Journal of Industrial Information
Technology and Application Vol.5 No.2 *ISSN(Online): 2586-0852*

Classification of Epileptic Seizure and Sleep Stage from EEG Signal Using Wavelet Transform and Deep Learning Techniques

M. Sornam*, E. Panneer Selvam
Department of Computer Science, University of Madras, Chennai – 600025

Abstract. Epilepsy is the fourth most common neurological problem in which brain activities becomes abnormal, causing seizure or unusual behaviour and sometimes loss of awareness. An electroencephalogram (EEG) signal is used to detect problems in electrical activity of the brain that is associated with certain brain disorders. In this work, electroencephalogram signals were decomposed into the frequency sub-bands using DWT and set of statistical features were extracted from the sub-bands to represent the distribution of wavelet coefficients. Extracted features are given as an input to the neural network for classification. Later, proposed method is used to classify different sleep stages as well. Classification of EEG signal is performed using BPN and RNN network on both the seizure and sleep dataset Experimental results show that BPN best suits for seizure classification with 99.8% accuracy and RNN for sleep stage classification with 99.6% accuracy.

Keywords; Artificial Neural Network, Back Propagation Neural Network, Discrete Wavelet Transform (DWT), Electroencephalogram (EEG), Epilepsy.

1. Introduction

Epilepsy is one of the most common neurological disorders which affecting more than 65 million number of people around the world. It is a neurological disease affecting the nervous system. Epilepsy is also known as a seizure disorder. It is usually diagnosed after a person has had at two seizures or more, that were not caused by some known medical condition. The seizures in epilepsy related to abnormal activity of brain signal. [28]

The usual method for sleep stage classification is based on visual inspection method by a sleep specialist. In this method it needs large data for sleep analysis that is eight EEG channels, EMG, and EOG. Since EMG and EOG shows lot of variation for

* Corresponding author: madasamy.sornam@gmail.com , panneeroctobus@gmail.com
Received: Feb 9, 2021; Revised: Feb 20, 2021; Accepted: Jun 30, 2021

different sleep stages. It is more time consuming technique and also real time sleep monitoring cannot be achieved by the subject with respect to more number of electrodes. Some brain disorders like narcolepsy (excessive day time sleepiness), requires real-time monitoring of sleep states which is not possible using conventional techniques [27].

Brain waves or neural signals obtained by Electroencephalogram (EEG) recordings is an important research area and plays a vital role in medical, health applications and Brain Computer Interface (BCI). There are two categorize in which the BCI systems can be categorized; invasive and non-invasive. These are the used categorized in which to measure the activity of the brain. For the system to be considered invasive BCI system the sensors used to measure the brain activity is placed inside the skull. The opposite of that is non-invasive system, which is having the sensors that measure brain activity be put outside the brain or surrounding the skull [2].

EEG activity can be broken down into 4 distinct frequency bands: Delta (<4Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), Gamma (>30 Hz).Analysis of EEG activity has been achieved in clinical settings to identify pathologies and epilepsies since Hans Berger's recording of rhythmic electrical activity from the human scalp. In the past, interpretation of EEG was limited to visual inspection by a neuro physiologist, an individual trained to qualitatively make a distinction between normal EEG activity and abnormalities contained within EEG records. The advance in computers and the technologies related to them has made it potential to successfully apply a host of methods to quantify EEG changes (Bronzino,2000).There is a strong demand for the development of automated device to diagnosis neurological disorder. The entire process can be generally subdivided into a number of disjoint processing modules: segment detection, feature extraction/selection and classification.

Wavelet Transformation (WT) is designed to address the problem of nonstationary signals (EEG is a nonstationary signal). It involves representing a time functions in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. The main advantage of WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges. The property of time and frequency localization is known as compact support and is one of the most attractive features of WT.

The EEG signal consisting of many data points, can be compressed into a few features by performing spectral analysis of the signals with the wavelets. The features characterize the behaviour of EEG signal. Using small number of features to represent the EEG signals is particularly important for recognition and diagnosis purpose. Therefore, EEG signals were decomposed into time-frequency representation using discrete wavelet transform (DWT). Wavelet coefficients were used as a feature vectors to classify frequency bands of eeg signal and to identify the characteristics of the signal.

Artificial neural network (ANN) have been used in a great number of medical diagnostic decision support system application because that they have great predictive power. In this work, EEG dataset is analyzed completely by using wavelet transformation and to extract all the fundamental frequency components of EEG signal that is Alpha, Beta, Gamma, Delta and Theta. In order to reduce the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients were used. Artificial neural network is trained with the extracted feature to classify signal into normal and epileptic [24].

