

EEG-Based Classification of Schizophrenia and Bipolar Disorder with the Fuzzy Method

Harurikson Lumbantobing^{a,1*}, Aryo De Wibowo^{b,2}, Anang Suryana^{c,3}, Marina Artiyasa^{d,4}, Muchtar Ali Setyo Yudone^{e,5}, Edwinanto^{f,6}, Yudha Putra^{g,7}, Yufriana Imamulhak^{h,8}, Bayu Indrawan^{i,9}

^{a,b,c,d,e,f,g,h,i}Department of Electronic Engineering, Nusa Putra University, Jl. Raya Cibolang Kaler No.21, Kab. Sukabumi 43152, Indonesia

¹harurikson.lumbantobing@nusaputra.ac.id; ²aryo.dewibowo@nusaputra.ac.id; ³anang.suryana@nusaputra.ac.id; ⁴

marina@nusaputra.ac.id; ⁵muchtar.alisetio@nusaputra.ac.id; ⁶edwinanto@nusaputra.ac.id; ⁷yudha.putra@nusaputra.ac.id;

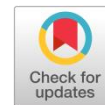
⁸yufriana.imamulhak@nusaputra.ac.id; ⁹bayu.indrawan@nusaputra.ac.id

* Corresponding Author

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ABSTRACT

This study demonstrates various fuzzy-based strategies for classifying and diagnosing people with mental illnesses such as schizophrenia and bipolar disorder. The signals collected from 32 unipolar electrodes during non-invasive electroencephalogram analysis were examined to determine their key characteristics. This research uses a sophisticated fuzzy-based radial basis function neural network. Entropy analysis and analysis of variance of other statistical parameters are also used. Three hundred and twelve schizophrenic patients and 105 individuals with bipolar disorder were examined. In contrast to healthy controls, the data indicated that the patients were correctly classified. With close to 96% accuracy, the suggested method outperforms existing machine learning methods, such as support vector machines and k-nearest neighbors. Conclusion: This categorization method will enable the development of highly accurate algorithms to identify and classify various mental illnesses



KEYWORDS

Load modeling
Realistic load
composite load
MATLAB



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1. Introduction

Bipolar disorder and schizophrenia share neuropsychological disorders that impact multiple domains. Schizophrenia is defined by substantial abnormalities in behavior and reality changes, such as hallucinations, delusions, and disorganized thinking, according to the American Psychiatric Association (DSM-IV)[1]. On the other hand, individuals with bipolar disorder display executive, working, verbal, visual, sustained attention, perception, and interpersonal connection issues. The first diagnosis of both mental diseases is typically determined based on personal observation, considering the patient's behaviors, changes in behavior, family history of mental illness, etc., in contrast to other patient groups and controls and DSM-IV criteria[2], [3], [4], [5].

However, this method often offers a complex diagnosis when the disease is still in its early stages. As a result, more analyzes and techniques are used. Electrophysiological activity may provide crucial information for a patient's clinical diagnosis in this way. The measured electroencephalogram (EEG) signal is highly beneficial for identifying brain rhythms, diagnosing brain diseases, detecting brain disorders, and, subsequently, offering suitable treatment to correct or enhance several issues connected to brain health.

This work shows how EEG recordings, feature analysis, and deep learning classifications can be used to differentiate different types of brain diseases. Radial fundamental function neural networks (NNs) (RBF), in particular, have been used [6], [7], [8]. This kind of network has qualities that make it the best for bipolar disorder or schizophrenia. You can get good performance with various patterns. RBF also uses a fast training process and specific network settings.

In addition, it can extend its network structure to the required level of precision[9]. The sections of this paper are as follows: The approach used for signal acquisition and processing is described in Section

2. It also shows how machine learning methods can be used for classification. The key findings are summarized in Section 3. Finally, Section 4 provides a summary of the work.

