences, time series have been successfully predicted by intelligent systems as reported in the literature [31]–[37].

In the field of medical, we can see different types of time series, which can be predicted by intelligent systems for understanding more about future activities of specific organs. In this context, some time series such as Electroencephalogram (EEG, for understanding brain activity), Electrocardiogram (ECG, for understanding heart activity), or Electromyogram (EMG, for understanding activity of muscles and nerve cells) are often included in research works by researchers interested in biomedical applications of artificial intelligence [38]–[41]. Prediction of such time series is important since it can be possible for researchers to develop automated diagnosis systems, which are more robust, accurate and rapid in analyze according to physicians or medical staff.

Objective of this paper is to introduce an Adaptive Neuro-Fuzzy Inference System (ANFIS) trained by a recent optimization algorithm: Electro-Search Optimization (ESO) for predicting Electroencephalogram (EEG) time series. In detail, the research was directed to EEG time series showing chaotic characteristics so that an effective hybrid system can be designed for having idea about future states of human brain activity in case of possible diseases. In order to understand more about effectiveness of the ANFIS-ESO system, it was aimed to apply it in five different chaotic EEG time series. Because it is also important to learn some about success of the system against alternative solution approaches-systems, ANFIS-ESO was aimed to compare with some alternative techniques and hybrid systems. The novelty of this research is associated with use of ESO as the first time for training an ANFIS for EEG prediction and the following motivations were also considered directly:

- It is important to design and develop alternative solutions for important fields like medical and healthcare.
- In terms of artificial intelligence, development of diagnosis and prediction oriented solutions is very critical for improving the recent literature.
- For improving the literature of artificial intelligence, it is remarkable to design hybrid systems with the support by recent techniques.
- Prediction of EEG time series is too important for understanding future states of a person's brain-signal so that diagnosing possible diseases.
- Prediction of EEG time series is important for also understanding more about mysteries of the brain.
- At the time of this study, ESO algorithm has not been used in any alternative applications yet. So, it is a motivating factor to evaluate its effectiveness in terms of training a machine learning technique for an advanced problem.

The remaining content of the paper is organized as follows: The next section is devoted to a literature review, which is supported with a general discussion on what can be understood from the associated literature and motivations that can be derived in this manner. Following to the second section, the third section explains the used artificial intelligence based techniques: ANFIS and ESO algorithm, and also followed prediction approach for EEG time series. After that section, the fourth section focuses on the applications done for five different chaotic EEG time series examples and the fifth section focuses on some evaluation works done for understanding better about success of the developed ANFIS-ESO system. After a general discussion about the results and active real case uses within the sixth section, the paper is ended by the seventh section including conclusions and some discussion about future works.

II. LITERATURE REVIEW

In order to understand more about the current state of the associated literature, some previously done, remarkable research works may be reviewed briefly. In this way, it is possible to understand which kind of intelligent systems (alternative solution ways) were employed for prediction tasks over EEG time series. The review has been done for works focused on especially EEG time series, but also some other ones including different time series with also EEG and similar biomedical oriented time series were examined accordingly.

Cui *et al.* [42] used a Single Multiplicative Neuron (SMN) system, which is trained by an improved version of Glowworm Swarm Optimization (GSO) algorithm to predict EEG time series. Their work included not only EEG time series but also Mackey-Glass, and gas furnace (Box-Jenkins) data. The findings reveal positive results in terms of the developed SMN-GSO system. Wei *et al.* [43] used Adaptive Projective Learning Algorithm for training Radial Basis Function Neural Networks on EEG time series prediction applications. They briefly introduced that when optimum alpha parameters are chosen, the formed intelligent system can effectively predict EEG time series. Their work shows also that the prediction performance is also associated with correlation dimension of target EEG time series. Kose [44] used a traditional Artificial Neural Networks (ANN) model and trained it with recently developed Ant-Lion Optimizer (ALO) algorithm to predict chaotic EEG time series. Results obtained with the ANN-ALO system showed a well-enough prediction performance. Hou *et al.* [45] introduced a Back-Propagation Neural Network to apply several prediction operations for EEG time series. In their work, a Brain Electrical Activity Mapping (BEAM) approach was also used to form an alternative solution approach. In their work, Wei *et al.* [46] used Bi-directional Recurrent Neural Network (BRNN) and Convolution Neural Network (CNN) to design-develop a universal prediction system two different medical time series: EEG and ECG. Their solution approach provided well-enough results in terms of predicting the chaotic time series of EEG and ECG. As a more general research work on predicting time series, Wu *et al.* used Iterated Extended Kalman Filter with the model of SMN for EEG time series [47]. In a similar study to [47], Zhao and Yang predicted EEG, Mackey-Glass, and gas furnace (Box-Jenkins) by using a hybrid system of SMN-PSO [48]. In the research by Samanta, an Adaptive Neuro-Fuzzy Inference System (ANFIS) and also a SMN model trained by co-operative sub-swarms PSO algorithm (COPSO) were both used for predicting different chaotic time series including EEG, Mackey-Glass, and gas furnace (Box-Jenkins) [49]. In their work, Blinowska and Malinowski [50] introduced non-linear and autoregressive (AR) techniques for predicting EEG and simulated time series. Yeh [51] introduced a parameter-free simplified swarm optimization oriented approach for training ANN and he has reported prediction performances over different time series in which EEG was included, too. Coyle *et al.* [52] introduced a two-Neural Network-model approach to realize prediction over EEG time series. That research was a part of an approach of feature extraction for a Brain-Computer Interface and the followed prediction was supported with a classification-extraction done via Linear Discriminant Analysis (LDA). By Kose and Arslan [53], a solution approach of hybrid system, which is formed by ANFIS and a recent optimization algorithm: Vortex Optimization Algorithm (VOA) was introduced to predict EEG time series. In detail, they obtained well-enough results in terms of predicting EEG time series with ANFIS-VOA. In their work, Komijani *et al.* [54] introduced an ANFIS approach to classify healthy individuals and the individuals with epilepsy, thanks to chaotic EEG time series samples. In another work, Lin *et al.* [55] introduced a third order Volterra filter for predicting chaotic time series in which some EEG data was included. In detail, they showed that the third order Volterra filter was better than the second order one when it comes to predict especially high-dimensional chaotic EEG time series. In [56], a Deep Recurrent Neural Networks (DRNN) based approach was used by Prasad and Prasad to predict chaotic EEG time series. In that work, the authors also developed a Dynamic Programming (DP) training stage for improving the general efficiency via matrix operations. In another work, Forney [57] used Elman RNN to classify EEG time series by including use of Winner-Takes-All, Linear Discriminant Analysis, and Quadratic Discriminant Analysis as well as alternative prediction stages. Chen *et al.* [58] used an improved Neuro-Endocrine Model (INEM), which was supported by Linearly Decreasing Weight Particle Swarm Optimization (LDWPSO) for predicting some chaotic time series including also EEG data. Obtained results reveal well-enough performances by the INEM-LDWPSO system developed by the authors. In the work by Du *et al.* [59], three different algorithms: adaptive differential evolution with knee-point strategy (ADE), non-dominated sorting adaptive differential evolution (NSADE), and its knee-point strategy supported version (KP-NSADE) were used for training Single Hidden-Layer Feedforward Neural Networks (SHLFNN) and the formed systems were used for predicting some chaotic time series including EEG. The performed research shows positive results at the end of the applications.