The rest of the work is organized as follows. Section II describes a review on previous methods. Summary of dataset and methods used is given in section III. Section IV gives result with discussion and Conclusion is given in Section V.

2. Literature Review

In the last two decades, many researchers addressed the problem of automatic seizure detection. It has been shown that all the methods fall into four categories: (a) time domain, (b) frequency domain, (c) time-frequency domain and (d) nonlinear methods. Abdulhamit et al. [4] used principal, independent, linear discriminate and support vector machine for the classification of epileptic EEG signals. Rafik et.al. [2] proposed Empirical mode decomposition (EMD) for feature extraction of EEG signal and artificial neural network for the classification. Arun chavan et al. [5] used wavelet transform and neural network for diagnosis and classification of EEG signal.

3. Materials and Methods

3.1 Dataset Description

a) Figure 1 shows a conventional electric APS and an electric APS using hydrogen fuel cells. Turbines in general APS generate CO_2 and have the disadvantage of low efficiency. Therefore, to replace turbines, hydrogen fuel cells were applied to aviation propulsion systems. Hydrogen is stored in a liquid state to minimize volume, and batteries are added to the electric drive system for reliable power supply. Liquid hydrogen is used as an energy source to generate power as a refrigerant to maintain its superconducting state.

b) The data were acquired in a sleep laboratory of a Belgium hospital using a digital 32-channel polygraph, which is publically available (http://www.tcts.fpms.ac.be/~devuyst/Databases/DatabaseSpindles/). It consists of 8 excerpts of 30 minutes of central EEG channel extracted from whole-night PSG recordings annotated independently by two experts in sleep spindles. Hypnogram file contains values correspond to the sleep stage (one value per 5 sec) annotated by the expert according to the Rechtschaffen and Kales criteria.

3.2 Wavelet Transform

transform with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space. Generally, the wavelet transform can be expressed by the following equation:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\,\psi^{*}_{(a,b)}(x)\,\mathrm{d}x \qquad (1)$$

where the * is the complex conjugate symbol and function ψ is some function. Wavelet transform is in fact an infinite set of various transforms, depending on the merit function used for its computation. There are different types of wavelet transforms are available and it has been mainly classified into two major types: Orthogonal wavelets for Discrete Wavelet transform and Non-Orthogonal wavelets for Continuous Wavelet transform. In this work, discrete wavelet transform is used as it reduce the redundancy and decompose the signal into multiple level which would be helpful to find out the different range of hidden frequency band from the eeg signal.

3.3 Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) decomposes the signal into mutually orthogonal set of wavelets. The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies mathematical conditions as follows:

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k) \qquad (2)$$

where S is a scaling factor (usually chosen as 2). Moreover, the area between the function must be normalized and scaling function must be orthogonal to its integer translations, i.e.

$$\int_{-\infty}^{\infty} \phi(x)\,\phi(x+l)\,\mathrm{d}x = \delta_{0,l} \qquad (3)$$

For most signal and image processing applications, DWT-based analysis is best described in terms of filter banks. The use of group of filters to divide up a signal into various spectral components is termed as sub-banding. This procedure is known as multi-resolution decomposition of a signal. Each stage of this scheme consists of two digital filters and two down-samplers by 2. The first filter, h[] is the discrete mother wavelet, high-pass in nature, and the second, g[] is its mirror version, low-pass in nature. The down-sampled outputs of first high-pass and low-pass filters provide the details D1 and the approximation A1 respectively. (Abdulhamit et al.)

3. 4 Artificial Neural Network

Artificial neural networks (ANN) were successfully used in a wide variety of medical applications. Neural Networks are highly interconnected and simple processing units which are designed to model the way human brain perform a particular task. Each unit is called a neuron. It forms a weighted sum of its inputs and a constant term called bias is added. This sum is passed through a transfer function such as linear, sigmoid or hyperbolic tangent. In the construction of neural architecture, it has three important layers: input, hidden and output. The choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems. In order to find the optimal network architecture, several combinations should be evaluated [10].

4. Results and Discussion

4.1 Proposed Method

The method proposed in this work is illustrated in Fig.1

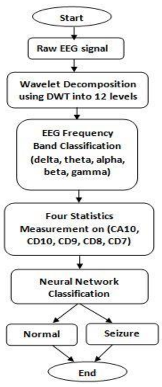

Fig. 1 Flow chart of the proposed seizure detection method.

