



Analyzing of EEG Signals with Deep Learning and Discrete Wavelet Transform

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(First received 22 June 2021 and in final form 22 February 2022)

(DOI: 10.31590/ejosat.953576)

ATIF/REFERENCE: Abukhettala, K. O. M., & Ata, O. (2022). Analyzing Of EEG Signals with Deep Learning and Discrete Wavelet Transform. *European Journal of Science and Technology*, (35), 514-521.

Abstract

In this study, the capability to study the effect of each feature on the accuracy of the classification, whereby in the mixture of features with the Convolutional Neural Networks (CNNs) to identify epilepsy seizure in EEGs was searched. The EEG signals were first analyzed within 5 subsignals at specific frequencies bands by using Discrete Wavelet Transforms (DWT) at 5 levels, and then features were extracted from each sub signal. Finally, there was convolutional neural network classification. The best classification accuracies obtained when extracted eight features from EEG signals 96.5%. That means these features are strong to catch epilepsy seizure. Usually, the smart methods could be utilized within a more broad range of identification model problems that are also relevant to humans, such as the epilepsy diseases discovery and judgment.

Keywords: Electroencephalogram, Discrete Wavelet Transforms, Convolutional Neural Networks.

1. Introduction

An epilepsy seizure is a sort of complex illness. Epilepsy seizure is a second most predominant complex issue in human after stroke. Approximately (40) million or (50) million people on planet experience the ill effects of epilepsy [1]. In epilepsy seizure, the typical example of complex neuronal activities winds up plainly aggravated, bringing about abnormal sensations, feelings, and conduct or some of the time shakings, muscle seizures, and absence of cognizance. Epilepsy seizure is portrayed repetitive seizure by utilizing strange electrical activity in the brain creates adjusted observation or conduct. Contingent upon the degree of the association of mind regions amid the seizure, epilepsy can be separated into two fundamental

sorts. Summed up seizures include nearly the whole mind, while incomplete seizures start from an encircled zone of the cerebrum and stay limited to this territory. The (EEG) electroencephalogram is the registration of the electrical activity in the mind. There were distinct two sorts of EEGs by relying upon the region of the terminal on the head: scalp (the skin covering the head) and within the skull. For scalp EEGs, those anodes set on the scalp with great mechanical and electrical connections. Be that as it may, intracranial EEG is acquired through exceptional terminals embedded in the mind amid an operation surgery. Scalp EEGs is that concentration on this exploration is a very widely recognized demonstrative technique to distinguish anomalies of the cerebrum's electrical movement. EEGs records contain amounts of important data such as identifying epilepsy. Inquiries about on program seizure

location started in the 1970s and different strategies tending to this issue have been exhibited. Chen et al. (2016), has proposed a system to utilize DWT what's more, (SVM) Support Vector Machine for epileptic concentrate restriction issue in view of EEG. To give a rule in choosing the best settings for DWT disintegrated the EEG fragments in 7 commonly utilized wavelet families to their greatest hypothetical levels [2]. Riaz, F., Hassan et al. (2016), this study, presented a system for the discovery of epilepsy seizures in the EEGs. this system depends on the extraction of temporal and spectral characteristics from (EMD) Empirical Mode Decomposition of the EEGs [3]. Singh et al. (2015), Wavelet transforms were utilized to depict the EEG motion in estimated and details coefficients. Spike associated characteristics were extricated for a preparation counterfeit normal system, which was utilized for characterization normal and epilepsy patterns in EEGs [4]. Abualsaud et al. (2015), has studied the utilization a new ensemble classification to identify an epileptic seizure in the state of compressed and vociferous EEGs. The (NSC) Noise Aware Signal Combination ensemble classification combines four grouping models on their single execution. The main goal from the proposed classification was to improve the order exactness within noisy and incomplete information while protecting a sensible measure of many sided quality [5]. Kumar et al. (2014), The study was presented discrete wavelet transforms (DWT) analysis and approximation entropy (ApEn) of EEGs Seizure discovery was performed in two steps [6]. Nanthini et al. (2015), the main goal was to examine the execution of the classification concerning (SVM) Support Vector Machine and (CNNs) Convolutional Neural Networks applying wavelet transforms for display epilepsy seizure. The study had used Discrete Wavelet Transform to analysis EEGs which is nonstationary [7]. Nunes et al. (2014), This study showed a regular offering valuation of the lately entered (OPF) Optimum Path Forest classification when working with the assignment of an epilepsy ill diagnosis straight in EEGs. The design had used a benchmark dataset huge include of five groups, the whole difference was a very difficult obtain. The four models from wavelet transform function and three famous of filter ways were examined for the feature extraction and determination, respectively. Furthermore, (SVM) Support Vector Machines composed with (SVM-RBF) Radial Basis Function kernel, (CNN-MLP) Multilayer Perceptron Neural Networks, and Bayesian classification were applied for compared with indications of efficiency and implementation [8]. Fathima et al. (2013), exhibited, a method depended on the wavelet analysis with the computation of certain statistical characteristics was reported. The wavelet analysis was made up to the fourth level, then by the computation of the statistical feature; interquartile range the wavelet coefficients. The features were excerpted for five kinds of