A. A BRIEF EVALUATION

Considering the review, it can be said that prediction of time series including EEG and different types of data is a popular research topic followed by researchers. The main reason lying on the background of that is the need for understanding more about the real-world, real cases thanks to some data, as it was mentioned before. When the research works are examined in terms of used solution approaches, it can be seen also that use of hybrid systems formed by some machine learning techniques and optimization oriented algorithms have been realizing widely for prediction purposes. In the context of machine learning techniques, it is observed that the ANN and its variations are dominating the literature of time series prediction. It is remarkable that there are examples of using ANFIS to predict EEG time series but using the Electro-Search Optimization (ESO) algorithm has not been reported yet. On the other hand, there is still need for evaluating alternative intelligent systems to predict EEG time series as it opens the doors of successful diagnosis of brain oriented diseases, possible future activities or brain, and also understanding it better for improving the field of medical.

After the brief but expansive enough review of the literature, it is better to explain some about the formed hybrid system of ANFIS-ESO in this study and also introduce the general EEG prediction approach followed within the system. In order to achieve that each artificial intelligence based technique and the prediction-solution mechanism considered in this study have been expressed to the readers, under to following section.

III. MATERIALS AND METHODS

Regarding materials and methods of this study, essentials of the employed techniques forming the ANFIS-ESO system and details of the used prediction approach can be explained as follows:

A. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a technique, which employs ANN and Fuzzy Logic (FL) in one hand to provide an advanced form of ANN model improved via fuzzy control. A typical ANFIS model includes a combination of human thinking-reasoning and intelligently learning behaviors to form a layer-oriented, rule supported model [53], [60]–[62]. As introduced by Jang [60], [61] first time, default ANFIS model uses FL and a Radial Basis Function Neural Network (RBFNN) structure including nodes with radial basis functions like Gaussian or Ellipsoidal ones. The FL side uses Takagi-Sugeno model-based inference approach to support the neural-network oriented model (The rule-base of the ANFIS model is supported with 'IF…THEN' rules designed with the function oriented mechanism of the first-order Takagi-Sugeno model). Default structure of an ANFIS model is shown in Figure 1 [63].

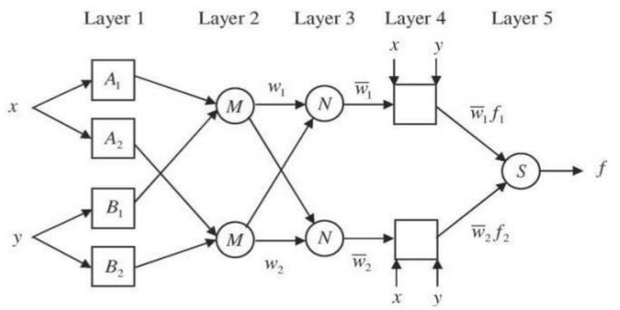

FIGURE 1. **Default structure of an ANFIS model [63].**

An ANFIS model employs some parameters known as 'premise', 'consequent'' parameters respectively and learning algorithms in this context are used to optimize these parameters so that the ANFIS output can match with the data for training [53], [60]–[63]. Here, some learning algorithms such as Gradient-Decent Backpropagation (GDB), and One-Pass of Least Square Estimates (LSE) can be used for training phases [64].

ANFIS has been widely used for solving different types of real-world based problems. Because of its hybrid nature meeting ANN with FL, it is often used by researchers as among alternative ways of machine learning based solutions. Interested readers are referred to [65]–[71] in order to have idea about applications of ANFIS including also variations.

