

Epileptic Seizure Detection based on EEG Signal using Boosting Classifiers

Nasım MOSTAFA POUR¹, İbrahim Yücel ÖZBEK*¹

¹ Department of Electrical and Electronic Engineering, Faculty of Engineering, Ataturk University, Erzurum, Turkey

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Abstract

The detection of epileptic seizures by electroencephalography (EEG) signals has become a standard method in recent years for the diagnosis of epilepsy. Accurate and automatic detection of epileptic seizures is needed since manual identification of epileptic seizures by specialist neurologists is a time-consuming and labor-intensive process, which also leads to various errors. For this purpose, frequency-based features were extracted from the EEG signal and various classifiers based on ensemble learning were used to detect epileptic seizures automatically. The performance of the proposed method was tested using cross-validation and cross-patient experiments. According to the experimental results, sensitivity, specificity, and accuracy rates were obtained 94%, 93% and 93% for cross-validation and 76%, 90% and 90% for cross-patients, respectively.

Keywords: epileptic, EEG, ensemble learning, rusboost, robustboost, logitboost.

Yükseltme Sınıflandırıcıları kullanarak EEG Sinyaline dayalı Epileptik Nöbet Tespiti

Öz

Elektroensefalografi (EEG) sinyallerinin analizi ile epileptik nöbetlerin belirlenmesi, epilepsi hastalığı tanısı için standart bir yöntem haline gelmiştir. Epileptik nöbetlerin uzman nörologlar tarafından el ile belirlenmesi yoğun çalışma gerektiren, oldukça zaman alıcı bir işlem olduğu gibi kişilerden kaynaklanan çeşitli hataların oluşmasına sebep olmaktadır. Bu sebeple epileptik nöbetlerin doğru ve otomatik bir şekilde belirlenmesine ihtiyaç duyulmaktadır. Bu amaç doğrultusunda bu tez kapsamında, EEG sinyalinden frekans tabanlı öznitelikler çıkarılmış ve kolektif öğrenmeye dayalı sınıflandırıcılar kullanılması önerilmiştir. Önerilen yöntemin performansı çapraz doğrulama ve çapraz hasta deneyleri kullanılarak test edilmiştir. Elde edilen deneysel sonuçlara göre çapraz doğrulama deneyi için duyarlılık, özgüllük ve doğruluk oranları yaklaşık olarak sırayla %94, %93 ve %93 ve çapraz hasta için ise %76, %90 ve %90 olarak bulunmuştur.

Anahtar Kelimeler: epileptik, EEG, kolektif öğrenme, rusboost, robustboost, logitboost.

1. Introduction

Epilepsy is a chronic brain disease characterized by recurrent seizures. These are

short stretches of involuntary movements that affect part or all of the body, and are caused by excessive electrical discharges in a group of brain cells. The most common way to

*Corresponding Author: iozbek@atauni.edu.tr

reveal the onset of a seizure clinically before it occurs is through the use of electroencephalogram (EEG) analysis, a non-invasive, multi-channel recording of the electrical activity of the brain.

It was stated by (Mormann, Lehnertz, David, & Elger, 2000) that phase synchronization between different EEG channels can be used as a criterion to detect the pre-seizure stage. In another study for epileptic seizure detection, various machine learning techniques such as support vector machine (SVM), logistic regression and neural networks were used and reached 71% sensitivity (Mormann et al., 2003).

Many researchers have used Mel Frequency Cepstral Coefficient (MFCC) based features for speech signal processing, and this approach was also adopted for EEG signal (Feudjio, Noyum, Mofendjou, & Fokoué, 2021; Krishna, Tran, Han, Carnahan, & Tewfik, 2020; Kwon & Shin, 2009; Nor, Wahab, Kamaruddin, & Majid, 2011; Rathikarani & Dhanalakshmi, 2013).

