DOI: http://doi.org/10.32792/utq.jceps.10.01.01

Model for classifying EEG signals using deep learning to identify epileptic seizures

Zaman Gheni [1] , Raid Luaibi [2]

msc21co9@utq.edu.iq, Raidluaibi.lafta@utq.edu.iq

[1, 2] Department of Computer Science, College of Education for pure Sciences, University of Thi-Qar, Iraq

Received 11/1/2023, Accepted 5/3/2023, Published /March/2023

Abstract:

The neurological condition known as epilepsy affects the brain in a way that causes recurrent problems. As a result, seizure identification is crucial to the clinical treatment of epileptic patients. The electroencephalogram (EEG) has become a crucial tool most of the time, a small number of very competent professionals manually identify the epileptic EEG signal. Detecting and evaluating epileptic seizure activity in humans. In this paper, we attempt to automate the detecting procedure. We extract features using the wavelet transform and derive statistical parameters from the wavelet coefficients that have been decomposed. Artificial neural network (ANN) is used for the classification. By utilizing the University of Bonn's benchmark database.

Keywords: Artificial Neural Network (ANN),) Discrete Wavelet Transform(DWT), electroencephalogram (EEG)

Introduction:

Epilepsy is a non-communicable disease that affects many people and is one of the most common neurological conditions. It typically comes with unexpected bouts [1]. A sudden onset of a seizure is a brief and early disturbance in the electrical activity of the brain that disrupts a portion of the entire body[2]. Numerous epileptic seizures are experienced by about 60 million persons worldwide[3]. EEG signals are complicated, non-linear, non-stationary, and unpredictable because of the intricate connections among billions of neurons[4]. Many signal processing and analysis methods have recently been researched to identify epilepsy. In general, these methods' workflows can be divided into three steps: preprocessing, feature extraction, and classification. Artifact rejection and detection are carried out during preprocessing[5]. The final classification accuracy directly depends on feature extraction, which seeks to identify the significant and distinguishing properties concealed in EEG data. As a result, feature extraction is crucial to pattern recognition. Massive techniques, including spectrum analysis, have been used to extract EEG features[6]. Due to its noteworthy capabilities in multi-resolution representation and detail placement, WT is the strategy that is most frequently utilized in epilepsy detection among the range of methods that are now accessible. WT simultaneously displays temporal and frequency perspectives of a signal, allowing for the exact capture and localization of transitory features like epileptic spikes in the data. To identify epileptic seizures, a variety of machine-learning techniques have been developed[7] These techniques make use of statistical, temporal, frequency, time-frequency domain, and nonlinear aspects. Conventional machine learning algorithms use a trial-and-error strategy to choose features and classifiers[8]. Creating an accurate model requires knowledge of data mining and signal processing techniques. These models perform well for little amounts of data. The increased availability of data nowadays may make machine-learning approaches less effective. Machine learning approaches may not work effectively nowadays given the increased availability of data. To do this, cutting-edge Deep learning techniques have been applied [9]. Deep learning DL models require a lot of data during the training phase, in contrast to conventional machine learning techniques [10].