B. ELECTRO-SEARCH OPTIMIZATION ALGORITHM

As introduced by Tabari and Ahmad, Electro-Search Optimization (ESO) algorithm is a recent intelligent optimization technique, which inspires from moves of electrons over the orbits around an atom nucleus [72]. Roots of the algorithm are associated with some known principles like Bohr Model, Rydberg Formula [72] and the steps are designed to create a metaphor of electron movements in the context of a three-stage optimization process. ESO also employs an in-system optimization approach called as Orbital-Tuner in order to adjust some parameters within iterations. Algorithmic flow of the ESO can be expressed briefly as follows, by considering the three stages [72]:

- **1st Stage (Atom Spreading):** In this stage, n atoms (particles) are randomly located in the solution space. As based on Bohr Model, each atom has a nucleus around which electrons can orbit and those electrons may make transitions between orbits by absorbing or emitting some energy. As it can be understood, atoms (particles) are candidate solutions considering the fitness function(s) of the optimization problem.
- **2nd Stage (Transition Between Orbits):** In this stage, electrons around each of nucleus start to move to larger orbits for getting orbits having higher energy (better fitness). That transition can be expressed as follows:

$$e_i = pos_i + (2 * rand - 1)(1 - 1/n^2)r \qquad (1)$$

where e is the electron, pos is the current position of the i^{th} nucleus, $rand$ is a random number from the range: [0, 1], n is the energy level (vicinity in which electrons can be positioned) that can be from {2, 3, 4, 5}, and r is the orbital radius determined by D_k (Equation 2). After the transition between orbits, the electron having the highest energy (best fitness) around each nucleus is accepted as the best electron (e_{best}).
- **3rd Stage (Relocation of Nucleus):** In this stage, the position of the new nucleus (pos_{new}) is determined according to the energy of an emitted photon, calculated with the difference of energy between two atoms (considering Rydberg Formula). In this context, the following equations are used for each nucleus:

$$\vec{D}_k = (\vec{e}_{best} - \vec{pos}_{best}) + \mathrm{Re}_k \otimes (1/\vec{pos}^2_{best} - 1/\vec{pos}^2_k) \qquad (2)$$

$$\vec{pos}_{new,k} = \vec{pos}_k + Ac_k * \vec{D}_k \qquad (3)$$

where k is the iteration number, $\vec{D}_k$ is the relocation distance, $\vec{pos}_{best}$ is currently best nucleus position, $\vec{e}_{best}$ is the best electron around the nucleus, $\vec{pos}_k$ is current position of the nucleus, Re_k is the Rydberg's energy constant-coefficient, Ac_k is the accelerator coefficient, and the $\vec{pos}_{new,k}$ is the new position of the nucleus at the k^{th} iteration. In the Equation 2, ⊗ defines the vector multiplication. The mentioned calculations (Stage 3) are for enabling the atoms (particles) to move toward currently global optimum. Here, two coefficients: Re and Ac are also re-calculated with the Orbital-Tuner in-system optimization approach, if the stopping criteria is now met yet (at the 1st iteration, these coefficients are set randomly). Orbital-Tuner consists of the following equations:

$$\mathrm{Re}_{k+1} = \mathrm{Re}_k + (\mathrm{Re}_{best} + \sum_{i=1}^{n} \frac{\mathrm{Re}_i / f_{N_i|\mathrm{Re}_i}}{1/f_{N_i|\mathrm{Re}_i}})/2 \qquad (4)$$

$$Ac_{k+1} = Ac_k + (Ac_{best} + \sum_{i=1}^{n} \frac{Ac_i / f_{N_i|Ac_i}}{1/f_{N_i|Ac_i}})/2 \qquad (5)$$

where n is the number of atoms (particles), f is the fitness function, Re_{best} and Ac_{best} are coefficient values regarding pos_{best}. As it was indicated in [72], initially chosen values for Re and Ac do not affect the performance (function evaluation, trajectory of the atoms-particles towards the global optimum, or convergence speed) of the ESO too much, thanks to that in-system optimization: Orbital-Tuner.

Considering the explained details of the algorithm, general flow-chart of the ESO is represented in Figure 2 [72].

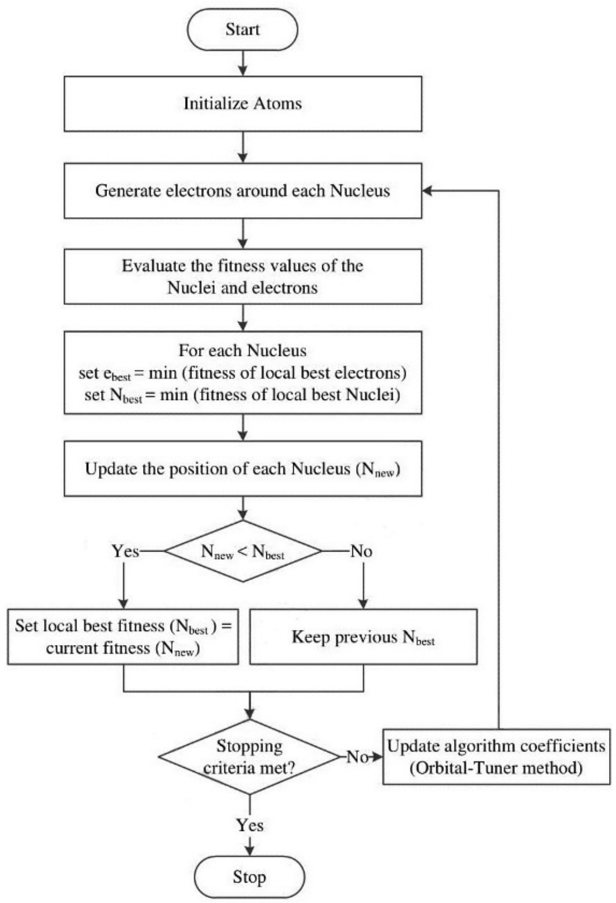

FIGURE 2. Flow-chart of the ESO [72].

C. EEG PREDICTION APPROACH WITH ANFIS-ESO

The hybrid system of this study is formed by ANFIS and its trainer algorithm: ESO. Use of intelligent optimization algorithms to train machine learning techniques (optimize their parameters) is a popular trend in the literature. In terms of ANN and its variations like ANFIS, it is possible to see use of different optimization algorithms rather than using traditional learning algorithms [44], [53], [73]–[78]. That is done because of more accurate and robust results often found by combination of such machine learning-optimization algorithm couples. Because of that, a very recent ESO algorithm was used in this study as it also gives a novelty in terms of training ANFIS and also predicting chaotic EEG time series. It is also important to mention that prediction of EEG time series having chaotic characteristics is a challenging issue so that an alternative solution approach of ANFIS-ESO was decided to be employed in this study.