(Alvarado-Rojas et al., 2014) classified the EEG signal of an epileptic patient into four states as inter-ictal, pre-ictal, ictal, and post-ictal. They used 22 features such as energy, average, power, Hjorth parameters, etc., in a multi-class SVM classifier. They also generated a comprehensive patient database of 278 patients. As is the case in many databases tailored for medical signal processing applications, there is class imbalance problem in EEG signals, and some techniques have been proposed in the literature to solve this problem. One of them is the use of algorithms

based on an ensemble learning method (Ogawa, Sumi, Matsuo, & Kadotani; Rao, Li, Wu, & Mu, 2021; Taran & Bajaj, 2018; Weiss, 2004). In these studies, it is examined ensemble learning, especially RusBoost and RobustBoost methods, to eliminate the database imbalance problem. In addition, (Taherzhad-Javazm, Azimirad, & Shoaran, 2018; Zhang, Zhou, Wang, & Sung, 2017) (Ghritlahare, Sahu, & Kumar, 2019; Karunakaran et al., 2021; Zuo et al., 2021) examined another ensemble learning method, LogitBoost, for the same problem.

In this study, the performance of some the ensemble learning algorithms, used to detect epileptic seizures from EEG data, were first examined, and then obtained results by using the proposed algorithm were compared with the other results available in the literature.

2. Material and Methods

The aim of this study is to predict epilepsy seizures using EEG signals. For this purpose, EEG signals were divided into 10-second segments, their MFCC-based attributes were extracted, and epileptic seizure presence/absence dual classification was performed using Boosting-based classifiers. Also, the results obtained with the proposed model were compared with the results in the literature. The block diagram of the proposed method is shown in Figure 1. This model consists of four main stages: receiving EEG signals, applying pre-processing steps to these signals, feature extraction, and classification.

These steps are explained in detail below.

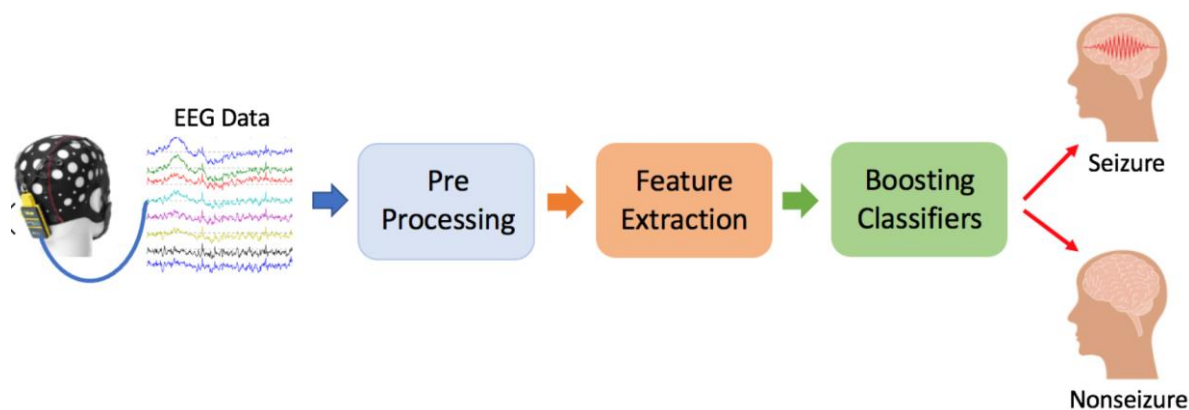


Figure 1. Main block diagram of the proposed model

Electroencephalography (EEG) data collection

EEG is an electrophysiological monitoring method that records the electrical activity of the brain and is a non-invasive method that has a wide and important usage in diagnosing epilepsy. Figure 2 shows 16-channel electrode placement to obtain EEG recordings used in this study.