EEG signal is decomposed into 12 levels using db1 filter, where CA10 (0-3.5 Hz), CD10 (3.5-7.8 Hz), CD9 (7.8-11.4 Hz), CD8 (11.4-31.6) Hz), CD7 (31.6-43.2) and rest of the decomposition contain the frequency >43.2 Hz. Since the EEG signals do not have any useful frequency components above 30 Hz, the decomposed level chosen for feature extractions are CA10 to CD7. In order to further decrease the dimensionality of the extracted feature vectors statistics over the set of the wavelet coefficients were used. The following statistical features were used to represent the time-frequency distribution of the EEG signals:

1. Maximum wavelet coefficients in each subband.
2. Minimum wavelet coefficients in each subband.
3. Mean of the wavelet coefficients in each subband.
4. Standard deviation of the wavelet coefficient in each subband.

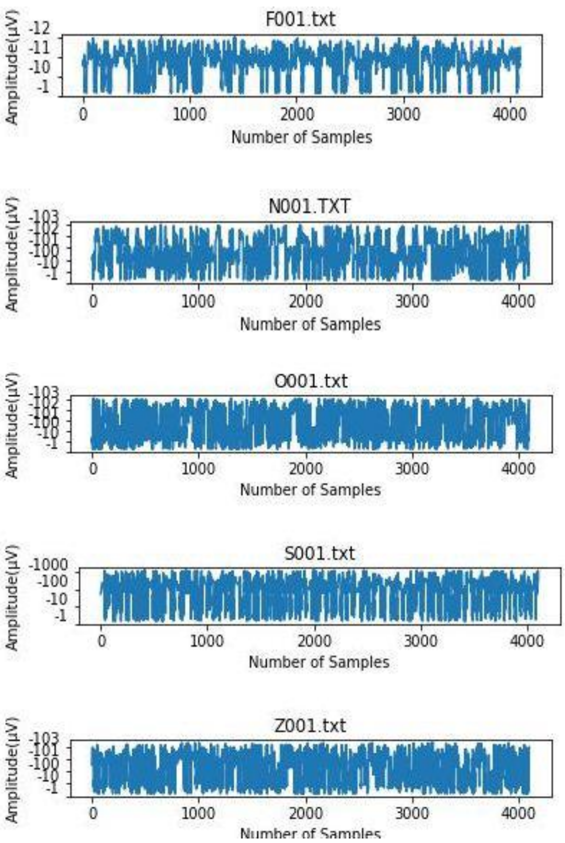

Fig. 2 Five different sets of EEG signals from different subjects.