2. Method

Actual EEG recordings have been used in this study to examine how the suggested NN system functions[10], [11], [12]. Brain disorders were identified using EEG recordings from 312 people with schizophrenia and 105 people with euthymic bipolar disorder. To receive a DSM-IV diagnosis, each patient underwent a structured clinical interview for DSM-IV (SCID). All participants were informed of the research's goals and methods before providing their written informed consent. The Cuenca Health Area Study received approval from the clinical research ethics committee[13]. EEG is performed using hospital equipment. Medical staff members are electrodes using the International 10-20 System[14]. The EEG recording of each patient includes various noise samples, including baseline, baseline artifacts, muscle noise, and so on. To improve the accuracy of the neural network, these signals are filtered. Maps are produced using knowledge of the location of the electrodes. According to the 10-20 system for data collection in our situation.

Table 1. Methodological steps followed for patient classification

Step	Action	Sub Action
1	EEG records	32 EEG signals
2	Pre-processing	- Filter Notch - High pass filter
3	Processing	- Electrode signal - Windowing
4	Feature extraction	- Mean - Entropy
5	Classification	- ANOVA - Deep learning

The procedure from EEG measurement to patient classification is shown in Table 1. The initial phase employed a 32-channel Brain Vision system with a sampling rate of 500Hz and a signal gain of 75 K to record electrophysiological data (150x in the headbox). EEG data from 32 electrodes was continuously recorded using a worldwide 10–20 system (Z: Midline; F_Z: Midline Frontal; C_Z: Midline Central; P_Z: Midline Parietal; Even number, location of the corresponding hemisphere; odd number, location left hemisphere; F_p: Frontopolar; F: Frontal; C: Middle; T: Temporal; P: Parietal; O: Occipital).

The stored data is then pre-processed to eliminate outside interference. Signal noise is caused by electrical distribution networks and nearby electronic devices or may be caused by bodily functions, including body movements, eye blinking, breathing, or sweating. Notch and high-pass filtering remove these noise elements in the signal. Feature extraction (using mean and entropy) is performed when the brain signal is free from interference and artifacts. Using ANOVA and machine learning techniques determines the nature of the signal for categorization[14]. Using a radial basis function (RBF) neural network (NN) based on the fuzzy means (FM) method, deep learning approaches are utilized to categorize signals.

The proposed method uses an initial fuzzy partition (FP) of the input space and several fuzzy sets created for each input variable[15], [16]. It is implemented using MATLAB to select the NN structure and the center of the hidden nodes. The novel RBF technique successfully separates the discourse universe uniformly into fuzzy sets. $c_j, F_{j1}, F_{j2}, \dots, F_{jC}$ with the following form function for the input p_j ($j = 1, 2, \dots, M$) :

$$\sigma F_j^s(p_j) = 1 - \frac{|a_j - v_j^s|}{l_j^s} \text{ if } p_j \in [v_j^s - l_j^s, v_j^s + l_j^s] (s = 1, \dots, c_j)$$

$$\sigma F_j^s(p_j) = 0 \text{ for anything else}$$

where the L_{sj} equals half the corresponding width, v_{sj} is the central element where the unit membership value is assigned. The sum of the degrees of correspondence at every given location in the discourse universe approaches unity for any input variable. Our conception of FP generates each initial input into an M-dimensional input space. Keeping this in mind, the approaches listed below are suggested to find the closest fuzzy subspace of the input data vector.

According to research, bipolar disease patients can be correctly identified from recorded EEG data[17]. The Balanced Accuracy, Recall, Precision, and F1 values, as well as the suggested approach for schizophrenia and bipolar disorder[18], are shown in Tables 1 and 2, respectively. Support vector machine (SVM) and K-nearest neighbor (KNN) are well-known classification algorithms[19], [20], [21].

Table 1 shows the F1 values, accuracy, recall, and precision for several machine learning models and suggested approaches for schizophrenic patients.