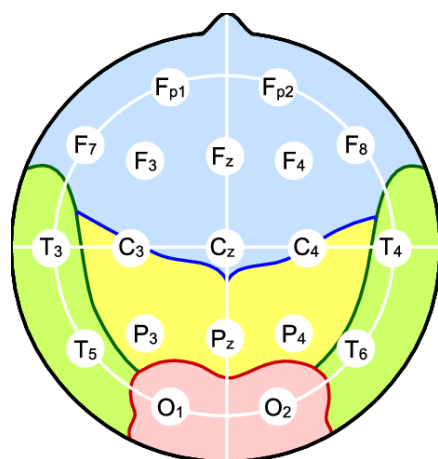


Figure 2. EEG electrode locations (Oude Bos, 2006)

A sample EEG signal of a subject with epilepsy seizure, recorded on FP1-F3 electrode, is shown in Figure 3. The Seizure time window is marked with red lines in this figure.

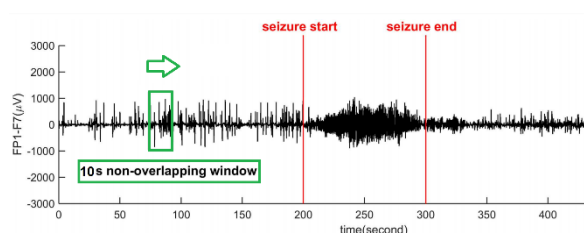


Figure 3. A sample EEG signal of a subject with epilepsy seizure (Chen, Wan, Xiang, & Bao, 2017)

Pre-Processing of EEG Signals

EEG signals contain 50 Hz power line noise, and this needs to be removed. For this purpose, an IIR-based bandpass filter was designed, and this noise was removed from obtained EEG signals with this filter. In addition, the observations, captured on each EEG channel, were normalized to a zero mean and unit standard deviation signal so that they can be used together more efficiently.

Feature Extraction

At this stage, the feature extraction was applied to remove the redundant information in the EEG signals so that the abstract information that is needed in the classification process can be captured. A wide variety of feature extraction methods have been used for that purpose in the literature, and also various studies have been performed.

In this study, MFCC based features were obtained in order to obtain the characteristics of EEG signals. MFCCs have been used successfully in many applications such as speech recognition, music modelling or emotion recognition as well as in the detection of epileptic seizures (Davis & Mermelstein, 1980). The extraction of MFCC features from EEG signals is shown in Figure 4.

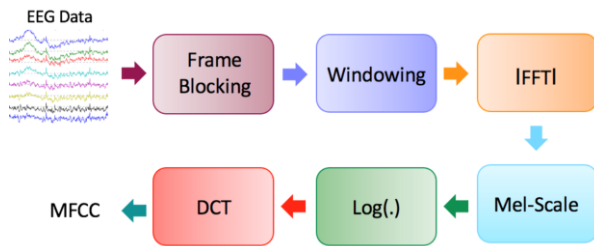


Figure 4. MFCC based feature extraction from EEG signals

The EEG signal is split into 10s-long frames that do not overlap with each other. Then, Hamming windowing is applied to eliminate discontinuities at both ends of frames. In the next step, frequency components of each frame are determined by calculating their Fourier Transform. Then the transformed signal is pass through a filter bank consisting triangular filters followed by logarithm of each frequency band that is the output of each filter in the filter bank. At the final step, MFCC features are obtained by applying Discrete Cosine Transform (DCT).

Boosting Classifiers

In this study, RUSBoost, RobustBoost and LogitBoost methods based on collective learning techniques were used to overcome the class imbalance problem in EEG signals, and they are briefly explained here.

RUSBoost

RUS data sampling techniques try to eliminate class imbalance problem by adjusting the class distribution of the training data set samples. This can be accomplished by removing samples from the majority class (sub-sampling) or by adding samples to the minority class (over-sampling). One of the most common data sampling techniques, largely because of its simplicity, is RUS. Unlike more sophisticated data sampling algorithms, RUS does not try to intelligently remove the samples from training data. Instead, it removes samples from the majority class randomly until the desired class distribution is reached. The RUSBoost algorithm randomly samples the data set in each iteration, removing instances from the majority class. In this case, it is not necessary to assign new weights to the samples. For this reason, the RUSBoost algorithm is a simpler algorithm with faster model training times and satisfactory performance.