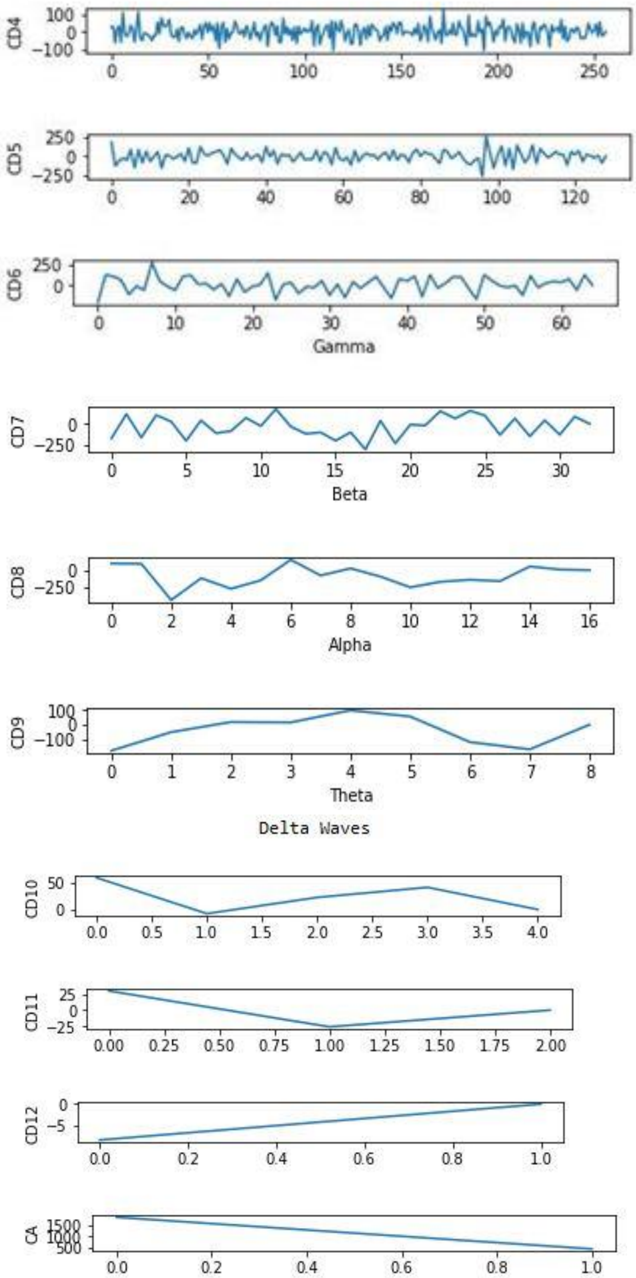

Fig. 3 Gamma, Beta, Alpha, Theta, Delta Frequencies.

4.2 Epileptic Seizure Classification

A. Classification using Back Propagation Neural Network

The Back Propagation neural network (BPN) used for classification of EEG segments. The network topology has two hidden layer with 20 input neurons, equal to the number of input feature vectors. The number of hidden layer was 15, 10 and the number of output unit is 2. The network is trained with 400 and tested with 100 samples of EEG. Out of 500 samples 400 were normal and 100 were abnormal samples. The network correctly able to classify EEG signals with an accuracy of 99.80%.

B. Classification using LSTM Recurrent Neural Network

Recurrent Neural Networks (RNN) with sophisticated recurrent hidden units such as Long-Short-Term Memory (LSTM) unit has become popular choice for modeling time series data [26][27]. Motivated from these recent successes, we proposed RNN architecture for the classification of EEG data. EEG segment in the dataset consists of 4097 data samples (23.6 x 173.61). In order to facilitate RNN training, divided the long temporal sequence of 4097 sample of EEG segments into 23 sub segments, each 178 samples long. Dropout is used in this architecture to avoid overfitting and softmax activation function is used in the output layer. The model achieved classification accuracy of 98.3%.

4.3 Classifier Performance Assessment

Classification results of the Artificial Neural Network were displayed by confusion matrix. (Table 1) The test performance of the classifiers can be determined by the computation of specificity, sensitivity and total classification accuracy.

Table 1. Confusion Matrix

n = 100	Predicted: NO	Predicted: YES	Total
Actual NO	TN = 74	FP = 1	75
Actual Yes	FN = 0	TP = 25	25
Total	74	26	100

Specificity: number of true negative decisions / number of actually negative cases
Sensitivity**:** number of positive decisions / number of actually positive cases
Classification Accuracy: number of correct decisions / total number of cases

- **True Positive (TP):** These are cases in which we predicted yes (they have diseases), and they do have diseases.
- **True Negative (TN):** We predicted no, and they don’t have the diseases.
- **False Positive (FP):** We predicted yes, but they don’t actually have disease.
- **False Negative (FN):** We predicted no, but they actually do have the diseases.

Table 2: Classification accuracies

Statistical Parameters	Values
Specificity	98.6
Sensitivity	100
Total Classification Accuracy	99.8

4. 4 Sleep Stage Classification

Usually sleepers pass through five stages: 1,2,3,4 and REM (rapid eye movement) sleep. Where, stages 1- 4 are non-REM sleep. These stages progress cyclically from 1 through REM then begin with stage 1. A complete cycle takes an average of 90 to 110 minutes, with each stage lasting between 5 to 15 minutes.

A. Classification using Back Propagation Neural Network

This experiment takes 15 minutes eeg data of different sleep stags. Each state contains 200 files where each of the file contains 5 second of eeg data with 1000 data sample in it with sampling frequency of 200Hz. EEG signal is decomposed into 9 levels using db1 and the remaining procedures are followed as per the proposed method and it can able to correctly classify sleep stages with an accuracy of 87.5%.