EEG signals. A linear classifier trained on these features could classify normal and epilepsy EEG signals with 100 % sensitivity and specificity were the accuracy of 95.6% for five states [9]. Omerhodzic et al. (2013), presented, Discrete Wavelet Transforms by t using (MRA) Multi Resolution Analysis was applied for analysis EEGs determination levels of ingredients of the EEGs and the Parseval's theory was applied at obtaining the rate distribute of energy characteristics of the EEGs at various decision levels. Second, (CNNs) Convolutional neural network, the Features groups of the EEGs depending on the rate distribute of the strength of the signal features [10]. Übeyli et al. (2009), EEGs was analyzed into time–frequency simulations utilizing discrete wavelet transforms with Daubechies function (order 2) and analytical characteristics were determined to describe their distribution as supplies to the mixed neural network model [11]. Subasi et al. (2007), The discrete wavelet transforms have been used to process and analyze the signal to select the features of the extract features and then presented ME (Mixture Of Experts), a classification for epileptic seizure discovery dependent on a mixture of expert types [12]. Mohseni et al. (2006), has utilized a (STFT) Short Time Fourier Transform to decompose of EEG signals and extracted properties depending on the imaginary Vigner-Ville distribution and pseudo Wagnerville. These characteristics have been used as data for Convolutional neural network classification [13]. The EEG signals essentially have a tiny boundary of amplitude (nearly 100 Microvolt) and the spectrum of frequency. Features extraction is the best representation of the method for EEGs and is extraordinary for program seizure revelation execution. Include extraction trains to take the fundamental and unmistakable elements covered up in EEG signal that promptly command the last arrangement exactness. In this way, highlight extraction plays out an exceptionally significant capacity in model acknowledgment.

In this investigation, every EEG window has broken down into five essential EEGs subgroups by using discrete wavelet change, where is used time recurrence examination for giving an enough assessment of different recurrence wave levels in the brain. The EEGs window is dissected into different recurrence levels by using fourth request Daubechies (db4) wavelet work up to five level of the investigation. The statistical characteristics such as (Entropy, Minimum, Maximum, Mean, Standard Deviation, Energy, and Ratio Mean of Adjacent Sub-Bands) are calculated in 6 different cases for feature extraction, then, these features become input to classification Convolutional neural network (CNNs), for study the effect of each feature on the classification accuracy.

2. Methodology

Recently, As shown in Figure 1, our method consists of eight sections; discrete wavelet transform is applied to decompose the EEGs into five sub-bands at specific frequencies.