RobustBoost

Many ensemble learning classifiers rely on some assumptions such as normally distributed training set noise. As a result, they may perform very poorly especially for noisy real-world data. For example, if methods, that first eliminate the inconsistent data and then perform, fail to detect such data properly, the weights of such samples may be increased at every boosting step and this may result in concentrating on a few deviating data while neglecting the necessary training samples. In other words, this datum significantly degrades the performance of these methods. RobustBoost, however, does not aim to minimize a particular loss function. Instead, it maximizes the observations whose classification margin is above a certain

threshold. The outliers are then removed from the next boosting step by means of a carefully selected loss function. This method tries to make a design suitable for most of the data. That is, even if a small part of the data set consists of deviating values, the remaining part gives reliable results.

LogitBoost

LogitBoost algorithm is another boosting algorithm. This algorithm has been developed to solve the problem of overfitting caused by very noisy data that AdaBoost algorithm has problems with. LogitBoost linearly reduces training error to solve this problem. Therefore, it provides a better generalization. In short, AdaBoost reduces exponential loss, while LogitBoost decreases the logistic loss function. As a result, LogitBoost further increase the weight of the data that causes the overfitting problem. Thus, it overcomes the overfitting problem better than the AdaBoost algorithm.

Dataset:

In this study, CHB-MIT database, composed of EEG recordings, was used. All signals were recorded at Boston Children's Hospital (<https://physionet.org/content/chbmit/1.0.0/>).

Most recordings are an hour long while some are two or four hours long. EEG recordings are divided into 24 sections and stored in EDF data format. Each EDF file corresponds to an EEG recording. CHB-MIT dataset signals consist of 23 individuals, aged 1.5 to 17 years old, and contains approximately 686 EEG records. The used sampling frequency of the dataset is 256 Hz, and each subject is represented with multiple EEG signals of different channels. In this database, the Chb01 (1st subject) and Chb21 are the same person who was registered with an interval of 1.5

years. In addition, there are recordings with some missing channels such as Chb12-27.edf, Chb12-28.edf and Chb12-29.edf.

In this study, 17 common channels were selected for each patient, and the data of these channels were used to extract seizure and non-seizure features. These common channels are P4-O2, FP2-F4, P7-O1, C4-P4, F7-T7, C3-P3, FP1-F7, F8-T8, FZ-CZ, CZ-PZ, F3-C3, T7-P7, P8-O2, FP1-F3, F4-C4, FP2-F8 and P3-O1.

Performance measures

To measure the performance of the proposed method, confusion matrix, shown in Figure 5, is obtained. In this table, (TP) represents true positive (epileptic region predicted as epileptic), TN represents true negative (non-epileptic region predicted as non-epileptic), FP represents false positive (non-epileptic region predicted as epileptic) and FN represents false negative (epileptic region predicted as non-epileptic).

Predicted Class	Seizure	Non-Seizure
	Seizure	Non-Seizure
Non-Seizure	TP	FP
Seizure	FN	TN
	True Class	

Figure 5. Confusion matrix layout

The related measures, on the other hand, such as accuracy, sensitivity and specificity are calculated using this matrix. Here, accuracy is the correct classification rate, sensitivity is the proportion of the epileptic regions that are correctly classified while specificity is the

proportion of the non-epileptic regions that are correctly classified, and they are defined as follows.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

These values vary in the range 0 to 1. Hence, higher the value, better the performance is achieved.

3. Results

In this study, experimental results are given for two cases as cross-validation and cross-patient.

In cross-validation test results, all EEG signals in CHP-MIT dataset, obtained from 24 subjects, are divided into 10-second long segments. Then using 10-Fold Cross Validation method, dataset is divided into train and test partitions. Based on these, training sessions are performed using 9 out of 10 folds while the remaining fold is used for testing. Hence, the test fold is shifted through available 10 folds to ensure that all data is used.

