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New Approach for Automated Epileptic Disease Diagnosis Using an Integrated Self-Organization Map and Radial Basis Function Neural Network Algorithm

AHMED HAMZA OSMAN[1] AND AHMAD A. ALZAHRANI[2]
[1]Department of Information System, Faculty of Computing and Information Technology, King Abdulaziz University, Rabigh 25732, Saudi Arabia
[2]Department of Information Technology, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia

Corresponding author: Ahmed Hamza Osman (ahoahmad@kau.edu.sa)

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ABSTRACT Currently, epilepsy disease (ED) is considered to be one of the gradual diseases in brain function over a period of several months or years. Seizure status is the primary common cause of ED. The main goal of this paper is to discover the seizure and epilepsy status using the prediction algorithm on the test results received from patient medical reports. This paper proposed an automatic epilepsy diagnostic method based on a self-organization map (SOM) method using a radial basis function (RBF) neural networks approach. The hybrid technique sought to enhance epilepsy diagnosis precision and to decrease the misdiagnosis of seizure disease. The SOM algorithm was employed to differentiate the unknown patterns of the seizure and epilepsy dataset. The experiments were performed on various RBF neural network algorithms with integrated SOM algorithms to predict and classify the standard epilepsy disease dataset. The hybrid method was tested on the UCI epilepsy dataset. The overall detection accuracy with 10-fold cross validation using SOM-RBF method achieved 97.47%. The results were compared with other modern classification techniques for seizure prediction and detection in terms of the evaluation factor.

INDEX TERMS Epilepsy disease, SOM, classification, RBF, neural network.

I. INTRODUCTION

Epilepsy is a chronic neurological disease affecting approximately 70 million persons universal. An abrupt burst of additional electricity in the brain generates abnormal movements resulting in unexpected seizure attacks [1], [2]. These attacks are a major sign of epilepsy. Around 8% of people will have a seizure during their lifetime, but only 1-2% will be diagnosed with epilepsy [3]. Recurrent epileptic seizures affect the lives of patients and their families. Sometimes these seizures lead to death.

Electroencephalogram (EEG) is used to capture brain signals. In EEG, there are five bands (Delta, Theta, Alpha, Beta, and Gamma) that are generally used for clinical analysis [4]. Hens Berger, a German neurologist, was the first to use an EEG to record the electrical action of the human brain. Electrodes are placed at several situations on the scalp to record the neural activity of the cerebral cortex. The voltage differences are measured between each pair of scalp electrodes. During the initial stages of EEG scanning of the brain, normal activity is observed; however, very high amplitude and rhythmic activity is soon observed for some time. Later, the signal again returns to normal. These rhythmic activities are called spikes during a seizure. These seizures are very short, and a seizure patient may not be aware of it. During seizures, complex spike-and-wave patterns generated by the brain can be recorded on the electroencephalogram (EEG). Commonly, diagnosis of epilepsy is made by a neurologist [5]. We need a trained specialist to perform the interpretation. EEG captures and clarification is time-consuming and exclusive. Furthermore, it is difficult to detect early stages of epilepsy. Therefore, automatic computer-based detection of seizure activity is a requirement. A machine learning algorithm-based predictive model can be used to differentiate between patients with and without seizures.

This study focused on the design of a global prediction model of conservative SOM by integrating the impression of a neural network classification algorithm with SOM in what we call a NN-SOM. In this study, an integrated technique that was created by clustering (data reduction) and classification approaches will be suggested. It is comprised of radial basis function neural networks (RBF), involving supervised learning, and a self-organization map algorithm (SOM), involving unsupervised learning. This integrated technique works on the principle of competitive learning, co-operation, and synaptic.

The Kohonen's self-organizing map algorithm clusters the instances in groups. Using SOM in epilepsy, the dataset produces low-dimensional (typically 1-D, 2-D, and 3-D) or reduced dimensionality of the dataset. It is based on the minimum Euclidean distance between an input vector and a weight vector. Finally, we generated non-linear decision boundaries using RBF to identify seizures in the dataset. Moreover, the predicted target values of an item were the same as other items that had close values to the predictor variables.

This study is systematized into six sections. Section 1 explains the introduction of this study. Section 2 deliberates the related works. Section 3 discusses the enhanced technique and its essential method. Data classification using RBF neural network will be explained in Section 4. A discussion of the experiments and outcomes of the study will be demonstrated in Section 5. Lastly, the study conclusions will be summarized in Section 6.

