Mental Disorder Diagnosis from EEG Signals Employing Automated Leaning Procedures Based on Radial Basis Functions

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Abstract
Purpose In this paper, a new automated procedure based on deep learning methods for schizophrenia diagnosis is presented.
Methods To this aim, electroencephalogram signals obtained using a 32-channel helmet are prominently used to analyze high temporal resolution information from the brain. By these means, the data collected is employed to evaluate the class likelihoods using a neuronal network based on radial basis functions and a fuzzy means algorithm.
Results The results obtained with real datasets validate the high accuracy of the proposed classification method. Thus, effectively characterizing the changes in EEG signals acquired from schizophrenia patients and healthy volunteers. More specifically, values of accuracy better than 93% has been obtained in the present research. Additionally, a comparative study with other approaches based on well-knows machine learning methods shows that the proposed method provides better results than recently proposed algorithms in schizophrenia detection.
Conclusion The proposed method can be used as a diagnostic tool in the detection of the schizophrenia, helping for early diagnosis and treatment.

Keywords Electroencephalogram (EEG) · Neural network · Deep learning · Radial Basis Function (RBF) · Fuzzy Means · Schizophrenia

1 Introduction

The early diagnosis of mental disorders such as schizophrenia is essential for its successful treatment. Nevertheless, this diagnosis is not trivial and generally may become a difficult task even though the clinical guidelines to follow are well established [1, 2]. Generally, these guidelines involve a clinical interview carried out by psychiatrists where two different tests are usually employed: the International Classification of Diseases (ICD) [3] of the World Health Organization (WHO) [4] and the Diagnostic and Statistical Manual of Mental Disorders (DSM) [5] of the American Psychiatric Association [6]. In this regard, the expertise of the clinical staff that perform these tests and interviews is decisive, as it is a subjective process, where depending on the previous experience of clinical staff and understanding of the results obtained the correct diagnosis can be successful or not.

Concerning one the most important mental illness, schizophrenia is a serious psychiatric disorder whose main symptoms are related to hallucinations as well as delusions, and patients can suffer from instabilities in perception, cognition, and thoughts [7–9]. These disturbances involve the development...
of complications in the most basic functions connected to the concepts of feeling of individuality, uniqueness, and self-direction. Consequently, the cost of schizophrenia in both medical and social aspects can be huge if the illness is not detected in the early stages [10–12]. Therefore, the development of classification techniques for diagnosis is crucial in order to solve the aforementioned costs and help during the diagnosis process.

The use of electroencephalograms (EEGs) combined with machine learning or deep learning has become a helpful tool that permits to classify EEG signal characteristics depending on mental states and illness [13–19]. Automatic learning i.e., machine learning or deep learning, extracts and recognizes the main features of EEG signals without human intervention. Generally, EEG signals are separated into short time data windows [20] to estimate its characteristics and reflect the main statistical features that will be used as input data for the automatic classifiers.

In this regard, the classification of this input data may be performed by machine/deep learning techniques, which use has greatly increased in the medical field because of their high accuracy [21–23]. For instance, different machine learning techniques have been successfully applied in the past in various areas including clinical decision support in infectious diseases [24], drug discovery [25], ophthalmology [26], oncologic histopathology [27], COVID-19 [28], genomics [29], biosensors [30] or anesthesiology [31], to name a few. Specifically, well-known supervised methods [32] such as Support Vector machines, k-Nearest Neighbors, Decision Trees, Linear Regression, Naive Bayes or Logistic Regression, and unsupervised techniques [32] like k-Means, k-Medoids, Hierarchical Clustering, Principal Component Analysis, Independent Component Analysis or Neural Networks have been applied.

In this research study, a novel deep learning technique based on radial basis functions (RBF) combined with a fuzzy means algorithm to detect schizophrenia patients from EEG data has been employed. The use of RBF deep learning methods has shown a great classification accuracy compared with other classical methods [33]. As a result, and as it will be shown, the proposed algorithm can improve the classification accuracy when compared with other classic supervised and unsupervised methods published up to date. This type of proposed prediction method could be embraced by the medical community, being integrated within appropriately designed health interventions, and assessed in real-life analyses with patients and health professionals.

### 2 Materials and Equipment

This study was conducted as follows: EEGs were recorded continuously using a 32-channel brain vision system employing sintered Ag/AgCl electrodes. Electrode placement was performed according to the International 10–20 system [34] and the sampling frequency used was 500 Hz. Artefacts in the EEG signals and external interferences were filtered out [35–37] using a notch filter at 50 Hz and a low-pass filter with a cut-off frequency of 40 Hz.