For cross-patient test results, on the other hand, all data of 23 people are used for training each time and data of remaining 1 subject is used for the test. This time, the test fold is shifted through all available 24 subjects to ensure that all data is used.

Results based on cross-validation:

In this section, the results obtained from RUSBoost, LogitBoost and RobustBoost methods in cross validation experiments are

given in Table-1, Table-2 and Table-3, respectively. The sensitivity, specificity and accuracy values for each fold along with mean and standard deviation of the obtained results are shown in these tables. Summary of these three tables are given in Table 4. From the examination of this table, it is observed that the LogitBoost algorithm gives better results in all values compared to the other two algorithms in cross validation experiments.

Table-1. Cross-validation test results for RUSBoost method

	Sensitivity	Specificity	Accuracy
1	0.795	0.815	0.815
2	0.711	0.855	0.854
3	0.720	0.803	0.803
4	0.819	0.837	0.830
5	0.760	0.787	0.789
6	0.696	0.835	0.835
7	0.695	0.845	0.845
8	0.734	0.854	0.853
9	0.666	0.854	0.854
10	0.758	0.81	0.816
mean	0.735	0.830	0.830
std	0.045	0.022	0.022

Table-2. Cross-validation test results for LogitBoost method

	Sensitivity	Specificity	Accuracy
1	0.976	0.941	0.941
2	0.916	0.937	0.937
3	0.961	0.940	0.940
4	0.930	0.938	0.938
5	0.970	0.938	0.938
6	0.952	0.940	0.940
7	0.944	0.937	0.937
8	0.890	0.940	0.939
9	0.941	0.942	0.942
10	0.916	0.934	0.9341
mean	0.940	0.939	0.939
std	0.025	0.0022	0.0028

Results based on cross-patient

Results obtained from RUSBoost, LogitBoost and RobustBoost methods in cross-patient experiments are given in Figure 6 - Figure 8, respectively.

Table-3. Cross-validation test results for RobustBoost method

	Sensitivity	Specificity	Accuracy
1	0.896	0.918	0.918
2	0.88	0.919	0.918
3	0.925	0.916	0.917
4	0.921	0.919	0.919
5	0.938	0.920	0.920
6	0.926	0.917	0.917
7	0.902	0.920	0.919
8	0.928	0.915	0.915
9	0.935	0.914	0.914
10	0.953	0.914	0.915
mean	0.921	0.917	0.917
std	0.0201	0.002	0.0020

Table-4. Summary of Cross-validation test mean values

	Sensitivity	Specificity	Accuracy
RUS-Boost	0.735	0.830	0.830
Logit-Boost	0.940	0.939	0.939
Robust-Boost	0.921	0.917	0.917

From the examination of these figures, it is observed that especially the sensitivity values of subjects 12-15 fall below the average. This is due to the fact that these subjects' EEG electrodes are connected in a different layout than that of Figure 2.

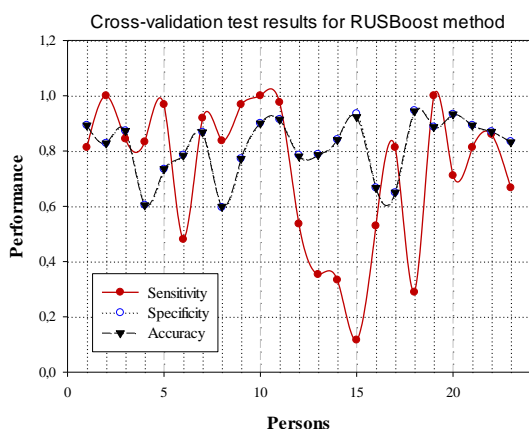


Figure 6. Graphical representation of cross-patient test results for RUSBoost method