II. RELATED WORKS

In recent years, many studies on the prediction and classification of epilepsy and seizure have been done. The detection of seizure in epilepsy is primarily focused on both imaging and EEG data. Analysis and interpretation of EEG signals require expertise, and they are time-consuming. In this regard, we are focused on data mining and machine learning-based techniques.

Shoeb and Guttag [6] presented a paper in which the machine learning algorithm "SVM" was applied to a scalp EEG dataset to detect epileptic seizures. This approach achieved 96% accuracy in terms of test data. Abualsaud *et al.* [7] performed a preformation comparison of BayesNet, decision table, IBK, J48/C4.5, and VFI prediction methods for EEG-based epileptic seizure data to classify seizures. Finally, through IBK, a classifier of 99% accuracy was achieved. By contrast, VFI had the lowest accuracy, and j48 had the most stable accuracy.

Kassahun *et al.* [8] classified a different type of epilepsy using data mining method, first by an ontology-based prediction and second by a genetic-based data mining algorithm. The abovementioned methods were tested on a dataset containing 129 patients with seven expert clinicians. The algorithm showed slightly better performance than that of the clinicians.

Wang *et al.* [9] proposed an epilepsy detection framework, evaluated the accuracy and classified two, three and five group classifications of EEG signals using c4.5 decision tree algorithm, support vector machine (SVM) random forest technique, svm+c4.5 and svm+RF. RF outperformed in three-group classification. Zainuddin *et al.* [10] suggested a feature selection method with the help of a harmony search algorithm; later, upon feature selection, the dataset was classified using a wavelet neural network. Moreover, the robustness and efficiency of the proposed algorithm was demonstrated in an epileptic seizure prediction and detection problem.

Song *et al.* [11] presented an innovative method for automatic epileptic seizure recognition. This approach consisted of an extreme learning machine (ELM) and a sample entropy feature extraction-based framework. Good accuracy and fast computation speed was achieved. Ghosh-Dastidar *et al.* [12] proposed a new EEG classifier based on integrated PCA with cosine RBFNN. The two-stage classifier is combined with the mixed-band wavelet-chaos methodology to generate a precise predication of electroencephalogram (EEGs) into three different groups (healthy, ictal, and interictal EEGs) achieved from healthy and epileptic subjects. The proposed method achieved 98.4%, 97.0%, and 94.8%, for normal healthy EEGs, interacted EEGs, and ictal EEGs respectively. The classifier is incapable to classify normal EEG into any of the three sets 1% of the time. Patnaik and Manyam [13] proposed a wavelet-based feature extraction and back-propagation ANN classifier-based detection of epileptic EEG signals. There are three steps in building a classification of an epileptic seizure system: feature extraction, feature space dimension reduction and application of different base classifiers to a dataset with selected features [14].

Faust *et al.* [15] discussed a review of wavelet systems for epilepsy diagnosis and computer assisted seizure detection with a highlighting on investigation described during the past decade.

A nonlinear-dynamics and chaos model, multiparadigm method based on the combination of wavelets, and neural networks progressive by Adeli *et al.* [16] and associates is the most effective techniques for automatic EEG-based diagnosis of epilepsy [15].

Acharya *et al.* [17] proposed a new method can be time-consuming, inadequate by practical artifact, offers variable results secondary to reader knowledge level, and is limited in defining irregularities. Consequently, it is important to design a CAD method to automatically discriminate the class of these EEG signals using data mining methods. Their system pays the convolutional neural network algorithm (CNNA) for the EEG signals investigation. The study implemented a 13-layer deep (CNNA) to identify preictal, seizure classes, and normal cases.

Cheng *et al.* [18] implement the two-step algorithm to classify the Epileptic Seizures dataset automatically. The model used three entropies (permutation, sample, and approximate) as new features to improve the classification process. Then extreme learning machine is employed to comprehend feature prediction.