1.RELATED WORKS

Professionals with extensive training are needed to visually screen EEG records. This medical diagnosis could be much enhanced with the aid of an automated EEG epilepsy diagnostic system. For this task, several strategies have been suggested. We give a quick overview of some publications, which is employed in our study. In the frequency domain, an artificial neural network (ANN) predicted seizures with 92.3% accuracy, 100% sensitivity, and 83.3% specificity [11]. Hybrid SVM demonstrated significantly improved performance for EEG classification while being a sophisticated algorithm. Multistage state classifier based on Random Forest was used to predict seizures with a performance of 87.9% for sensitivity, 82.4% for specificity, and 93.4% for Area under the Curve (AUC) of Receiver Operating Characteristic (ROC) (RF)[12]. The neural network technique is trained, validated, and tested using signals gathered from the Temple University Hospital Seizure Detection Corpus (TUH EEG Corpus) database. The results of this study demonstrate that epilepsy diagnosis may be accomplished with a high degree of accuracy (95.14%) utilizing an FPGA-implemented (5-12-3) MLP ANN [13]. proposed using the discrete wavelet transform (DWT) and approximative entropy of EEG data a method for detecting epileptic seizures. Two-class EEG categorization was 96% accurate with this system[1]. used the five-class EEG data identification method offered by the multivariate empirical mode decomposition (MEMD) method. In addition, ANN was employed as a classifier, with an accuracy rate of 87.2%[14]. A 13-layer deep convolutional neural network (CNN) method was utilized to distinguish between the normal, preictal, and seizure classes. Five max-pooling layers, three fully connected (FC) layers, and five convolutional (Conv) layers make up this model. In this three-class detection problem, it achieved accuracy, specificity, and sensitivity of 88.67%, 90.00%, and 95.00%, respectively [15].

2:EEG DATA SEGMENTATION

German University of Bonn's Department of Epileptology's open-source epileptic data, consists of 100 single-channel EEG data sets from five different EEG data sets for a total of 23.6 seconds [16].Data sets A and B show the EEG recordings of five healthy people with their eyes open and closed, respectively. The data sets C and E were collected from an epileptogenic zone before an epileptic attack at the hemispheric hippocampal formation and during an epileptic episode inside an epileptogenic zone, respectively.The data were digitally sampled at a rate of 173.61 Hz and recorded using a 128-channel amplifier setup. Each channel's 4097 samples are divided into 8 equal segments of 512 bytes in this study, with the final data segment being discarded. As a result, each data set receives a total of 800 data segments from its 100 single channels. Utilizing pattern recognition techniques, statistical features are created from discrete wavelet transform coefficients of each data segment to identify epileptic seizures**.**

3.Feature Extract

Any prediction model used for classification and detection must take into account two key factors. These include the features that are taken from pre-processed EEG data and the methods used to analyze the features that are extracted. These extracted features make decisions regarding a variety of resources needed for the appropriate description of the entire dataset and help to limit the loss of important information from the signal**.**

3.1 (DWT) Discrete wavelet transform

A signal is divided into a group of coefficients known as wavelet coefficients via the wavelet transform (WT). Due to its adaptability for employing varying-size windows, it delivers precise frequency and time information at low and high frequency[1]. Within this piece, The discrete wavelet transform was employed (DWT). The EEG segment is divided into approximation (A1) and detailed coefficient (D1) by the DWT algorithm to provide the first step of decomposition. Each step further divides the approximation coefficients into approximation and detail coefficients. The number of decomposition levels determines how many times this process is done. In the discrete wavelet transform(DWT). the choice of how many decomposition steps is extremely important . In this study, the decomposition level is chosen to be 8, and db8 is used. Each subband's variance, standard deviation, mean, and entropy were all retrieved as features, along with its subband-specific entropy.

Coefficient of variation

The series' normalized variance is measured by the coefficient of variation. The coefficient of variation is a normalized indicator of the rate of change in a data series. A typical measure of change in a data series is the coefficient of variation [17].

Standard deviation

It is used to show the largest possible deviation between a wave's peaks and troughs and the mean denoised EEG signal. When the SD is low, the data values are in close proximity to the mean denoised EEG voltage, and when the SD is high, the data values are widely spread. After signal decomposition, SD can be used to obtain a small number of important features[18].

Entropy

Entropy can be utilized for both exploratory and predictive purposes and is used to discover complex measurements. Information regarding when the EEG signal drops on its own can be obtained by comparing time series that are lagged by a specified amount of time[19].

Mean

It is the total of many numbers. The mean is calculated by adding together all the data points and dividing by the total number of items in the data set, the mean is calculated (Underhill & Bradfield, 1996).

4.PROPOSED METHOD

The suggested artificial neural network-based seizure detection system is depicted in figure 1. Three steps comprise the ANN seizure detection process.