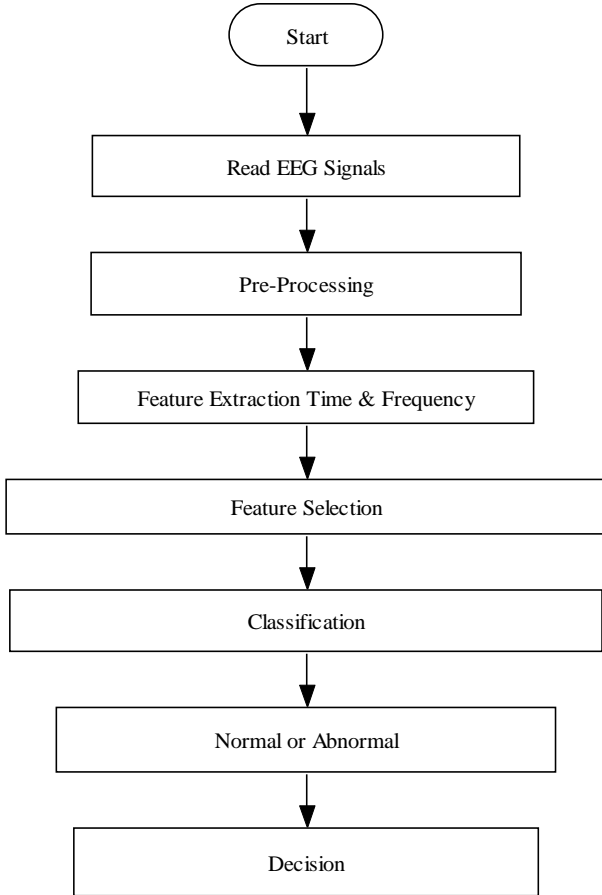


Figure 1. flowchart of the proposed method for EEG signal classification

After decomposition will compute features eight EEGs in time and frequency domain in different cases of number features. Finally, these features are fed into a Convolutional Neural Networks to obtain a decision as to the kind of signal.

Foretelling in a seizure epilepsy start is an extensive complex biomedical trouble that begets many studies of the smart computing field across the prior two decades [18, 19]. The neural network pattern with applying wavelet *eISSN:21482683*

analysis was used to the problem. The (WT) Wavelet Transform gives exceptionally broad techniques, which can be utilized to a few occupations in flag handling. One extremely critical application is the capacity to ascertain and handle information in packed parameters, that are regularly named highlights [18, 22, 23]. Along these lines, the EEG signal, incorporate of numerous information focuses, can be reduced to a couple of parameters. These parameters portray the conduct of the EEG signal. This element of utilizing a less number of parameters to depict the EEG signal is particularly imperative for recognizable proof and recognizing purposes.

The wavelet transformation can be arranged into two sorts.

- 1) Continuous Wavelet Transforms (CWT).
- 2) Discrete Wavelet Transforms (DWT).

Continuous Wavelet Transforms (CWT).

$$cwt(a, b) = \int_{-\infty}^{+\infty} x(t) \varphi * a, b(t) dt \quad (1)$$

Where $x(t)$ depicts the examined signal a and b portray the scaling element (dilatation/pressure coefficient) and interpretation along the time hub (moving coefficient), individually, and the superscript reference bullet demonstrates the unpredictable conjugation. $\varphi * a, b$ is accomplished by scaling the wavelet at time b and scale.

$$\varphi * a, b = \frac{1}{\sqrt{|a|}} \varphi\left(\frac{t-b}{a}\right) \quad (2)$$

Where $\varphi(t)$ describe the wavelet [20]. The primary estimate, A1 is additionally broke down and this strategy is reached out as appeared in figure 2, [20, 21].

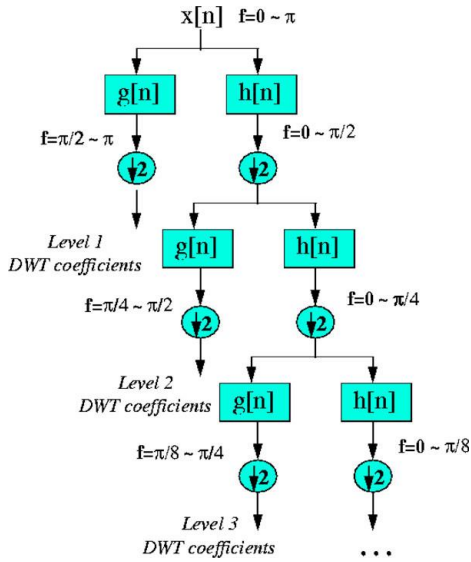


Figure 2. Levels analysis by using discrete wavelet; $g[n]$ is the high-pass filter, $h[n]$ is the low-pass filter

Any window in the UBONN dataset has 4097 sampling points and each wavelet has a highest theoretical level of analysis provided in the column Max Level as shown in table 1.

Table 1. Max level for Daubechies wavelet function on the UBonn dataset (http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3).