In the literature, there are many approaches used to expolit the features from EEG data: 1) genetic algorithm (GA); 2) autoregressive (AR); 3) discrete wavelet transform (DWT); 4) Particle swarm optimization (PSO); and 5) Fourier

Transforms (FT), among others [19], [20]. Among all the aforementioned methods, DWT was the best method for features extraction for EEG data. Through DWT, it is easier to capture repeated, irregular and sudden changes in signals. Second, feature reduction could be done using a scatter matrix. Finally, by applying classification techniques (i.e., K-Nearest Neighbor (K-NN), Artificial Neural network (ANN), Naive Bayesian (NB), support vector machine (SVM), with different kernel, decision tree, k-means clustering (k-MC) and self-organizing Maps (SOMs)), patients in various phases, namely, (1) pre-seizure, 2) seizure and 3) seizure-free, can be differentiated [19].

Supriya *et al.* [21] Proposed a complex network characteristic with graph to detect the EEG signals epilepsy cases. The method transformed the epileptic EEG signals into complex network and then the significant statistical properties of a network such as average weighted degree and modularity employed for exploiting the important features from a network of EEG signals. After that, the exploited characteristics are assessed using SVM with a different kernel function and KNN classification methods.

Therefore, the goal of the present study was to generate a classification model using the dataset obtained from the UCI data repository, a publicly available dataset. Moreover, using a classification model, we tried to identify epilepsy patients with or without seizures.

III. SUGGESTED MODEL

The vastness of a joint framework is not far from being obviously true, in light of the way that a distinct framework has its inadequacy, and an upgraded framework is planned to supplement the deficiency of these distinct canny frameworks. A splendid blend of two-advance batching computation and key backslide procedures is queried, considering the true objective to complement the parameters of each portion of the framework by using the advantages of a distinct framework against its burdens while exciting each weak section distinct from the two frameworks to achieve consistency, trustworthiness and an exact sharp framework extendable for use in gathering. The suggested improved model is made out of self-organization map (SOM) calculation and strategic relapse utilized, interestingly to form a greater improved scheme with grouping rudiments in light of similar epilepsy disease features.

The suggested technique has integrated self-organization map (SOM) clustering algorithm and RBF neural network in order to make it effective and efficient. The combined methods are then utilized through different stages, including preprocessing (organized the EEG-dataset into learning and testing parts) and calculating the similarity between the elements for each attribute. The suggested framework is shown in Figure 1.

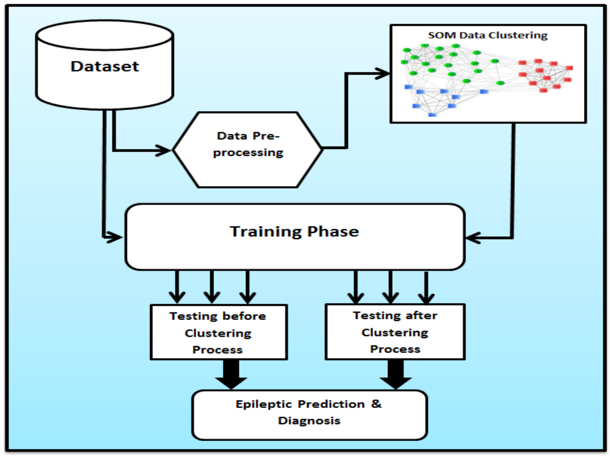

FIGURE 1. Suggested framework.

A. PRE-PROCESSING STAGE

Pre-processing is a significant machine learning stage to cook the corpus before the learning process. In the current study, the corpus was divided into a learning (training) phase and examining (testing) phase. For cooking the corpus, numerous baseline data sets for epilepsy disease prediction and detection roles were used [22]. One of these data sets is named Epileptic Seizure Recognition Data Set, which was described by the UCI data set. The chief purpose of this data set was to classify and examine epilepsy status patents.

The Epileptic Seizure Recognition Data Set consists of five unique files, each with 100 documents, with each document representing a single person/subject. Each document is a recording of brain activity for 23.6 seconds. The consistent time-series was cased into 4097 data points. Each data point was the value of the EEG recording at a different point in time. The inspiration against this creation was to improve access to the data through the production of a .csv form. Despite the fact that there were five classes, most authors have done binary classification, namely, class 1 (epileptic seizure) against the rest [22].

The response variable is y in column 179; y covers the group of the 178-dimensional input vector. Specifically, y in [1 4, 5].

5- eyes open, meaning that when they were recording the EEG signal of the brain, the patient had their eyes open.

4- eyes closed, meaning that when they were recording the EEG signal the patient had their eyes closed.