As general, the prediction mechanism included in the ANFIS-ESO system can be explained briefly as follows:

- ANFIS model employs four inputs (with Gaussian sets) and uses a total of 10 fuzzy rules. In detail, ANFIS is a predictor with four inputs and one output.
- ANFIS side of the system tries to predict the output value in the form of *x(time + 3)* according to the input values in the forms of *x(time)*, *x(time – 3)*, *x(time – 6)*, and *x(time – 9)*. There may be different combinations of lags to be used for prediction but the lags used in [44] and [79] for time series prediction purpose were chosen to be used in this study.
- ESO side of the system is responsible for optimizing membership functions of the ANFIS model for better matching outputs with the data for training, during the training phase. In this context, atoms-particles of the ESO run through the algorithm steps and optimum values associated with lower error levels at the output are kept for getting well-trained ANFIS.

Figure 3 represents general scheme of the prediction approach by the ANFIS-ESO system.

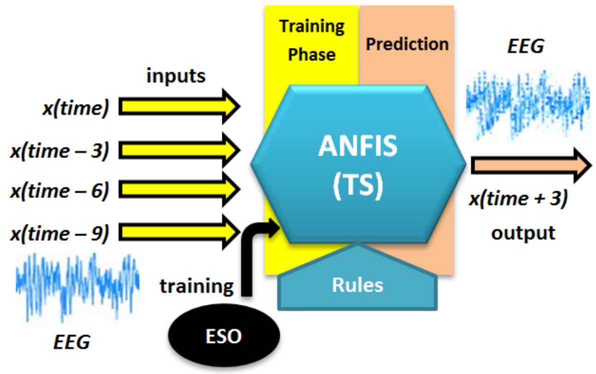

FIGURE 3. General scheme of the prediction approach by ANFIS-ESO.

As it was mentioned before, applications of this research-study have been realized over five different chaotic EEG time series, in order to obtain an effective enough prediction system against even chaotic forms of that medical data type. The fourth section explains the applications in detail.

IV. APPLICATIONS WITH ANFIS-ESO

Electroencephalogram (EEG) is known as a monitoring method for seeing electrical activities occurred in the brain and its electrical activities are generally observed in chaotic forms [44]. At this point, analyzes over the time series of EEG has vital importance because early diagnosis of some diseases such as epilepsy, autism, depression, and Alzheimer can be done and even it is possible to understand more about interactions of the brain with its surroundings, which means eliminating mysteries over it or explaining some environmental factors affecting its health [44]. So, predicting future flows of an EEG data is important for physicians and medical staff.

In this study, a total of five different EEG data have been recorded from people came to the Davraz Life Hospital, a private hospital located in the city center of Isparta, Turkey. A typical EEG data is obtained by using some electrodes on certain points over the person's head, by following some placement systems [80]. At the Davraz Life Hospital, widely used 10-20 system is used for placing the electrodes and a sampling frequency of 250 Hz was used to record EEG data.

In order to ensure that all EEG time series data are ready for prediction applications, they were pre-processed against noises, muscular artifacts, and eye blink. For the removal of noise-artifact, FastICA, a simple, Wavelet Transform oriented technique by Jadhav *et al.* [81] was used accordingly. Five EEG data are briefly from three male and two female (from whom required ethical permissions were taken). In detail, three of these people were ill while two remaining were healthy at the time of recordings. Chaotic nature of these EEG data has been observed as explained under next paragraphs. The exact number of data points for each EEG time series were 3000 and they are named as 'Data' and followed by a number; in the order as 'Data-1' to 'Data-5' respectively. Figure 4 shows the related chaotic EEG time series included in this study.

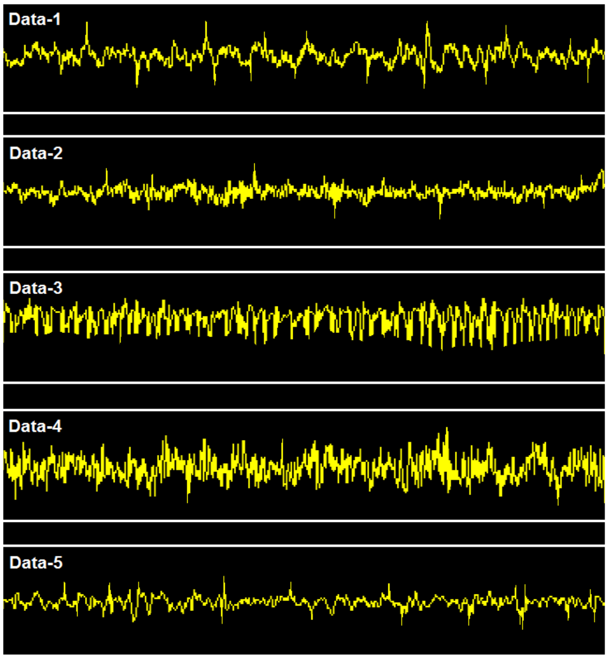

FIGURE 4. Chaotic EEG time series included in this study.

Characteristics of each chaotic EEG data is as follows: 'Data-1' is from a person experiencing depression, 'Data-2' is from a healthy person, 'Data-3' is from a person with active epilepsy seizure, 'Data-4' is from a healthy person, and finally 'Data-5' is from a person with a possible Alzheimer diagnosis.