Stage 1: Removal of artifacts or noise

Stage 2: Feature Extraction

Stage 3: Classification

The DWT method is used in the first stage of preprocessing to eliminate noise or artifacts from the input signal. The features are taken from the signal after the noise has been eliminated in the second stage, and the suggested ANN classifier is trained using the features in the third stage.

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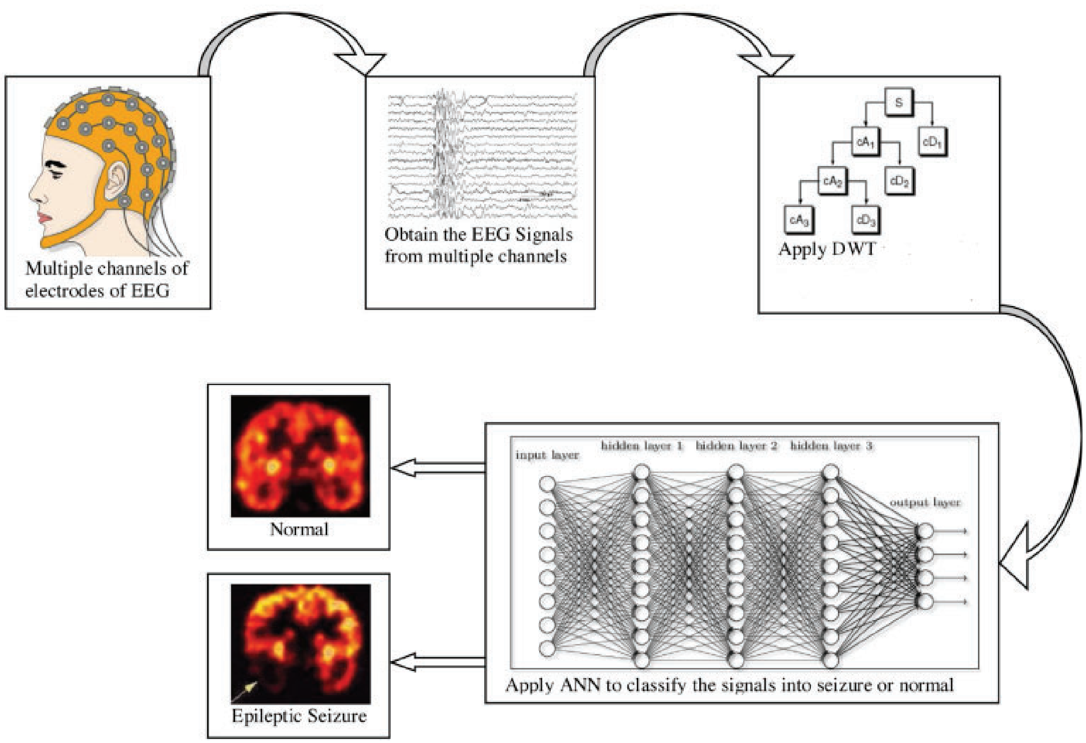

Figure1:The proposed system architecture

4.1performance

Sensitivity, specificity, and accuracy metrics are used to evaluate the effectiveness of the proposed neural network system. These parameters are tested for True Positive (TP), True Negative (TN), False Positive (FP), and False Negative answers using a simulation in a math lab (FN). This confusion matrix has two classes, such as class 1 and class 2. In class 1, the positive values (TP and FP), and in class 2, the negative values. Both TN and FN are the values for TP, FP, TN, and FN that are used to derive the metrics Accuracy, Sensitivity, and Specificity.

Accuracy

The degree of accuracy is determined by comparing the value to a true or acceptable standard.