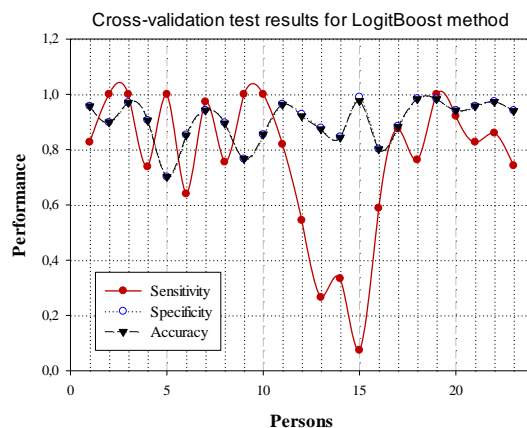


Figure 7. Graphical representation of cross-patient test results for LogitBoost method

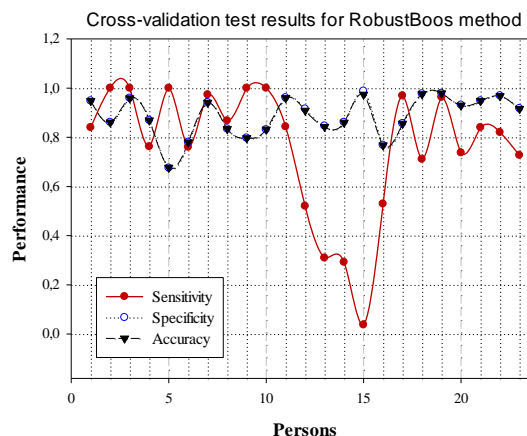


Figure 8. Graphical representation of cross-patient test results for RobustBoost method

Summary of these three figures are given in Table 5. From its evaluation, it is observed that the best results are obtained for the LogitBoost algorithm in the cross-patient experiments.

Çizelge 1. **Table-5.** Summary of Cross-patients test results

	Sensitivity	Specificity	Accuracy
RUS-Boost	0.725	0.810	0.797
Logit-Boost	0.762	0.905	0.903
Robust-Boost	0.761	0.887	0.886

Here, the experimental results obtained with proposed method are compared with similar studies in the literature. For that, the results of LogitBoost method are compared with literature since this method produces best results in both experiments. Corresponding cross-validation test results are given in Table 6. From the examination of this table, it is observed that the results of the proposed method are better than most of the results available in the literature. Cross-patient results, on the other hand, are given in Table-7. When this table is examined, it is clear that the proposed method is better than others in terms of specificity and accuracy while some literature studies have better results in terms of sensitivity.

Table-6. Comparison of cross validation test results with literature

	Sen.	Spe.	Acc.
LSTM(Yao, Cheng, & Zhang, 2019b)	0.844	0.843	0.8435
CNN (Yao et al., 2019b)	0.848	0.81	0.829
BiLSTM (Yao et al., 2018)	0.87	0.886	0.878
BNN (Hussein, Palangi, Ward, & Wang, 2019)	0.91	0.95	0.93
ME (Hussein et al., 2019)	0.95	0.94	0.945
SVM(Chandaka, Chatterjee, & Munshi, 2009)	0.92	1.000	0.955
ELM (Yuan, Kewley, & Sanders, 2010)	0.925	0.96	0.965
LDA (Khan, Rafiuddin, & Farooq, 2012)	0.836	1.000	0.918
SVM (Nicolaou & Georgiou, 2012)	0.943	0.933	0.938
BLDA (Xin, Jianjun, & Zhong-Can, 2000)	0.952	0.967	0.966
SVM (Kumar & Kolekar, 2014)	0.98	0.967	0.985
SVM (Song, Wang, Cai, Deng, & Qin, 2016)	0.945	1.000	1.000
The Proposed (LogitBoost)	0.94	0.939	0.939

4. Research Findings

In this study, various methods were investigated to automatically determine

epileptic seizures using EEG signals. With this, it is aimed to aid the work of neurologists and reduce person dependent errors. For this

Table-7. Comparison of cross-patients test results with literature

	Sensitivity	Specificity	Accuracy
LSTM (Yao et al., 2019b)	0,863	0,828	0,845
CNN (Yao et al., 2019b)	0,834	0,887	0,86
BiLSTM (Yao, Cheng, & Zhang, 2019a)	0,87	0,886	0,878
The Proposed (LogitBoost)	0.762	0.905	0.903

purpose, RUSBoost, LogitBoost and RobustBoost, machine learning based ensemble learning algorithms, are used for classification utilizing MFCC based features. The CHB-MIT data set is used in the current study to measure the performance of the classification results. In this data set, there are multi-channel EEG signals collected from 23 people. They are split into 10s long frames, their MFCC based features are calculated and used in the classifiers.