A. VALIDATION OF CHAOS

For validating chaotic nature of the related EEG time series are, the largest Lyapunov exponents have been calculated for each of them. In order to be sure that a time series is chaotic, at least one of the calculated exponents should be positive. The calculation of the largest Lyapunov exponents is as follows [82]:

$$\lambda = \frac{1}{C} \sum_{t=1}^{C} \ln \frac{ed(r(n+1), r(m+1))}{ed(r(n), r(m))} \tag{6}$$

where ed is the Euclidian distance between two points, $r(n)$ is the reference point, $r(m)$ is the nearest neighbor to it and C is the number of Euclidian distance calculations.

Table 1 represents the calculated Lyapunov exponents for each EEG time series (positive values are shown in bold style). As it can be seen from Table 1, all EEG time series included in this study are chaotic because at least one positive Lyapunov exponent was calculated for each of them.

TABLE 1. Lyapunov exponents calculated for each EEG time series.

EEG Time Series Data	Lyapunov Exponent-1*	Lyapunov Exponent-2*	Lyapunov Exponent-3*
Data-1	-0,5024 e-003	**0,4109 e-003**	-0,0641 e-003
Data-2	**0,3490 e-003**	**0,1507 e-003**	-0,4780 e-003
Data-3	**0,1033 e-003**	-0,7235 e-003	**0,5144 e-003**
Data-4	-0,3019 e-003	**0,1545 e-003**	**0,2170 e-003**
Data-5	-0,6120 e-003	-0,1016 e-003	**0,3058 e-003**

*Positive values are in bold.

B. SETTING ANFIS-ESO

Before using the ANFIS-ESO system for the target chaotic EEG time series in this study, a pre-evaluation was done for setting the optimum solution approach in terms of employed particles by the trainer algorithm and also required iteration number for good prediction accuracy. In order to achieve that, some previously studied four EEG data from [53] was used. In detail, each data includes 4000 data points and the data points were divided into two groups as 50% for training and %50 for test phase (2000 data points for each). For the pre-evaluation work, six different settings of ANFIS-ESO system were run 20 times for training and testing purposes and average accuracy values of true prediction over test data were considered for determining which setting of the ANFIS-ESO will be used for further prediction applications. Table 2 presents the alternative settings of ANFIS-ESO system.

TABLE 2. Six different ANFIS-ESO settings for pre-evaluation.

Parameter	Setting-1	Setting-2	Setting-3	Setting-4	Setting-5	Setting-6
Number of atoms (particles)	50	75	100	100	100	120
Total iteration	3000	4000	4000	5000	6000	6000

Considering six different settings for ANFIS-ESO, Table 3 shows average accuracy findings by each setting for the target four EEG time series from [53] (best values are shown in bold style). As it can be seen from the findings, 'Setting-5' with 100 particles (atoms for ESO) and 6000 iterations had more number of highest accuracy values than other settings, for the EEG data.

For further applications over five chaotic EEG time series (Data-1 to Data-5), the ANFIS-ESO with the 'Setting-5' was

TABLE 3. Average accuracy values by different ANFIS-ESO settings.

ANFIS-ESO Setting	Average Accuracy of true prediction for*;			
	Z023 [53]	N052 [53]	First sample [53]	Second sample [53]
Setting-1	75.64%	80.62%	70.73%	78.10%
Setting-2	79.51%	82.92%	79.90%	81.26%
Setting-3	83.92%	83.31%	83.49%	86.59%
Setting-4	92.81%	87.50%	86.61%	88.63%
Setting-5	**94.52%**	**90.09%**	88.38%	**89.51%**
Setting-6	91.62%	86.23%	**93.48%**	87.82%

*Best values are in bold.

used accordingly. Here, 3000 data points by each chaotic EEG time series have been transformed into a data-file with 3000 rows including to *x(time + 3); x(time), x(time – 3), x(time – 6)*, and *x(time – 9)* data points. In the context of the applications, 70% of the data for each EEG time series (2100 rows) were included in the 'training' phase and predictions were evaluated with the whole data points including both training data (2100 rows) and testing data (900 rows). In addition to the evaluation done for ANFIS-ESO, also comparative evaluations were done with different techniques-systems by following the same way. Findings and evaluations are presented within the next section.

V. FINDINGS AND EVALUATION

For evaluating effectiveness of the ANFIS-ESO system in predicting the chaotic EEG time series, accuracy and two additional error criteria were used. Calculations in this manner were done for predictions over the whole data of each time series. In addition to the accuracy value of true prediction, other two error criteria were chosen as Mean Absolute Error (MAE), and Mean Squared Error (MSE). MAE and MSE can be represented as [83], [84]:

Let n is the total data, ob_i is the observation i, and pr_i is the prediction for ob_i;

$$MAE = MeanValueOf(|ob_i - pr_i|) \tag{7}$$

$$MSE = MeanValueOf(\sum_{i=1}^{n} ob_i - pr_i) \tag{8}$$

Training-testing phases for the ANFIS-ESO were done as 50 times and average values for the evaluation criterions were considered. In this context, average values for accuracy (of true prediction), MAE and MSE obtained with ANFIS-ESO for the five chaotic EEG time series in this study are provided in Table 4 (best values are in bold style).

As it can be seen from Table 4, ANFIS-ESO generally provided an average of more than 80% accuracy for predicting chaotic EEG time series true. It can be seen that the performance of the system is better for the EEG time series from healthy people but the EEG data from other people

TABLE 4. Accuracy, MAE, and MSE obtained with ANFIS-ESO system for the Chaotic EEG time series.

EEG Time Series Data	Accuracy*	MAE*	MSE*
Data-1	87.69%	14.6588	0.0798
Data-2	**93.14%**	**11.5874**	**0.0635**
Data-3	83.72%	17.5041	0.0934
Data-4	91.58%	12.2380	0.0741
Data-5	86.29%	13.5966	0.0876

* Best values are in bold.

have also been predicted at well-enough accuracy values. Figure 5 represents visualization of the predictions done by ANFIS-ESO for both training and test data of the each chaotic EEG time series are shown. In the figure, red lines separate training and test data while the original data are with yellow line, and the predictions are with red line. Some remarkable errors in predictions are pointed in white squares.