Wavelet	Max level
Db1	12
Db2	10
Db3	9
Db4	9
Db5	8
Db6	8
Db7	8
Db8	8
Db9	7
Db10	7

Normally, experiments are conducted with various kinds of wavelet function and the one that provides the best performance is chosen for the appropriate application. The Similarity features in the Daubechies wavelet of order (4). It's more fitting to identify changes of the EEGs.

eISSN:21482683

One approximation wavelet coefficient (A5) at the 5th level (134 wavelet coefficients) was calculated as shown in Figure 4.

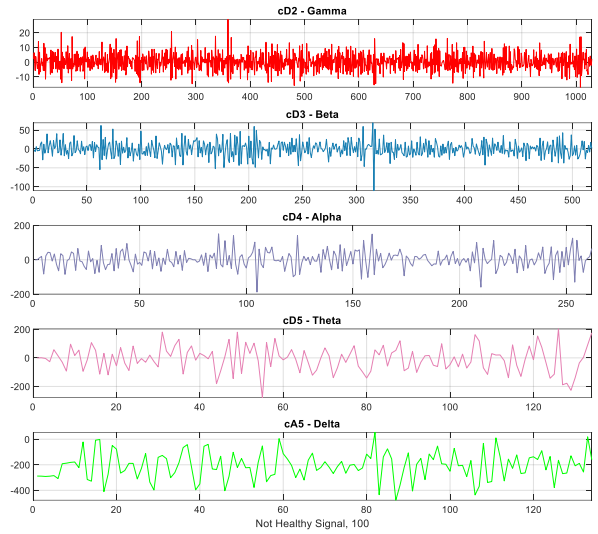


Figure 4. (a) Brain rhythm analysis by using Daubechies (4) wavelet for Healthy Subject (window 37),(b) For non-Healthy Subject (window 93).

At that point 4097 coefficients of wavelet were taken for every window of EEGs. In this way, the time space of sign ought to be changed to the recurrence area for taking additional data about the sign highlights. The wavelet change can get the data on schedule or recurrence do fundamental. In this way, it gives the client to pick that fitting data they required. Plus, it is additionally helpful in wiping out the (EMG) Electromyography and (EOG) Electro oculography curios in the EEG signals. This examination, the accompanying factual boundaries were applied for portraying the time recurrence dissemination of the EEGs. To limit the dimensionality of the extricated vectors of the element, the measurements on the arrangement of the wavelet coefficients were used from each sub band which was chosen to realize EEG signals type:

- 1) Maximum of the wavelet coefficients in each sub band.
- 2) Minimum of the wavelet coefficients in each sub band.
- 3) Mean of the wavelet coefficients in each sub band is got by this Equation:

$$\mu_i = \frac{1}{n} \sum_{j=1}^n D_{ij} \quad i = 1,2,3 \dots \dots I \quad (10)$$

4) The standard deviation (SD) of the wavelet coefficients in each subband.

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{l=1}^N (D_l - \mu)^2} \quad (11)$$

5) Entropy in the sub-band is a mathematical pattern of the distrust of result wherever signal included a thousand folds of bits of data. The analytical description is

$$Entropy (EN) = \sum_{j=1}^N D_i^2 \log(D_i^2 j) \quad i = 1,2,3 \dots \dots I \quad (12)$$

6) The energy of the wavelet coefficients in each sub band. Shows the power of the signal since it provides the region below the curve line of power in any period. The energy of EEGs of the limited period is provided as:

$$Energy (EN) = \sum_{i=1}^N |D_{ij}|^2 \quad i = 1,2,3 \dots \dots I \quad (13)$$

7) The medium power in each sub band for the wavelet coefficients.

8) The rate of the absolute mean values of nearby in each sub band.

2.1. Convolutional Neural Network

Convolutional neural organizations are like ordinary Convolutional neural organizations. The greatest change is that the design of a CNN makes the suspicion that the sources of info are pictures, which considers certain properties to be encoded into the organization. This implies that the forward capacity of these organizations will be more productive to execute, and that the quantity of boundaries required for the organizations can be enormously decreased. Dissimilar to in normal neural organizations, CNNs orchestrate their neurons in three measurements: width, tallness, and profundity. Rather than the entirety of the neurons being completely connected to the past layer, in a CNN the neurons in each layer are simply associated with a little locale of the layer before it. The yield layer of the CNN contains a solitary vector of class scores, which are masterminded along the profundity measurement. As such, the yield measurement would have the state of $1 \times 1 \times n$, where n is the quantity of classes being ordered. A perception of a CNN can be seen beneath in Figure 5 [25].