3- Yes, they identify where the region of the tumor was in the brain and recording EEG activity from the healthy brain area.

2- They recorded the EEG from the area where the tumor was located.

All subjects falling in classes 2, 3, 4, and 5 were subjects who did not have epileptic seizures.

1-Recording of seizure activity The Explanatory variables X1, X2, . . . , X178.

Each 178-dimensional vector contained in a row, representing a randomly selected 1-second long sample picked from a single file.

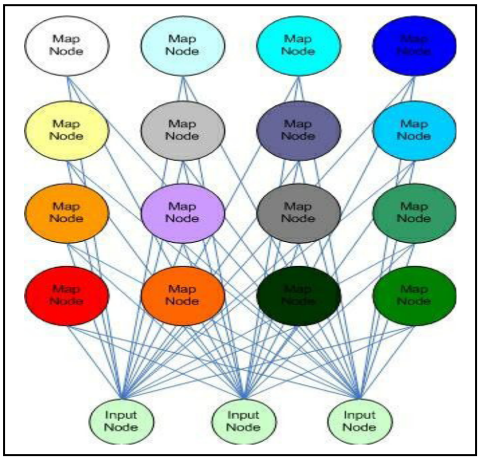

FIGURE 2. Self-organization map structure.

IV. DATA CLUSTERING USING SELF ORGANIZATION MAP ALGORITHM (SOM)

Kohonen's or self-organizing map (SOM) [23] is an unsupervised learning calculation for producing topology preservative change from a high-dimensional information vector-space to a low-dimensional guide space, and it is a capable apparatus utilized as a part of numerous zones, for example, information mining, investigation, grouping, and perception. Uses of SOM have spread into various regions, for example, online pursuit [24], bioinformatics [25], and back [26], and its significance continues expanding. Regardless of its expanding significance, ordinary SOM and the greater part of its augmentations can only manage vectorized information. On the off-chance that one wishes to manage a non-vector dataset, one would need to create the information vectorized ahead of time or to adjust the Kohonen itself to adjust to the information composition. In this manner, summing up the Kohonen family is an inevitable issue in which the Kohonen calculation is depicted autonomously of the written information.

A. SOM CLUSTERING FUNDAMENTAL

The Kohonen method can be organized into six stages:

i. Each node's weights were initialized.

ii. A vector was selected at random from the set of training data and was presented to the network.

iii. Every node in the network was tested to compute which ones' weights were most similar to the input vector. The winning was usually identified as the best matching unit (BMU). (Equation 1). The BMU was calculated as:

$$DistFtromInput^2 = \sum\nolimits_{i=0}^{i=n}(I_i - w_i) \tag{1}$$

where I = *existing input vector*, n = *number of weights*, $W = node's\ weight\ vector$

iv. The radius of the neighborhood of the BMU was computed. This value starts large. Typically, it was set to be the radius of the map, diminishing each time-step. (Equation 2, 3). The radius of the neighborhood and time constant were computed as:

$$\sigma(t) = \sigma_0 e^{-t/\lambda} \tag{2}$$

$$\lambda = numIterations/mapRadious \tag{3}$$

where t = *existing iteration*, $\sigma 0$ = *radius of the ma*, λ = *time constant*

v. Any nodes found within the radius of the BMU, computed in 4), were adjusted to make them more similar to the input vector (Equation 4, 5). The closer a node was to the BMU, the more its weights changed to (Equation 6). The new weight of a node was calculated as equation (4), where the learning rate as calculated as equation (5), and the distance from BMU as computed as equation (6):

$$\mathrm{W}(t+1) = W(t) + \theta(t)L(t)(I(t) - W(t)) \tag{4}$$

$$L(t) = L_0 e^{\frac{t}{\lambda}} \tag{5}$$

$$\theta = e^{(-distFromBMU^2/(2\sigma^2(t)))} \tag{6}$$

vi. Repeat (2) for N iterations.

V. DATA CLASSIFICATION USING RBF NEURAL NETWORK

The RBF network framework was introduced by Broomhead and Lowe [27]. A neural network is considered one of the significant learning techniques for data prediction. The RBF network organization has its basis in the traditional estimate hypothesis. It has the ability of widespread estimation. The RBF organization is a well-known, contrasting option to the outstanding multilayer perceptron (MLP), since it has an easier structure and a considerably speedier preparing procedure.