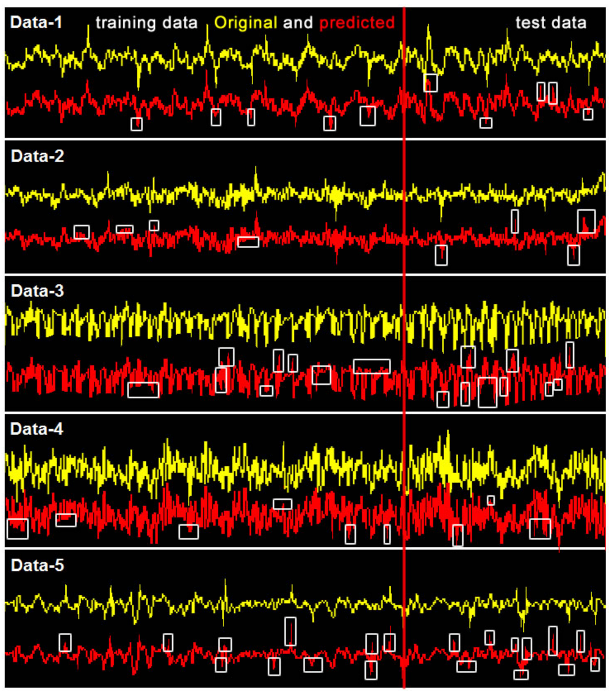

FIGURE 5. Predictions by ANFIS-ESO for five chaotic EEG time series.

Figure 5 shows that the introduced ANFIS-ESO system is well-enough at predicting future states of the target chaotic EEG time series in this study. For being sure, chaotic flows of the predicted points-time series were confirmed and there were not any overfitting problem seen along the application phases. In addition to that single evaluation of that ANFIS-ESO hybrid system, it is also too important for evaluating it further with a comparison including some alternative solution approaches (techniques-systems). That time the validation has been done also statistically.

A. COMPARATIVE EVALUATION

Regarding evaluation works, a comparative evaluation was also done in order to learn more about success of the ANFIS-ESO hybrid system against alternative solution approaches. In this context, previously obtained findings by ANFIS-ESO were compared with the findings by some other alternative techniques or hybrid systems, by running them 50 times and considering average values for the evaluation criterions including accuracy (of true prediction), MAE, and MSE. At this point, comparative evaluation consisted of the following techniques or systems:

- Traditional ANN trained by BP algorithm [85] (formed with the optimum model reported by [44]),
- Traditional ANN trained by ESO algorithm (formed with the optimum model reported by [44]),
- ANFIS model of this study trained by three alternative intelligent optimization algorithms as the trainers. These include Particle Swarm Optimization (PSO) [86]–[88], Cuckoo Search (CS) [89], [90], and Differential Evolution (DE) [91], [92] (with the default parameters by their referencing sources but same number of particles and iteration limit used for the ANFIS-ESO).
- Alternative techniques as Support Vector Machine (SVM) [93], Dynamic Boltzmann Machine (DyBM) [94], Autoregressive Integrated Moving Average (ARIMA) [95], Hidden Markov (HM) [96], K-Nearest Neighbor Algorithm (K-NN) [97], and Bayesian Learning Gaussian process model (BG) [98].

Average of accuracy, MAE, and MSE are provided in Table 5-7 for ANFIS-ESO and ANN hybrid systems comparison, Table 8-10 for ANFIS-ESO and alternative trainers supported ANFIS approaches comparison, Table 11-13 for ANFIS and alternative techniques comparison set-1, and Table 14-16 for ANFIS and alternative techniques comparison set-2 (best values are shown in bold style).

TABLE 5. Accuracy comparison for ANFIS-ESO and ANN based hybrid systems.

EEG Time Series Data	ANFIS-ESO*	ANN-BP*	ANN-ESO*
Data-1	**87.69%**	80.16%	84.09%
Data-2	**93.14%**	82.61%	88.66%
Data-3	**83.72%**	76.61%	81.07%
Data-4	90.67%	84.12%	**91.58%**
Data-5	**86.29%**	77.09%	81.25%

* Best values are in bold.

According to the findings, it can be expressed that the developed ANFIS-ESO hybrid systems shows better performance than other techniques-systems, for the five chaotic EEG time series predicted. It is also remarkable that the top performances are shared among ANFIS-ESO, ANFIS-CS, and ANFIS-DE systems.

TABLE 6. MAE comparison for ANFIS-ESO and ANN based hybrid systems.

EEG Time Series Data	ANFIS-ESO*	ANN-BP*	ANN-ESO*
Data-1	**14.6588**	16.3447	15.1611
Data-2	**11.5874**	12.2364	11.9318
Data-3	**17.5041**	18.2087	17.7598
Data-4	12.3268	12.7108	**12.2380**
Data-5	**13.5966**	15.0083	14.0155

* Best values are in bold.

TABLE 7. MSE comparison for ANFIS-ESO and ANN based hybrid systems.

EEG Time Series Data	ANFIS-ESO*	ANN-BP*	ANN-ESO*
Data-1	**0.0798**	0.0944	0.0805
Data-2	**0.0635**	0.0834	0.0722
Data-3	**0.0934**	0.1097	0.0951
Data-4	**0.0741**	0.0924	0.0784
Data-5	**0.0876**	0.1036	0.0951

* Best values are in bold.

TABLE 8. Accuracy comparison for ANFIS-ESO and alternative trainers supported ANFIS approaches.

EEG Time Series Data	ANFIS-ESO*	ANFIS-PSO*	ANFIS-CS*	ANFIS-DE*
Data-1	87.69%	80.61%	**89.63%**	82.57%
Data-2	90.14%	84.23%	91.55%	**93.74%**
Data-3	**83.72%**	79.84%	82.98%	80.36%
Data-4	91.58%	86.04%	**91.86%**	91.73%
Data-5	**86.29%**	79.69%	82.91%	82.18%

* Best values are in bold.