The study was conducted between May 2013 and April 2020 on patients and controls residing in Cuenca (Spain) who were enrolled in the Severe Mental Disorders Programme of the Psychiatry Service of the Hospital Virgen de la Luz in Cuenca. Specifically, 312 patients with schizophrenia and 320 healthy controls were included. Patients who participated in the study were diagnosed with schizophrenia and were under medical treatment. The classification results obtained were in all cases correlated with the list of diagnosed patients, thus verifying the accuracy predicted by the proposed method and discriminating between patients and controls. Inclusion criteria comprised symptoms present for at least 6 months and age between 10 and 90 years old (excluding patients with medical instability and pregnant or breastfeeding women). The age distribution of the volunteers included in the study is divided in four different groups i.e., 15–30, 30–45, 45–60 and 60–90 years old, as it can be seen in Table 1.

All patients underwent a DSM-IV clinical interview from the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) by healthcare personnel with experience in diagnostic evaluations of the pathology to be treated once they had given us the corresponding informed consent and the baseline evaluations for the diagnosis of schizophrenia. All evaluations and results obtained were approved by the Clinical Research Ethics Committee of the Health Area.

### 3 Methodology

The structure of the neuronal network proposed can be seen in Fig. 1. It has an input layer, only one hidden layer, and the output layer.

The data associated with each layer of the network is distributed as follows: the input layer is obtained from the data vectors acquired by the 32 electrodes. The only hidden layer is composed of N gaussian radial basis functions \( \mu_N(r) \) and are employed to calculate the Euclidean distance from the data provided at the input layer. The output layer

| Age  | Patients | Controls |
|------|----------|----------|
| 15–30| 72       | 65       |
| 30–45| 87       | 93       |
| 45–60| 95       | 98       |
| 60–90| 58       | 64       |
classifies the data processed in the hidden layer, discriminating between schizophrenic and healthy patients.

The network used for the classification is trained in two different phases, in contrast to other neural network training procedures that can be generally trained in just one single phase. In the RBF network training proposed, first, the hidden layer parameters are calculated and then the connection weights between the hidden layer and the output layer are determined. In the first training step, the prediction capabilities of the network are selected by choosing the number of hidden nodes, where a trial-and-error procedure is used. In addition, the centers of the hidden nodes are obtained by means of a heuristic adaptive process of the k-means clustering algorithm. In the second training step, the output is obtained by solving a simple linear regression problem.

The method proposed creates a fuzzy partition (FP) defining an input space and several fuzzy sets that are defined for each input variable independently. Thereafter, the RBF method divides the inputs into separate areas and assign different membership functions. More specifically, the input data is separated in triangular fuzzy sets named $T^1_s, T^2_s, \ldots, T^n_s$ with membership functions as follows:

$$
\mu_{T_l}(i_d) = \begin{cases} 
1 - \frac{|i_d - t^l_i|}{d^l_i} & \text{if } i_d \in [t^l_i - d^l_i, t^l_i + d^l_i], \ l = 1, \ldots, n_s \\
0 & \text{otherwise}
\end{cases}
$$

where $t^l_i$ is the central element with membership value equal to unity and $d^l_i$ is half of the respective width. It is worthwhile to mention that for each input variable, the sum up of the membership quantities is the unity.

The validation of the model proposed was accomplished by a K-fold cross-validation procedure [38], see Fig. 2.

It is an iterative procedure that divides the recorded input data from the electrodes randomly into K groups or folds of approximately the same size. K-1 groups are used to train the model and the remaining one is used for validation. This process is repeated K times using a different group for validation in each iteration. The process generates K estimates of the error, which average is considered the final estimation. In the present study, the input recorded dataset was divided 70% for training and 30% for testing. To avoid overtraining the cross-validation analysis was performed without sharing data across training and validation groups.

A comparison among different classical machine learning algorithms i.e., Support Vector Machine (SVM), Bayesian Linear Discriminant Analysis (BLDA), Gaussian Naive Bayes (GNB), K-Nearest Neighbour (KNN) and Adaboost were also included in the study to check the advantages of the proposed model.

The hyperparameters of the algorithms implemented with MATLAB were set using a Bayesian approach. In this regard, the Bayesian optimization creates different combinations of the hyperparameters and chooses the values that yields the best area under the curve (AUC) and balanced accuracy.

Finally, the parameters checked to measure performance are:

$$
\text{Recall}(\%) = \frac{TP}{TP + FN} \times 100 
$$

(2)

$$
\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100 
$$

(3)

$$
\text{Precision}(\%) = \frac{TP}{FP + FP} \times 100 
$$

(4)

$$
\text{Balancedaccuracy}(\%) = \frac{\text{Recall} + \text{Specificity}}{2} \times 100 
$$

(5)
In these equations, \( TP \) indicates the number of positive cases, \( TN \) is the true negatives, \( FN \) the false negatives and \( FP \) indicates the false positive cases. In addition, the \( F_1 \) score and Matthew’s correlation coefficient (MCC) were employed during the study. The \( F_1 \) score is defined as:

\[
F_1 \text{score} = \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \times 100
\]  

(6)

and the MCC [39], that measures the overall model performance, is described as:

\[
MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \times 100
\]

(7)

Lastly, two additional metrics assessing the overall model performance, namely Cohen’s Kappa (CK) and degenerated Youden’s index (DYI) [39], have also been included in the study.