B. Classification using LSTM Recurrent Neural Network

Extracted feature is given as an input to the Long-Short-Term Memory. Dataset consists of 1800 features out of which 1400 (80%) are taken for training the network (6 x 240) and 400 (20%) is taken for testing. In order to facilitate RNN training, divided the long temporal sequence of 1800 sample of extracted features segments into 6 sub segments, each 20 samples long. Dropout is used in this architecture to avoid overfitting and softmax activation function is used in the output layer. The model achieved classification accuracy of 99.6%.

```
Epoch 186/200
240/240 [==============================] - 68s 284ms/step - loss: 0.0013 - categorical_accuracy: 1.0000
Epoch 187/200
240/240 [==============================] - 69s 287ms/step - loss: 5.5888e-04 - categorical_accuracy: 1.0000
Epoch 188/200
240/240 [==============================] - 69s 287ms/step - loss: 1.8202e-04 - categorical_accuracy: 1.0000
Epoch 189/200
240/240 [==============================] - 68s 285ms/step - loss: 0.0014 - categorical_accuracy: 1.0000
Epoch 190/200
240/240 [==============================] - 68s 284ms/step - loss: 0.0013 - categorical_accuracy: 1.0000
Epoch 191/200
240/240 [==============================] - 69s 286ms/step - loss: 0.0011 - categorical_accuracy: 1.0000
Epoch 192/200
240/240 [==============================] - 69s 287ms/step - loss: 3.6225e-04 - categorical_accuracy: 1.0000
Epoch 193/200
240/240 [==============================] - 68s 284ms/step - loss: 0.0011 - categorical_accuracy: 1.0000
Epoch 194/200
240/240 [==============================] - 69s 286ms/step - loss: 0.0010 - categorical_accuracy: 1.0000
Epoch 195/200
240/240 [==============================] - 69s 287ms/step - loss: 1.9909e-04 - categorical_accuracy: 1.0000
Epoch 196/200
240/240 [==============================] - 69s 287ms/step - loss: 3.9336e-04 - categorical_accuracy: 1.0000
Epoch 197/200
240/240 [==============================] - 68s 285ms/step - loss: 3.7193e-04 - categorical_accuracy: 1.0000
Epoch 198/200
240/240 [==============================] - 69s 286ms/step - loss: 1.5405e-04 - categorical_accuracy: 1.0000
Epoch 199/200
240/240 [==============================] - 69s 287ms/step - loss: 2.0448e-04 - categorical_accuracy: 1.0000
Epoch 200/200
240/240 [==============================] - 68s 285ms/step - loss: 7.6184e-04 - categorical_accuracy: 1.0000
60/60 [==============================] - 4s 63ms/step
```

Fig. 4 Sleep stage classification using Long-Short-Term Memory Network

Table 3: Total Classification accuracies

Classification	BPN	LSTM
Epileptic Seizure	99.8	98..3
Sleep Stage	87.5	99.6

5. Conclusions

In this work, daubechies1 is used as a mother wavelet for decomposition of EEG signal. Since other wavelet filters such as symlet, coiflet and biorthogonal with its wavelist gives average of decomposition level as 9 where db1 gives 12 level of decomposition for 4097 data points of seizure data and 9 level of decomposition for 1000 data points of sleep data which properly decompose the signal upto last level and also it makes the frequency band classification of eeg process as simple. Then statistical features were calculated over the decomposed level to further reduce the dimensionality to train with the neural network. Experimental result shows an accurate classification performance for normal and seizure signal with an accuracy of 99.8% and sleep stage classification with an accuracy of 87.5%. The future work includes identifying Alzheimer disease using the proposed method.

References

[1] Tapan Gandhi, Bijay Ketan Panigrahi, Sneh Anand, "A comparative study of wavelet families for EEG signal classification," *Neurocomputing*, pp. 3051-3057 doi:10.1013/j.neucom.2011.04.029

[2] Rafik Djemili, Hocine Bourouba, M.C. Amara Korba, "Application of empirical mode decomposition and artificial neural network for the classification of normal and epileptic EEG signals," *Biocybernetics and Biomedical Engineering*, pp. 285-291, doi: http://dx.doi.org/10.1016/j.bbe.2015.10.006

[3] Elif Derya Ubeyil, "Combined neural network model employing wavelet coefficients for EEG signals Classification," *Digital Signal Processing*, pp. 297-308, doi: 10.1016/j.dsp.2008.07.004

[4] Abdulhamit Subasi, M.Ismail Gursoy, "EEG signal classification using PCA,ICA,LDA and support vector machines," *Expert Systems with Applications*, pp. 8659-8666, doi:10.1016/j.eswa.2010.06.065

[5] Arun Chavan, Mahesh Kolte, "EEG Signals Classification and Diagnosis Using Wavelet Transform and Artificial Neural Network," *International Conference on Nascent Technologies in the Engineering Field*, pp. 1-6, 2017

[6] S. Ghosh-Dastidar, H. Adeli, "Improved spiking neural networks for EEG classification and epilepsy and seizure detection," *Integrated Computer-Aided Engineering*, pp.187-212, 2007.