TABLE 9. MAE comparison for ANFIS-ESO and alternative trainers supported ANFIS approaches.

EEG Time Series Data	ANFIS-ESO*	ANFIS-PSO*	ANFIS-CS*	ANFIS-DE*
Data-1	14.6588	16.1207	**14.1322**	15.8319
Data-2	11.8057	12.5361	11.6298	**11.5874**
Data-3	**17.5041**	18.0261	17.7631	18.0099
Data-4	12.2380	12.6344	**12.0199**	12.1073
Data-5	**13.5966**	14.1571	13.7258	13.9367

* Best values are in bold.

Considering the error values obtained by all compared techniques-systems, a statistical validation should also be done. In this way, it can be understood that the obtained

TABLE 10. MSE comparison for ANFIS-ESO and alternative trainers supported ANFIS approaches.

EEG Time Series Data	ANFIS-ESO*	ANFIS-PSO*	ANFIS-CS*	ANFIS-DE*
Data-1	0.0798	0.0921	**0.0615**	0.0883
Data-2	0.0749	0.0871	0.0651	**0.0635**
Data-3	**0.0934**	0.1028	0.0979	0.1013
Data-4	0.0741	0.0899	**0.0703**	0.0733
Data-5	**0.0876**	0.0966	0.0911	0.0936

* Best values are in bold.

TABLE 11. Accuracy comparison for ANFIS-ESO and alter. tech. set-1.

EEG Time Series Data	ANFIS-ESO*	SVM*	DyBM*	ARIMA*
Data-1	**87.69%**	83.97%	74.81%	79.61%
Data-2	**93.14%**	88.09%	78.36%	80.06%
Data-3	**83.72%**	80.73%	75.71%	75.11%
Data-4	**91.58%**	90.44%	79.06%	82.60%
Data-5	**86.29%**	80.60%	74.20%	76.81%

* Best values are in bold.

TABLE 12. MAE comparison for ANFIS-ESO and alter. tech. set-1.

EEG Time Series Data	ANFIS-ESO*	SVM*	DyBM*	ARIMA*
Data-1	**14.6588**	15.5307	17.5036	17.1218
Data-2	**11.5874**	12.0658	13.1633	12.5096
Data-3	**17.5041**	17.9522	18.6189	19.1631
Data-4	**12.2380**	12.3349	13.5988	13.1807
Data-5	**13.5966**	14.2606	15.6099	15.2080

* Best values are in bold.

TABLE 13. MSE comparison for ANFIS-ESO and alter. tech. set-1.

EEG Time Series Data	ANFIS-ESO*	SVM*	DyBM*	ARIMA*
Data-1	**0.0798**	0.0861	0.0980	0.0957
Data-2	**0.0635**	0.0799	0.0953	0.0898
Data-3	**0.0934**	0.0986	0.1061	0.1159
Data-4	**0.0741**	0.0809	0.0977	0.0958
Data-5	**0.0876**	0.0983	0.1069	0.1048

* Best values are in bold.

findings for all techniques-systems were as a chance or not. Furthermore, it is also possible to see which techniques-systems were good enough for each EEG time series predicted. In order to realize that, Giacomini-White Test [99] was used over the findings. The test is applied for understanding

TABLE 14. Accuracy comparison for ANFIS-ESO and alter. tech. set-2.

EEG Time Series Data	ANFIS-ESO*	HM*	K-NN*	BG*
Data-1	**87.69%**	77.94%	82.87%	73.61%
Data-2	**93.14%**	80.19%	87.03%	76.11%
Data-3	**83.72%**	76.29%	79.91%	73.28%
Data-4	**91.58%**	80.07%	88.96%	78.66%
Data-5	**86.29%**	74.92%	78.19%	72.01%

* Best values are in bold.

TABLE 15. MAE comparison for ANFIS-ESO and alter. tech. set-2.

EEG Time Series Data	ANFIS-ESO*	HM*	K-NN*	BG*
Data-1	**14.6588**	17.3668	15.7811	17.6087
Data-2	**11.5874**	12.6588	12.2631	14.0098
Data-3	**17.5041**	18.2336	18.1112	19.6214
Data-4	**12.2380**	13.5628	12.5181	13.7204
Data-5	**13.5966**	15.4149	14.6211	15.9225

* Best values are in bold.

TABLE 16. MSE comparison for ANFIS-ESO and alter. tech. set-2.

EEG Time Series Data	ANFIS-ESO*	HM*	K-NN*	BG*
Data-1	**0.0798**	0.0971	0.0842	0.0991
Data-2	**0.0635**	0.0927	0.0809	0.0982
Data-3	**0.0934**	0.1106	0.1097	0.1191
Data-4	**0.0741**	0.1016	0.0861	0.1037
Data-5	**0.0876**	0.1056	0.1022	0.1106

* Best values are in bold.

if the minimum mean value of the calculated MAE means also that the associated technique-system is performing well-enough at the prediction. As considering the pairwise comparison done, Table 17 presents the numerical findings revealing which technique-system achieves better performance (statistically outperforms the others in the context of a significance level of 5%) within the prediction applications.

TABLE 17. Results of the Giacomini-White Test.

EEG Time Series Data	The Best Performance(s)
Data-1	ANFIS-ESO, ANFIS-CS
Data-2	ANFIS-ESO, ANFIS-CS, ANFIS-DE
Data-3	ANFIS-ESO, ANFIS-CS
Data-4	ANFIS-ESO, ANFIS-CS, ANN-ESO
Data-5	ANFIS-ESO

Table 17 shows that the performances of ANFIS-ESO for the chaotic EEG time series are validated statistically. In detail, the table rows with more than one best performance mean that there is equivalence among the mentioned techniques-systems for the prediction of the target EEG data. While ANFIS-ESO takes its place in the best performances for all EEG time series, especially ANFIS-CS and ANFIS-DE gets equivalence performance for four EEG data, except from Data-5. It also remarkable that the traditional ANN model trained by ESO is among best techniques-systems predicted the Data-4.