In order to measure the performance of the proposed method, training of the learning algorithms was performed in two different categories as cross-validation and cross-patient, and the experimental results were obtained accordingly. It has been observed that the LogitBoost method is more successful than the others. In addition, the experimental results were compared with the literature and it was observed that the obtained results are better than many others available in the literature in terms of accuracy rates. In this study, the best sensitivity, specificity and accuracy rates obtained for the cross-validation experiment were calculated as approximately 94%, 94% and 94%, and 76%, 90% and 90% for the cross-patient, respectively.

5. References

- Chandaka, S., Chatterjee, A., & Munshi, S. (2009). Cross-correlation aided support vector machine classifier for classification of EEG signals. *Expert Systems with Applications*, 36(2), 1329-1336.
- Chen, D., Wan, S., Xiang, J., & Bao, F. S. (2017). A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG. *PloS one*, 12(3), e0173138.
- Davis, S., & Mermelstein, P. (1980). Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences. *IEEE transactions on acoustics, speech, and signal processing*, 28(4), 357-366.
- Hussein, R., Palangi, H., Ward, R. K., & Wang, Z. J. (2019). Optimized deep neural network architecture for robust detection of epileptic seizures using EEG signals. *Clinical Neurophysiology*, 130(1), 25-37.
- Khan, Y. U., Rafiuddin, N., & Farooq, O. (2012). *Automated seizure detection in scalp EEG using multiple wavelet scales*. Paper presented at the 2012 IEEE international conference on signal processing, computing and control.
- Kumar, A., & Kolekar, M. H. (2014). *Machine learning approach for epileptic seizure detection using wavelet analysis of EEG signals*. Paper presented at the 2014 International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom).
- Nicolaou, N., & Georgiou, J. (2012). Detection of epileptic electroencephalogram based on permutation entropy and support vector machines. *Expert Systems with Applications*, 39(1), 202-209.
- Oude Bos, D. (2006). EEG-based emotion recognition-The Influence of Visual and Auditory Stimuli. *Capita Selecta (MSc course)*.
- Song, Z., Wang, J., Cai, L., Deng, B., & Qin, Y. (2016). *Epileptic seizure detection of electroencephalogram based on weighted-permutation entropy*. Paper presented at the 2016 12th World Congress on Intelligent Control and Automation (WCICA).
- Xin, Z., Jianjun, Z., & Zhong-Can, O.-Y. (2000). Strain energy and Young's modulus of single-wall carbon nanotubes calculated from electronic energy-band theory. *Physical Review B*, 62(20), 13692.
- Yao, X., Cheng, Q., & Zhang, G.-Q. (2019a). Automated Classification of Seizures against Nonseizures: A Deep Learning Approach. *arXiv preprint arXiv:1906.02745*.
- Yao, X., Cheng, Q., & Zhang, G.-Q. (2019b). A novel independent RNN approach to classification of seizures against non-seizures. *arXiv preprint arXiv:1903.09326*.
- Yao, X., Li, X., Ye, Q., Huang, Y., Cheng, Q., & Zhang, G.-Q. (2018). A robust deep learning approach for automatic classification of seizures against non-seizures. *Biomedical Signal Processing and Control*, 64, 102215.
- Yuan, T.-T., Kewley, L., & Sanders, D. (2010). The role of starburst-active galactic nucleus composites in luminous infrared galaxy mergers: insights from the new optical classification scheme. *The Astrophysical Journal*, 709(2), 884.