The appropriate accuracy measurement is available. Any classifier has a maximum accuracy dependent on performance[2]. This is typically stated as a percentage.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

Sensitivity

Another statistical measure that can be used to determine the accurate rate of identification is this one. Known as the real positive rate[3], this is Typically, this is stated as a percentage.

$$\text{Sensitivity} = \frac{TN}{TP + FN}$$

Specificity

It serves as a statistical metric for evaluating output. This rate, which is also referred to as the "true negative rate," is used to calculate the percentage of negatively identified parameters (Atlan & Margulies, 2019). This is usually expressed as a percentage.

$$\text{Specificity}=\frac{TN}{TP + FP}$$

4.2 Artificial Neural Networks (ANN)

It is a classification model that uses mathematical ideas to address classification problems. It has motivated numerous scientists and developers to overcome biological issues[4]. Neurons, which are mathematical functions that change input data using weights and biases to produce an output, are the fundamental building blocks of an ANN. These neurons have the ability to be arranged into groups that can be cascaded to create multi-layered networks. Supervised learning is used in a feed-forward backpropagating neural network. where in each neuron's computed outputs advance through other layers until they finally create an output. The mean-squared error (MSE) number is used to determine whether the computed output is near to the expected output by the backpropagation approach, which repeatedly modifies the weights and biases. Levenberg-Marquardt training methods are used to determine how the randomly initialized weights and biases change, Quasi-Newton algorithms, and robust backpropagation.

5. EXPERIMENTS ANALYSIS

A substantial portion of the research on epileptic seizure detection uses the Bonn dataset. It is frequently seen using EEG signals. Earlier, a variety of methods for spotting epileptic convulsions were put forth. Our algorithm can perform better than current approaches in terms of evaluation measures. With the relevant data from the dataset still present, Artificial Neural Networks (ANNs) were utilized to convert high-dimensional data to low-dimensional data. The DWT output is fed to the ANN, which then processes it. This inquiry uses db8 and a decomposition level of 8, or level 8. Each subband's variance, standard deviation, mean, and entropy were measured, and these characteristics were the features that were obtained. The suggested algorithm performs more accurately and efficiently. According to Tables (1-2-3-4), we increased the efficiency of epileptic seizure detection in the field of medical diagnosis of a brain tumor by implementing an automated epileptic seizures detection system to precisely identify patients' epileptic and non-epileptic seizures by improving the performance of the classification and identification of epileptic seizures from a set of various metrics.

Table1: Results of the proposed method's experiments setA

Performance Measures	A-E
Accuracy (%)	98%
Sensitivity (%)	98%
Specificity (%)	99%

Teble2: Results of the proposed method's experiments set B

Performance Measures	B-E
Accuracy (%)	98%
Sensitivity (%)	98%
Specificity (%)	99%

Teble3: Results of the proposed method's experiments set C

Performance Measures	C-E
Accuracy (%)	99%
Sensitivity (%)	98%
Specificity (%)	99%

Teble4: Results of the proposed method's experiments set D

Performance Measures	D-E
Accuracy (%)	97%
Sensitivity (%)	96%
Specificity (%)	97%

Table 5: ANALYSIS IN RELATION TO OTHER METHODS

Author	Methodology	performance metrics
[6]	Time–Frequency Analysis	89%
[20]	Nonlinear Vector Decomposed Neural Network (NVDN)	95%
[21]	Entropy of the fuzzy distribution and wavelet packet decomposition	98%

CONCLUSION

This research paper provided a neural network technique for EEG-based epileptic seizure identification, using a Bonn database. Three steps make up the proposed method, preprocessing, feature extraction, and classification. The input EEG signal underwent discrete wavelet transformation during the preprocessing stage to remove any noise or artifacts. Frequency wavelet decomposition techniques are used to recover the various features from each subband of the noise-removed signal after the noise has been eliminated. The method then classifies the output based on whether or not the seizure is present by taking all the extracted attributes. Results of the suggested technique's experiments show that the proposed ANN method outperforms existing methods in terms of classification rate As shown in Table 5. Time-Frequency Analysis [6], Nonlinear Vector Decomposed Neural Network (NVDN) [20], Wavelet Packet Decomposition, and Fuzzy Distribution Entropy [21], and will boost the classification rate and use the suggested EEG technique for large datasets with a focused strategy**.**

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