VI. DISCUSSION

By considering the obtained findings, and also both objective and motivations of the study, it is possible to mention the following points: Generally, findings show that the use of ESO for training ANFIS has enabled authors to develop a new, novel hybrid system, which is able to predict EEG time series in even chaotic forms. Pre-evaluation works included just before the exact applications side of the research reveal that the system can be used for solving some EEG data from the reported literature and that can be used to design an optimum form of system for further applications. Further applications over five different chaotic EEG time series have shown that the ANFIS-ESO can predict chaotic EEG time series with the accuracy value of true prediction changing from 83% to 93%. EEG data from healthy people can be better predicted while there were more efforts for EEG data with specific diseases like depression, epilepsy, or Alzheimer. But the ANFIS-ESO was again well-enough at predicting such challenging data. When the perspective is taken to a wider view, it can be seen that use of ANFIS and intelligent optimization algorithms for developing a prediction system resulted into positive outcomes as the systems with ANFIS took top places in comparative evaluation for the EEG time series. The most challenging opponents of the ESO for training the ANFIS model have been CS and DE respectively. It is remarkable that even a traditional ANN model trained by ESO provided good results at the end. That may be because of the formed structure according to [44] as the system of ANN-ALO had provided positive results, too. By considering the dominance seen in comparative evaluation, it can be expressed that the use of machine learning gives effective and robust results. The dominance by the machine learning and the hybrid systems here can be seen very well in the results by the Giacomini-White Test (Table 17). For this study, the related results are all associated with the medical chaotic time series. However, it is believed that these positive results can be expended to more different types of data from real-world. Turning back to the comparative evaluation, SVM also showed remarkable findings among successful hybrid systems and it is followed by the K-NN, which is a simple but effective technique used widely. The worst cases for target chaotic EEG time series were shown by DyBM and BG. Among all findings, it is critical to mention that it is possible to design an intelligent system for diagnosing brain oriented diseases and also understanding the electrical flow of a brain thanks to such a simple-to-design and apply hybrid approach. During the Age of Informatics, use of such supportive technology can greatly enable physicians and medical staff to eliminate disadvantages of time, location and resources and they can be assisted by expert systems or immediate diagnosis platforms including automated analyze and prediction approaches provided by such ANFIS-ESO-like hybrid machine learning systems.

A. ACTIVE USE OF THE SYSTEM

After positive findings were obtained for the developed ANFIS-ESO hybrid system, it was transformed into a more stable software system for brain disease diagnosis. In detail, the software system was coded by using Java programming language (A previous study was done by the third author with the ANN-ALO system in [44]). It is actively used by a total of four physicians and some associated staff at two hospitals: Isparta State Hospital, and Meddem Hospital located in Isparta, Turkey. Use of the software system based on ANFIS-ESO include analyze and prediction of real EEG data instantly. According to the received feedback, it is possible to mention the followings:

- One physician from Meddem Hospital is using the system for investigations regarding epilepsy. So far, more positive experiences have been reported in terms of especially prediction performance and also a need for improving the analyze speed of the system a little more was reported.
- The physicians generally feel that the system is an automated assistive technology, which is good at thinking better about diagnose or treatment processes, thanks to the prediction mechanism.
- The physicians have also reported that the system is a very effective tool for eliminating mistakes made by humans by analyzing and predicting the time series accurately.
- More than 60 free tests done by four physicians and the associated medical staff report that the system with ANFIS-ESO approach is successful at predicting EEG time series.

For the active use of the developed approach-system, more information about using experiences and the performance will be obtained for further evaluations.

VII. CONCLUSION AND FUTURE WORK

In this study, a novel hybrid system of Electro-Search Optimization (ESO) algorithm trained Adaptive Neuro-Fuzzy Inference System (ANFIS) has been introduced for predicting chaotic EEG time series. As EEG data is a vital data for understanding electrical activities of brain, design and development of an artificial intelligence based prediction system will be very useful for physicians and medical staff, in order to diagnose diseases and learn more about working flow of the brain. ANFIS-ESO system, which was developed in this study, ensures the use of a recent optimization algorithm for training the ANFIS for the first time employs that advanced form of a Fuzzy Logic (FL) supported neural networks model for predicting chaotic EEG time series. In the study, five EEG data were real samples (including healthy and ill people) from Davraz Life Hospital (Isparta, Turkey) and they were tried to be predicted by an optimum form of ANFIS-ESO, which was previously organized by considering some other EEG data studied before. After evaluation oriented tasks including single prediction applications and a general comparison with the performances by eleven alternative techniques-systems for the same EEG data, it has been seen that the developed ANFIS-ESO is well-enough at predicting EEG time series even they include chaotic characteristics. The research here also revealed that the use of intelligent optimization algorithms can affect the prediction abilities of ANFIS model and hybrid systems are key components for showing power of artificial intelligence for solving advanced real-world problems. It is also important to mention that the ANFIS-ESO hybrid system is used actively at two hospitals (Isparta, Turkey) and positive feedback has been obtained so far, considering using experience and prediction capabilities of the developed system.

Obtained positive results have motivated the authors to move forward for further studies. According to more feedback gathered from use of the system at hospitals, it is aimed to improve prediction ability of the system with additional experiments over more EEG data. Also, it is aimed to use the ANFIS-ESO system for alternative medical data in the form of signals. Finally, future works also include using ESO for developing alternative hybrid systems with different machine learning techniques and trying to develop new hybrid systems with better performance.

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