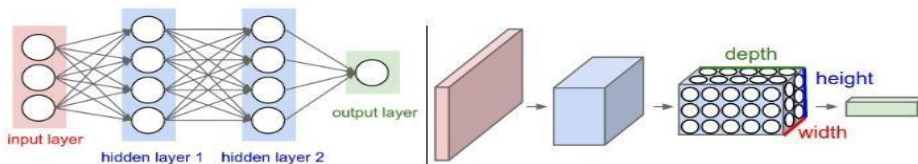


Figure 5: Convolutional Neural Network [25]

Each layer of a CNN changes one volume of actuations to another utilizing a differentiable capacity. The three primary kinds of layers in CNN engineering are the convolutional layer, pooling layer, and the fully associated layer. With these essential layers, the full engineering has the accompanying construction: input layer to convolutional layer to amended direct unit (RELU) layer to pooling layer to completely associated (FC) layer. The input layer contains the crude pixel upsides of the picture. The convolutional layer registers the yield of every neuron that is associated with nearby regions of the info. Every one of these neurons registers the dab item between their loads and the little district that they are associated with the information locale. The profundity of the volume will be equivalent to the quantity of filters utilized in this layer. The RELU layer

applies an enactment work for every one of the convolutional neurons, which doesn't change the general volume. The pooling layer plays out a down examining procedure on the width and stature measurements of the volume. At long last, the FC layer computes the class scores for each class wanted. Each neuron in this layer is associated with all numbers in the past volume. Through this interaction, each layer attempts to change the first information picture to the last vector of class scores [25].

3. Experimental result

EEG signals from all sets (A and D) are analysed to the details and approximations wavelet coefficients by applying the discrete wavelet transform with wavelet

function Daubechies order (4) because it produces well into (D1-D5) and one approximation (A5). The details and approximations wavelet coefficients are calculated using the MATLAB software. The configured of the convolutional neural networks: layers of input, hidden and output are shown in figure 7.

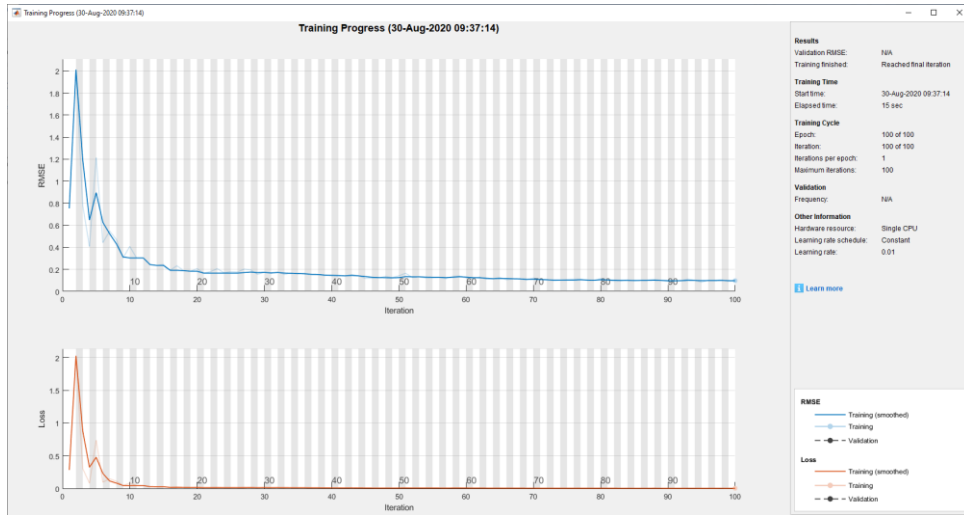


Figure 7. The configured of the convolutional neural networks: layers of input, hidden and output.