3. Results and Discussion

According to research, bipolar disease patients can be correctly identified from recorded EEG data. The Balanced Accuracy, Recall, Precision, and F1 values, as well as the suggested approach for schizophrenia and bipolar disorder[22], [23], [24] are shown in Tables 1 and 2, respectively. Support vector machine (SVM) and K-nearest neighbor (KNN) are well-known classification algorithms[25].

Table 1 shows the F1 values, accuracy, recall, and precision for several machine learning models and suggested approaches for schizophrenic patients.

Table 2. Shows the F1 values, accuracy, recall, and precision for several machine learning models and suggested approaches for schizophrenic patients.

Method	Balanced accuracy (%)	Recall (%)	Precision (%)	Score F1 (%)
SVM	84.74	84.84	84.64	84.14
KNN	87.94	88.08	87.81	87.68
Result	93.40	93.49	93.30	92.72

Table 2 shows the F1 values, accuracy, recall, and precision for several machine learning models and suggested treatments for people with bipolar disorder.

Table 3. Shows the F1 values, accuracy, recall, and precision for several machine learning models and suggested treatments for people with bipolar disorder.

Method	Balanced accuracy (%)	Recall (%)	Precision (%)	Score F1 (%)
SVM	88.17	88.28	87.54	87.91
KNN	89.63	89.74	88.99	89.36
Result	96.78	96.89	96.09	96.49

SVM and KNN-based systems consistently produce accuracy, recall, and precision values, as well as F1 values below 90%. The proposed strategy, based on NN, performed the best, with discounts for schizophrenia and bipolar disorder exceeding 93% and 96%, respectively. It is important to note that each performance score is obtained for an accurate EEG record. In addition, several retrieved parameters from the cleaned EEG signal were investigated, and variance was quantified using an ANOVA with Bonferroni testing. The EEG data were divided into a 5-second frame and then processed with MATLAB to produce

entropy for all electrodes and volunteers. The IBM SPSS Statistics application was then used to assess the significance between patients and healthy controls.

The left frontal and occipital lobes revealed substantial changes in ANOVA analysis with the Bonferroni test (see p-value below 0.005 in dark green), reflecting decreased brain synaptic connections above the area experienced by schizophrenic patients. The findings in this publication advance previous research in the related field. The various machine learning and deep learning algorithms used to identify schizophrenia and bipolar disorder obtain accuracy values of up to 91%, as seen from the summary in table 4.

Table 4. Shows the classification performance of the latest research publications using the latest deep learning and machine learning techniques.

Paper	Mental disorders	Method	Accuracy (%)
[10]	Skizofrenia	RF	70.80
	Skizofrenia	KNN	83.30
	Skizofrenia	RF	79.20
	Skizofrenia	SVM	91.70
[11]	Gangguan bipolar	SVM	80.19
[12]	Skizofrenia	RF	81.10
[13]	Skizofrenia	LSTM	72.50
	Gangguan bipolar	LSTM	67.50
[14]	Gangguan bipolar	ANN	89,80
Didapatkan	Skizofrenia	RBF+FM	93,40
Didapatkan	Gangguan bipolar	RBF+FM	96,78

These findings suggest that deep learning techniques can successfully classify patients with schizophrenia and bipolar disorder using the radial basis function. In addition, our results increase the value of accuracy, establishing a practical method for creating new and future classification algorithms.

4. Conclusion

According to this study, EEG recordings could be used to identify between patients with schizophrenia and bipolar illness and healthy controls. Before classification, the processed EEG signal data extracts key features, such as mean and entropy. Machine learning methods have also been used for variations. Several well-known classifiers, including the recently proposed SVM, KNN, and NN, have been used. Better results when using the RBF artificial neural network built using the FM algorithm. Better on the accuracy, memory, and precision balanced scale than 93% for schizophrenia and 96% for bipolar illness (F1). The left frontal and occipital lobes also showed significant modifications, according to several ANOVA examinations with the Bonferroni test. Last but not least, the experimental results in this study show the value of the recommended classification technique, which may be utilized as an additional tool during clinical analysis to help psychiatrists diagnose patients with mental illness.

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