The RBF arrangement has its cause in performing precise addition of an arrangement of information, focused in a multidimensional space [28]. It can be viewed as one sort of practical connection net [29]. It has a system design similar to the traditional regularization arrangement [30], in which the premise capacities are the Green's elements of the Gram's administrator related with the stabilizer. On the off-chance that the stabilizer displays outspread symmetry, an RBF organize is obtained. From the perspective of an estimation hypothesis, the regularization organization has three attractive properties [30], [31]: it can surmise any multivariate consistent capacity on a smaller space to a subjective exactness, given an adequate number of units; it has the best estimation property since the obscure coefficients are straight; and the arrangement is ideal by limiting a practical containing a regularization term.

The RBF function is a three-layer (J1-J2-J3) feedforward neural network, as shown in Figure 1. Each node in the hidden layer uses a radial basis function (RBF), represented (r) as its nonlinear activation function. The hidden layer achieves a nonlinear transform of the input, and the output layer is a linear integrator mapping the nonlinearity into a new space. Generally, the RBF is used on all nodes; that is, the RBF nodes have the nonlinearity $(\vec{x}) = \phi(\vec{x} - \vec{ci})$, $i = 1, \ldots, J2$, where $\vec{ci}$ is the prototype or center of the ith node and $\phi(\vec{x})$ is

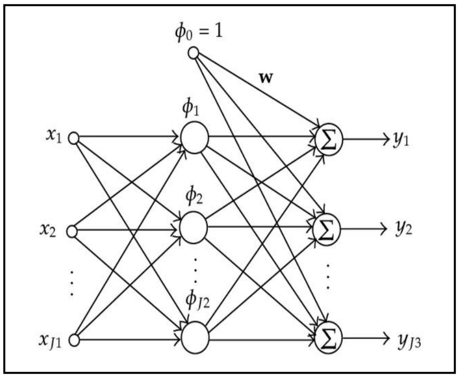

FIGURE 3. Architecture of the RBF network.

an RBF. The biases of the output layer neurons can be modeled by an additional neuron in the hidden layer, which has a constant activation function $\phi 0(r)$=1. The RBF network achieves a global optimum solution to the adjustable weights in the minimum mean square error (MSE) sense using the linear optimization technique.

The input, hidden, and output layers have $J1$, $J2$, and $J3$ neurons, respectively. $\phi 0(\vec{x}) = 1$ corresponds to the bias in the output layer, while $\phi i(\vec{x})$'s denote the nonlinearity at the hidden nodes.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

This experiment targeted to filter and detect EEG status as an epilepsy disease diagnosis. A technique was performed by looking for epilepsy status within the EEG data. The samples were divided into 10 categories. Each category had a specific number of samples (epilepsy cases). Nine sets were considered as learning phases while the remaining one was considered for testing dataset in a cross-validation process. The experiments were executed before data collection and after clustering using SOM. The basis of these experiments was to highlight the robustness of the prediction and classification of RBF neural network when integrated with the SOM algorithm.

In order to carry out the experimentation, the Epileptic Seizure Recognition Data was used. As it has been mentioned, the 10-fold cross-validation strategy was used in preparing and testing the data set. The examination connected across the dataset using an RBF classifier without clustering and with clustering results to examine the enhancement outcomes of the integrated method. The cross-validations procedure achieved judgment accuracy outcomes as follows:

$$\text{Acduracy} = \frac{(\text{TN} + \text{TP})}{(\text{TN} + \text{FP}) + (\text{TP} + \text{FN})} \tag{7}$$

True Negative (TN): The number of Not-Epilepsy and Epilepsy executables incorrectly diagnosed; True Positive (TP): The number of benign and Epilepsy executables correctly diagnosed; False Negative (FN): The number of Epilepsy executables diagnosed as Not-Epilepsy.; False Positive (FP): The number of benign executables diagnosed as Epilepsy.

In the experiments, the Epileptic Seizure Recognition Data Set were used as part of the request to decide the status (Epilepsy or Not). The integrated method was performed by learning and testing the Epileptic Seizure Recognition Data Set using the Kohonen-RBF technique. Using the Kohonen method, the EEG data set was then distributed into several clusters with each cluster having several cases. The primary goals of clustering in this study were to produce new structures and patterns by gathering epilepsy cases with related patterns together. Therefore, the computational efficiency will be decreased and the diagnosis prediction will be precise. The obtained performances from the learning and testing procedure on the Epileptic Seizure Recognition Data Set are represented in Table 1 and Table 2, in which arrangement outcomes were acquired by RBF method and SOM-RBF method respectively.

