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Improved Neurocognitive Classification by Means of Deep Learning Algorithms through Electroencephalograms

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Abstract **-** In this paper, different techniques based on deep learning algorithms used for the classification and diagnosis of patients with mental disorders i.e., bipolar disorder, are presented. To this aim, the potentials obtained from 32 unipolar electrodes of non-invasive electroencephalogram analysis are studied to obtain its main features. More specifically, the analysis performed utilizes an innovative radial basis function neural network based on fuzzy means algorithm. Furthermore, the analysis of the variance to statistical parameters and entropy is applied. In total, 105 patients with bipolar disorder and 205 control subjects have been evaluated. The results obtained shows a correct classification in patients with bipolar disorder compared to healthy controls. The proposed methods achieved a better performance than other machine learning techniques such as support vector machine or k-nearest neighbour, with an accuracy close to 96%. It can be concluded that this type of classifications will allow the training of algorithms that can be used to identify and classify different mental disorders with very high accuracy.

Keywords**:** EEG, Deep learning, Mental disorder, Bipolar disorder

1. Introduction

Bipolar disorder is related to a neurocognitive deficit that affects different domains. According to the diagnostic criteria of the American Psychiatric Association (DSM-IV) [1], patients show disturbances in executive, working memory, verbal memory, visual memory, sustained attention, perceptions, and difficulties in relationships with others. Generally, initial diagnosis of bipolar disorder is based on subjective observing, depending on patient's actions, behavioural changes, history of mental illnesses in the family, etc., following DSM-IV criteria and compared to other patient groups and controls.

However, these methods present, in many cases, difficult diagnosis in early disorder stages. Therefore, additional analysis and tools are employed. In this regard, the use of electrophysiological activity can provide important information for the clinical diagnosis of patients. The measured electroencephalogram (EEG) signals appear to be very useful for the identification of brain rhythms, diagnosis of brain disorders, detection of brain impairments, and consequently the possibility to provide precise treatment to correct or improve certain brain-health conditions [2]-[5].

In this study, the utility of EEG recordings together with feature analysis and deep leaning classification to distinguishing bipolar disorder and controls is presented. In particular, a radial basis function (RBF) neural network (NN) [6]-[8] has been employed. This type of network has some characteristics that make it ideal for bipolar (or similar) disorders. Good performance with different patterns can be achieved, also RBF employs fast training procedures, and it includes simple network configurations. In addition, its network structure can grow to the desired degree of accuracy [9].

The paper is divided into the following sections: In Section 2 the methods employed for signal acquisition and signal processing are presented. It also shows the machine learning techniques that can be applied for classification. Section 3 outlines the main results obtained. Finally, the conclusions of the work are summarized in Section 4.

2. Methodology

In this study, real EEG recordings have been used to investigate the operation of the NN system. One hundred and five euthymic bipolar disorder patients and two hundred and five comparison subjects were tested for brain-disorder diagnosis measured by EEG recordings. The structured clinical interview for DSM-IV (SCID) was administered to all subjects to obtain DSM-IV diagnoses. All participants provided written informed consent after being explained the study and the procedures involved. The study was approved by the Clinical Research Ethics Committee of the Cuenca Health Area. The EEG records were recorded at the Psychiatric Service of the Virgen de la Luz Hospital in Cuenca (Spain). The equipment available at the Hospital was used to perform the EEGs. The International System 10-20 was used to place the electrodes by the medical staff. The EEG records of the different patients presented various noise samples, such as muscle noise, artefacts, baseline etc. To get a more accurate result of the neural network these signals were filtered out. Information about the position of the electrodes is used to create the maps. In our case, according to the 10/20 system for data acquisition.

Figure 1 shows the steps followed from EEG measurements to patient classification. First, electrophysiological data were recorded using a 32-channel Brain Vision system with a sampling frequency of 500Hz and signal gain equal to 75 K (150x at the headbox). According to the international 10-20 system, EEG data were continuously recorded from the 32 electrodes (Z: Midline; FZ: Midline Frontal; CZ: Midline Central; PZ: Midline Parietal; Even numbers, right hemisphere locations; odd numbers, left hemisphere locations; Fp: Frontopolar; F: Frontal; C: Central; T: Temporal; P: Parietal; O: Occipital). Thereafter, the stored data was pre-processed in order to remove external interferences. The noise present in the signal was due to the electrical distribution network, the surrounding electronic equipment, or may be due to the body functioning i.e., body movements, eye-blinking, breathing, or sweating. To remove these noise components, present in the signal, a notch and a high pass filtering were applied. Once the brain signal is clear of interferences and artifacts, a feature extraction was performed. It determined the characteristics of the signal for classification during the execution of ANOVAS and machine learning methods. Specifically, a deep learning method by means of a radial basis function (RBF) neural network (NN) based on fuzzy means (FM) algorithm was used for signal classification.