[7] H.Adeli, Z.Zhou, N.Dadmehr, "Analysis of EEG records in an epileptic pattern using wavelet transform,"*Journal of Neuroscience Methods*, pp. 69-87, 2003.

[8] L.D. Iasemidis, "Epileptic seizure prediction and control," IEEE Transaction on Biomedical Engineering, pp.549-558, 2003.

[9] N. Hazarika, J.Z Chen,A.C. Tsoi, A.Sergejew, "Classification of EEG signals using the wavelet transform," *Signal Porcess*, pp.61-72, 1997.

[10] Ocak H, "Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy," *Expert System Application*, pp. 2027-2036, 2009.

[11] Acharya UR, vinitha Sree S, chattopadhyay S, Wenwei YU, Alvin APC, "Application of recurrence quantification analysis for the automated identification of epileptic EEG signals," *International Journal of Neural System*, pp. 1-12, 2011.

[12] Mc Sharry PE, He T, Smith LA, Tarassenko L. "Linear and nonlinear methods for automatic seizure detection in scalp electro-encephalogram recording," Medical Biological Engineering, pp.447-461, 2002.

[13] Liu A, Hahn JS, Heldt gp, Coen RW, "Detection of neonatal seizures through computerized EEG analysis," *Electroencephalogram Clinical Neurophysiol*, pp. 30-37, 1992.

[14] Kannathal N, Choo ML, Acharya UL, Sadasivan PK, "Entropies for detection of epilepsy in EEG," *Computer Methods Program Biomedical*, pp. 187-194, 2005.

[15] Huang NE,Shen Z, Long SR, Wu MC, Shih HH, Zheng Q et al. "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," pp.903-995, 1998.

[16] Bajaj V, Pachori RB, "Epileptic seizure detection based on the instantaneous area of analytic mode functions of EEG signals," *Biomedical Engineering*, pp. 17-21, 2013.

[17] Li S, Zhou W, Yuan Q, Geng S, Cai D, "Feature extraction and recognition of ictal EEG using EMD and SVM," *Computer Biomedical*, pp. 807-816, 2013.

[18] Sharma R, Pachori RB, "Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions," *Expert System Application*, pp.1106-1117, 2015

[19] Dipietro L, Sabatini AM, Dario P, "Artificial neural network model of the mapping between electromyographic activation and trajectory patterns in free-arm movements," *Medical Bio Engineering*, pp. 124-132, 2003.

[20] Mohamma H, Alomari, Aya Samaha, Khaled Alkamha, "Automated Classification of L/R Hand Movement EEG Signals using Advanced Feature Extraction and Machine Learning," *International Journal of Advanced Computer Science and Applications*, vol.4, pp. 207-212, 2013

[21] Andrzejak RG, Lehnertz K, Monmann F, Rieke C, David P, Elger CE., "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity," *Dependence on recording region and brain state, Phys Rev* 2001; 64(6):061907.

[22] Podgorelec V, "Analyzing EEG Signals with Machine Learning for Diagnosing Alzheimer's Disease," *Elektronika ir Elektrotechnika*, vol. 18, pp. 61-64, 2012.

[23] Chen G, "Automatic EEG seizure detection using dual-tree complex wavelet Fourier features," *Expert System Application*, pp. 2391-2394,2014.

[24] Sornam M, Panneer Selvam E, "Detection of Epileptic Seizure from EEG Signal using Wavelet Transform and Artificial Neural Network", *International Journal of Engineering Research and Applications*, vol:8, pp6-11, Oct 18

[25] Sirvan Khalighi, Teresa Sousa, Dulce Oliveira, Gabriel Pires, Urbano Nunes, "Efficient Featue Selection for sleep Staging Based on Maximal Overlap Discrete Wavelet Transform and SVM", International Conference of the IEEE EMBS, pp.3306-3309, 2011.

[26] Venkatesh K, Poonguzhali S, "Sleep Stage Classification Using Neural Network with Single Channel EEG". *IJREAT*, vol:2, pp.5-8, 2014.

[27] Xiaojing G, Xiaopei W, Dexiang Z, "Motor imagery EEG detection by empirical mode decomposition. *IEEE International Joint Conference Neural Networks*, 2008.

[28] Sornam M, Panneer Selvam E,, "Recent Advances in Deep Learning Techniques", *International Journal of Computer Science and Engineering*, vol:6, pp131-135, May-18.