These highlights are in the time recurrence investigation. In this investigation, the factual highlights are removed from every coefficient of the sign. These highlights are assessed by means of Kruskal–Wallis factual (can be applied to choose if there are measurably significant contrasts between at least two gatherings of an independent swinging variable). We have applied six cases to examine sway the kind of extraction include on the grouping exactness. The eight highlights are utilized in this examination four of them fundamental (mean of the wavelet coefficients in each sub band, The rate force of the wavelet coefficients in each sub band, the standard deviation of the wavelet coefficient in each sub band, and the pace of irrefutably the mean qualities for close by in each sub band) are utilized in all cases and other four of highlights are auxiliary (limit of the wavelet coefficients in each sub band, least of the wavelet coefficients in each sub band, entropy in each sub band and energy in each sub band) the put together are picked with respect to two of them (max, min) from (TDF) Time Domain Feature and another two optional highlights (entropy, energy) from (FDF) Frequency Domain Feature . In each of case 2 to case 5, we add one secondary feature to the four basic features to be five extraction features. Where 80 % dataset is employed for running (train neurons) and 20% data set used for validation (test). This 80 % dataset is utilized to guide a neural network whereas 20 % dataset is utilized to get an accurate result of the suggested method. The results show that suggested method in the first case gives 97%

accuracy, 100% specificity, and 94 % sensitivity as shown in figure 8 and figure 9.

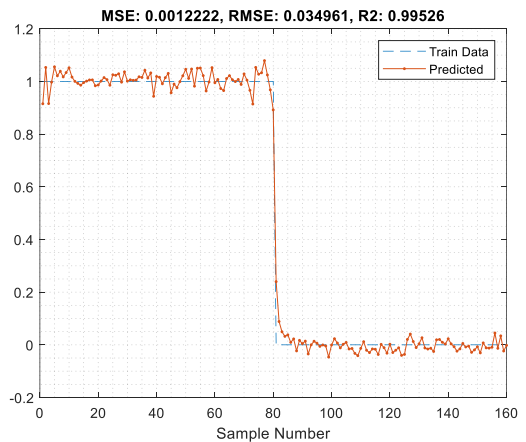


Figure 8. training data result

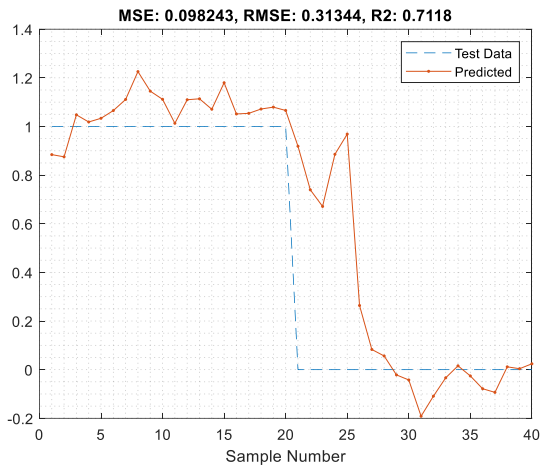


Figure 9. Test data result.

The comparison between our work and other study are available in table 3.

Table 3. Comparing the proposed method with previous studies

Author	Wavelet Function	Accuracy
Chen [2]	DWT(SYM5)	88.22 %
Abualsaud [5]	DWT(db6)	90 %
Nunes [8]	DWT (db4)	93 %
Fathima [9]	DWT (db4)	95.3 %
Omerhodzic [10]	DWT (db4)	94 %
Übeyli [11]	DWT (db6)	94.33 %
Proposed Method	DWT (db4)	96.00 %

5. Conclusion

In this paper, the ability to consider the impact of each element on the precision of the grouping, whereby in the combination of highlights with the Convolutional Neural Networks (CNNs) to distinguish epilepsy seizure in EEGs was looked. The EEG signals were first investigated inside 5 sub-signals at explicit frequencies groups by utilizing Discrete Wavelet Transforms (DWT) at 5 levels, and afterward includes were removed from each subsignal. At last, there was three layers of multi facet Perceptron neural organization (MLPNN) characterization. The best arrangement exactnesses obtained when separated eight highlights from EEG signals 98.5%. That implies these highlights are solid to get epilepsy seizure. Typically, the shrewd techniques could be used inside a wider scope of *eISSN:21482683*

distinguishing proof model issues that are additionally applicable to people, for example, the epilepsy disfacilitates disclosure and judgment.

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