TABLE 1. Results of the Epilepsy diagnosis using RBF and SOM-RBF classifiers.

Experiment No	Classification Accuracy TP/FN using SOM-RBF		Classification Accuracy TP/FN using RBF	
	Training	Testing	Training	Testing
Experiment No-1	96.01	97.56	77.543	79.024
Experiment No-2	96.075	97.902	77.53	21.74
Experiment No-3	96.06	97.111	77.574	76.7
Experiment No-4	96.079	97.07	77.49	78.73
Experiment No-5	96.09	97.232	77.57	76.03
Experiment No-6	96.028	97.726	77.646	77.89
Experiment No-7	96.093	97.272	77.45	78.752
Experiment No-8	96.048	97.606	77.71	78.128
Experiment No-9	96.044	97.669	77.48	76.89
Experiment No-10	96.0236	97.638	77.538	65.243
Average	96.05506	97.4786	77.5521	70.9127

TABLE 2. T-test Statistical significance outcomes.

	T-Test Paired Differences					
				95% Confidence Interval of the Difference		
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper	Sig. (2-tailed)
RBF – SOM-RBF	7.550	2.521	1.455	1.287	13.812	.035

In the mixture procedure, the yield of the SOM was used as a new attribute component to label each record in the Epileptic Seizure Recognition Data Set with a cluster label and rate of belonging to this cluster. This component can increase the coherence among the records by gathering the Epileptic Seizure Recognition Data Set into various clusters, each with similar records. The RBF technique was used again with the yield of the Kohonen algorithm for potential conceivable high diagnosis precision. A 10-fold cross-validation strategy was

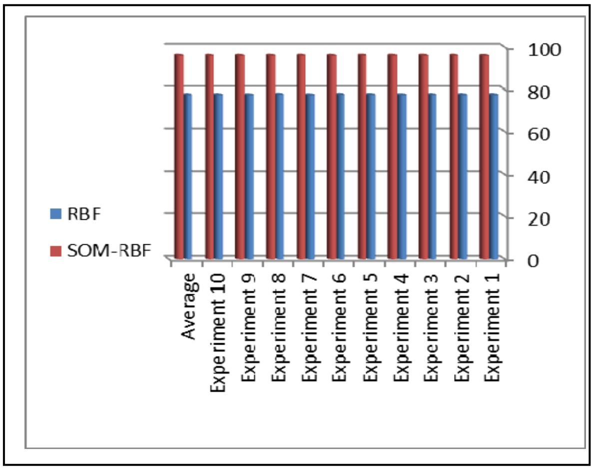

FIGURE 4. Training epilepsy diagnosis results.

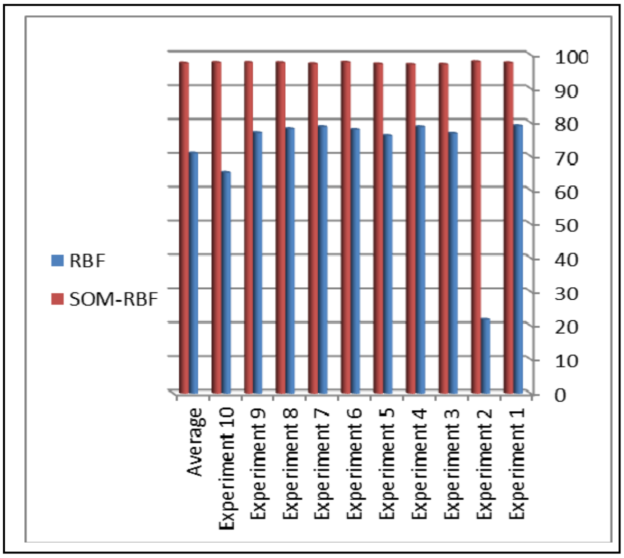

FIGURE 5. Testing epilepsy diagnosis results.

performed in the learning and testing procedures with and without SOM. Each learning and testing examination used Epileptic Seizure Recognition Data Set attributes as input layers to the RBF. Then, the output layer as a class component was used (from 1 to 5 status). The results of the RBF with Kohonen clustering showed enhanced outcomes when the RBF algorithm classified the Epileptic Seizure Recognition Data Set with the Kohonen clustering output. Curiously, the SOM-RBF technique improved the diagnosis precision by 97.47%, as shown in Table 1.