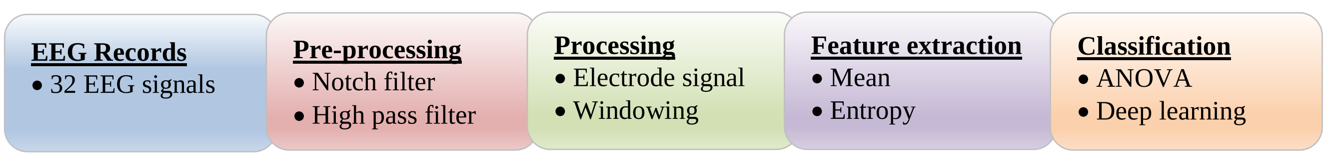

Fig. 1: Methodology steps followed for patient classification.

The FM algorithm was applied to choose the NN structure and the centres of the hidden nodes [7]-[8], where the proposed algorithm uses an initial fuzzy partition (FP) of input space and a number of fuzzy sets that are defined for each input variable. The novel RBF method realizes a uniform division of the discourse universe for its input p_j *(j = 1,2, ..., M)* into c_j fuzzy sets $F_j^1, F_j^2, ..., F_j^c$ with functions of form as follows:

$$\sigma F_j^s(p_j) = \begin{cases} 1 - \frac{|a_j - v_j^s|}{l_j^s} & if\ p \in [v_j^s - l_j^s, v_j^s + l_j^s] (s = 1, \dots, c_j) \\ 0 & otherwise \end{cases} \quad (1)$$

where v^s_j represents the central element to which the unit's membership value is set and l^s_j is half of the respective width. The sum of the degrees of correspondence at any point in the discourse universe is close to 1, for each input variable. Defining a FP into the M dimensional input space results in the initial FP of every input. From this, the following algorithm is proposed to find from the input data vector the nearest fuzzy subspace [7]-[8].

3. Results and Discussion

The results obtained during the study indicate that patients with bipolar disorder can be classified accurately from recorded EEG signals. Table 1 presents the values of Balanced Accuracy, Recall, Precision and F_1 score of well-known classification methods i.e., support vector machine (SVM) and K-nearest neighbors (KNN), and the proposed algorithm for for bipolar disorder and healthy patients. Systems based on SVM and KNN obtained values of accuracy, recall, precision and F_1 scores below 90 % in all cases. The proposed system, based on NN, obtained the highest performance, achieving values above 96 % in all cases for real EEG records.

Table 1: Balanced accuracy, recall, precision and F_1 score for different machine learning models and the proposed method.

Methods	Balanced Accuracy (%)	Recall (%)	Precision (%)	F_1 score (%)
SVM	88,17	88,28	87,54	87,91
KNN	89,63	89,74	88,99	89,36
Proposed NN	96,78	96,89	96,09	96,49

In addition, the featured parameters extracted i.e., mean and entropy, from the cleaned EEG signals and subsequently analysed by means of analysis of the variance (ANOVA) studies with Bonferroni tests showed important differences in the left part of the frontal and occipital lobes as it can be seen in figure 2. Executive functions are involved in the frontal lobe, associated with cognition, decision-making, and memory use. Thus, these results demonstrate that patients with bipolar disorder can alter normal brain functions due to abnormal neuronal connectivity.

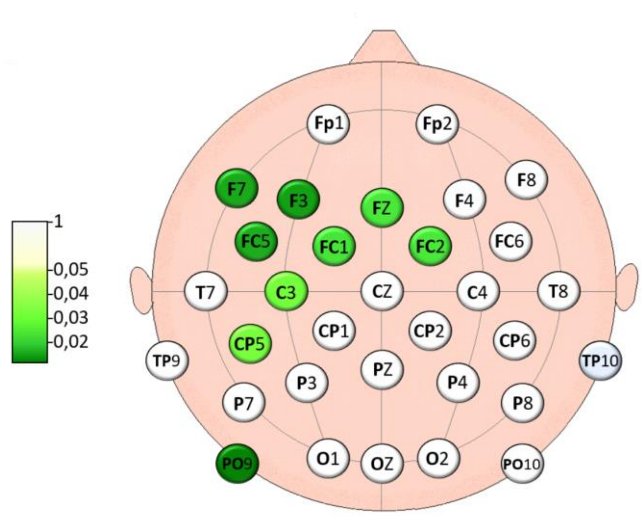

Fig. 2: P-value results for logarithmic entropies between bipolar disorder patients and controls.

4. Conclusion

The study performed proves that EEG records can be used for discrimination of bipolar disorder and control patients. Before classification, data obtained from EEG signals are processed so that the main features such as mean, or entropy can be extracted. Furthermore, machine learning techniques have been applied for classification. Two well-known classifiers namely, SVM and KNN, and a novel proposed NN have been employed. An RBF neural network based on FM algorithm shows the best results obtained with Balanced Accuracy, Recall, Precision and F1 score better than 96 % in all cases.

Furthermore, different ANOVAs studies with Bonferroni tests shows significant modifications in the left part of the frontal and occipital lobes. Finally, the experimental results presented in this paper demonstrate the usefulness of the proposed classification approach that could be employed during clinic analysis as a complementary tool to help psychiatrists diagnosing patients with bipolar disorder.

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