### 4 Results

The results achieved for the study are shown next. In addition, the metrics of the proposed method as well as the comparison with others classical algorithms are also shown. The machine learning toolbox included in MATLAB was used for the preprocessing of the EEG data and the development of the machine/deep learning models. Performance metrics, namely, balanced accuracy, recall, precision, precision and \( F_1 \) score were analyzed for the SVM, BLDA, GNB, KNN, Adaboost and RBF methods shown in Table 2.

As it can be seen, the highest metrics were obtained for the proposed method. Adaboost and KNN, in terms accuracy, were the next algorithms to obtain better metrics. SVM, BLDA, offered lower metrics in all the parameters assessed.

Furthermore, Table 3 shows the results for AUC, MCC, DYI and Kappa index. The proposed method based on radial functions possess the highest values near to 93% for AUC, DYI and Kappa index, and near to 83% for MCC. All the other algorithms behaved with lower performance values.

Thus, it can be inferred that the RBF model was significantly more accurate than the classical machine learning systems.

Figures 3 and 4 show the previous values of the metrics and indices obtained in Tables 2 and 3, respectively. The RBF model has the best values. Adaboost, KNN, SVM, BLDA and GNB were in that order following from highest to lowest accuracy compared to the proposed method.

Finally, the diagnostic accuracy of the method was also tested using the receiver operating characteristic (ROC) representing sensitivity versus (1-specificity). Figure 5 shows the data presented in Table 3, where the RBF based method achieves the best prediction accuracy for schizophrenia disease. This is because its ROC value is close to 1 and its area under the ROC curve, AUC, is also close to 1.
In addition, the features extracted from the cleaned EEG signals were analyzed using an analysis of variance (ANOVA) study with Bonferroni tests. Specifically, the EEG signals acquired were divided in windows of 5 s and subsequently processed with MATLAB to obtain the entropy for all electrodes and volunteers. Thereafter, the significance between patients and healthy controls was obtained by means of the software IBM SPSS Statistics.

The results exhibited significant differences in the left part of the frontal and occipital lobes as shown in Fig. 6. Executive functions involve the frontal lobe and are associated with cognition, decision-making, and memory use. Consequently, these outcomes suggest that people with schizophrenia can have altered brain functions due to anomalous neuronal connections.

5 Discussion

In this study we have developed a method using neural networks, specifically RBF functions combined with fuzzy C-means clusters, which is able to classify between healthy and schizophrenia patients with a high accuracy in the prediction of the diagnosis.

Comparisons with other classical algorithms were carried out and this method improved the results obtained. For this purpose, a MATLAB machine learning/deep learning toolbox was used in the analysis to determine the RBF system. The method was trained with 312 patients affected by schizophrenia and 320 controls by generating models based on machine learning algorithms.

The following factors were used to test the performance during classification: balanced accuracy, recall, precision, F1 score, AUC, MCC, DYI, and Kappa index. The best metrics were obtained for the method developed compared to other classical algorithms, where lower values (between 4% and 18%) were achieved. Specifically, the following results were obtained for the proposed method: balanced accuracy = 93.40%, recall = 93.49%, precision = 93.30%, F1 score = 92.73%, AUC = 93%, MCC = 83.13%, DYI = 93.40%, and Kappa = 83.02%. These results demonstrated that the proposed classification algorithm improves on existing classical classifiers.

From the analysis carried out in this study, it is concluded that RBF algorithms combined with fuzzy C-means can provide significant advantages for classification given their good generalization ability, stability, robust noise tolerance and simplification in network configuration, in addition to the fact that training and classification is very fast.

Furthermore, the ANOVAs analyses with Bonferroni tests show significant modifications in the left part of the frontal and occipital lobes, therefore demonstrating the deterioration suffered by patients with schizophrenia in synaptic connections of the aforementioned brain areas.

6 Conclusion

This paper has presented the development of an RBF model initialized with a fuzzy C-means algorithm. For this purpose, a compendium of methods has been proposed with the aim of increasing the possibility of discrimination between healthy patients and patients with schizophrenia pathology. In this study, different machine learning methods have been used in order to analyze the performance of the presented model and to make a comparison between them. From the results obtained, it can be concluded that the RBF algorithms combined with fuzzy clusters are the best classifiers.
between both patients (healthy and schizophrenia) where the balanced accuracy of around 93%, and the MCC and Kappa indexes close to 83% were reached. The proposed RBF classifier presented important advantages compared to other classical methods, such as simplicity, good generalizability, and robust noise tolerance. Thus, the results obtained lead to the conclusion that the application of RBF artificial neural network techniques to encephalogram data is a valid and potentially helpful tool for the automatic classification of patients in medical settings.

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