Figures 4 and 5 show both learning and testing results of the RBF and SOM-RBF algorithms. The 10-fold cross-validations were computed, and the average diagnosis outcomes using RBF without clustering achieved 77.5% and 70.9% for learning and testing tests, respectively. The figures also demonstrate the obtained outcomes of the SOM-RBF algorithm with 96.05% in the learning and 97.47% in the testing sets. The best diagnosis accuracy with RBF was only obtained in experiment number 2 with 97.9%.

To highlight the significance between this study's epilepsy diagnosis method using the RBF before and after the clustering process using the SOM technique, an independent sample T-test was applied as described [30]. The attained results could be significant if the test value was less than 0.05. In Table 3, the test value was (0.035) between this study's RBF before and after SOM clustering. This outcome indicates that the integrated SOM and RBF attained significant improvement on the accuracy outcomes. Therefore, a deduction was drawn that there was significant variance before and after the clustering procedure. Table 2 demonstrates the T-test statistical significance outcomes.

The complexity time of the hybrid SOM-RBF was calculated based on theoretical time complexity. As a result of the Epileptic Seizure Recognition Data Set structure (Vectors of data) that contain of amount of columns (n) and amount of rows (m), the complexity time can be calculated as (n*m) and it is fit to the (n*m) class. Where (n) is denotes the Epileptic Seizure features and (m) represents the Epileptic Seizure cases.

TABLE 3. A comparison between the suggested scheme and other Epilepsy diagnosis methods.

Epilepsy Diagnosis Method	Diagnosis Accuracy Results
SOM-RBF	**97.47%**
RBF	70.9%
RF (with three group)[9]	96.00%
RF (with five group) [9]	82. 60%
wavelet-chaos-neural network [10]	96.6%
PCA-enhanced cosine RBFNN [12]	95.8–96.6%
ELM[11]	96.00–97.50%
AHFSE (E-AB-CD)[32]	97 %

An additional assessment between the suggested scheme and other epilepsy diagnosis methods are shown in Table 3. Note that the integrated algorithm between the SOM and RBF classifier methods acquired optimal diagnosis outcomes based on the Epileptic Seizure Recognition Data Set.

VII. CONCLUSION

This investigation considered one of the fundamental challenges of the Epilepsy disease. Seizure detection and prediction give new and independent focus on diagnosis for the analysis, the intervention and the treatment of epilepsy. This framework may take into consideration the determination and recognition of seizures before their clinical onset. The proposed method aimed to examine epilepsy cases based on the SOM-RBF method to classify epilepsy status. The main contribution of this study was a combined method of the RBF and SOM clustering techniques to detect and determine epilepsy status. The advantage of applying the SOM clustering algorithm was to assemble similar epilepsy cases to investigate the shape of epilepsy by concentrating on their patient shapes regarding when epilepsy occurs. The suggested scheme used a UCI Epileptic Seizure Recognition

Data Set to construct the diagnosis framework. The suggested diagnosis solution was verified using T-test statistically significant tests to suggest improvement before and after the clustering procedure. We showed that SOM-RBF can significantly augment diagnosis outcomes and reduce the misdiagnosis of epilepsy.

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AHMED HAMZA OSMAN received the bachelor's degree in computer science from the International University of Africa, the master's degree in computer science from the Sudan University of Science and Technology, Sudan, and the Ph.D. degree in computer science with excellent academic achievements, from Universiti Teknologi Malaysia.

He was the Head of the Computer Science Department, Faculty of Computer Studies, International University of Africa. He is currently an Associate Professor with King Abduaziz University, Saudi Arabia.

His research interests include information retrieval, plagiarism detection, soft computing, data mining, natural language processing, and text summarization.

AHMAD A. ALZAHRANI received the Ph.D. degree in computer science from La Trobe University, in 2014. He is currently an Assistant Professor with the Faculty of Computing and Information Technology, King Abdulaziz University. His research interests include pervasive computing and human–computer interaction.