# Feature Extraction of EEG Signals for Seizure Detection Using Machine Learning Algorthims

Mohammed A. Alsuwaiket
Department of Computer Science and Engineering Technology
Hafar Al Batin University
Hafar Al Batin, Saudi Arabia
Malsuwaiket@uhb.edu.sa

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**Abstract-Epilepsy is a central nervous system disorder in which brain activity becomes abnormal and causes periods of unusual behavior and sometimes loss of awareness. Epilepsy is a disease that may affect males or females of all ethnic groups and ages. Detecting seizures is challenging due to the difference in human behaviors and brain signals. This paper aims to automate the extraction of electroencephalogram (EEG) signals without referring to doctors using two feature extraction methods, namely Wavelet Packet decomposition (WPD) and Genetic Algorithm-Based Frequency-Domain Feature Search (GAFDS). Three machine learning algorithms were applied, namely Conventional Neural Networks (CNNs), Support Vector Machine (SVM), and Random Forest (RF) to diagnose epileptic seizures. The results achieved from the classifiers show a higher accuracy rate using CNNs as a classifier and GAFDS as feature extraction reaching 97.93% accuracy while the accuracy rate of the SVM and RF was 94.49% and 88.03% respectively.**

***Keywords-EEG; CNN; SVM; seizure; feature extraction***

## I. INTRODUCTION

Epilepsy disorder is considered one of the most common brain diseases. According to the World Health Organization (WHO), this disease affects about sixty million people. Epilepsy is a brain disorder that causes the recurrent occurrence of epileptic seizures that can cause a possible dangerous life-threatening situation [1]. Brain seizures occur when a temporary and unexpected electrical disruption occurs in the brain along with the discharging of an excessive neuronal apparent in an EEG signal representative of the electrical activity in the brain. EEGs are most used in specifying brain disorders and predicting epileptic seizures. Epileptic seizure signals can be detected using image scanning of the EEG data, but unfortunately, this commonly requires a few days to collect the data. In addition, it also needs medical experts to study the length of the recorded EEG signals [2]. Improving the automated systems that detect seizures will reduce the error that could happen during the data reading process and will decrease the possibility of wrong decisions [3, 4]. Recently, other automated seizure detection systems, that use different methods and techniques like Machine Learning (ML) algorithms, have emerged.

The EEG signal has three characteristics that interpret signals as an intricate problem. The first characteristic is the non-stationary and stochastic signal behavior. The main reason for the non-stationary EEG signals is the brain neural activity that might not be in a coherent structure and thus neural charges/discharges of the same fraction of scalp change with different intensity levels over time [5]. The second characteristic is the low Signal to Noise Ratio (SNR). EEG signals usually maintain a low SNR because electrode conductivity on the scalp is affected by body motion, eye blinking, muscle movement, or other dynamic transitions in the environment. The third characteristic is the non-linearity of the EEG signals. The human brain is a complex system and EEG signals can be seen as a linear model, whereas some researchers have shown that EEG signals fit better in non-linear models [6].

A seizure is a transient extravagant electrical discharge of neurons in the human brain. Video monitoring is the most reliable technique for seizure diagnosis [7]. However, EEG signals are used for detection and seizure treatments. Also, exploring EEG epileptic records enables neurologists to determine the seizure type and its location in the brain. Seizure occurrences in EEG appear as low-frequency abnormal neuronal activities, such as spikes, which might be pre-dominated by high-frequency oscillations and sudden changes in signal amplitude [8]. Early seizure detection several hours before its onset is possible by monitoring spike discharge activities and amplitude dynamics of slow waves before seizure occurrences. There are multiple seizure diagnosis tools, such as CT-scan, MRI, ultrasound, EEG, and Positron Emission Tomography (PET), where ultrasounds, CT-scan, and MRI are too expensive and may not be utilized for extensive assessment. Thus, EEG could be one of the most utilized tools to assess epilepsy patients [4].

Some researchers tried to detect and select features according to the redundancy and relevancy assessment in seizure monitoring to lower computational complexity. This paper intends to extract the EEG features using two different feature extraction methods and apply two ML algorithms to achieve the best diagnosis of epileptic seizures. The main aim of this paper can be achieved through pre-processing of the

Corresponding author: Mohammed A. Alsuwaiket

EEG signals using different filters, then using two feature extraction methods, namely WPD and GAFDS to extract the main features from the EEG signal. Principal Component Analysis (PCA) method will be used to select the most useful features needed for the classification phase. Finally, SVM, RF, and CNN ML algorithms will be applied, and the results will be compared in terms of accuracy, speed, and complexity and the best classifier among them will be selected for EEG signal diagnosis.

Many researchers focused on the use of one classifier with or without the use of any feature extraction methods. Furthermore, there is no comprehensive comparison between the used classifiers or feature extraction methods with the evaluation for the running model from run time or performance perspectives. Authors in [9, 10] aimed to apply CNNs to detect epileptic seizures automatically by utilizing EEG signals to assist neurologists in the diagnostic process. This technique includes creating input data for the CNN model to detect the seizure accurately. The results showed that CNN has the ability to categorize the EEG signals and detect epileptic seizures with high accuracy. The effectiveness of different ML algorithms such as RF, SVM, and k-Nearest Neighbor (k-NN) was tested in [11, 12] to choose the best method with the best performance in detecting epileptic seizures. The ML algorithms were applied to pre-processed data and then to the original dataset. The results showed high accuracy of the RF, SVM, and k-NN with values 98.52%, 98.17%, and 96.52% respectively. Authors in [13] proposed an automated scheme to identify seizures. They used the SVM classifier with a Bayesian optimization algorithm to optimize the SVM hyper-parameters and integrated the Quadratic Linear Discriminant Analysis (QLDA) and Linear Discriminant Analysis (LDA) to match the findings. The proposed model was tested on a public dataset. The individual level of accuracy of the techniques was 97.05%, 76.41%, and 80.79% for SVM, LDA, and QLDA respectively. Epileptic seizure detection was achieved in [14] by applying both extreme gradient boosting (XGBoost) and Complementary Ensemble Empirical Mode Fecomposition (CEEMD). Two EEG datasets were used to estimate the performance of the suggested model. The results showed that the CEEMD-XG boost model is a promising method for epileptic seizure detection. In [15], selection and feature extraction methods were used and ML algorithms were applied to the diagnosis monitoring knowledge system.

## II. RESEARCH METHODOLOGY

The proposed methodology of this paper, as shown in Figure 1, starts with the raw data obtained from the EEG dataset. The dataset will be prepared and cleaned by removing the unwanted and noisy data. After that, the data will be ready for the preprocessing phase to be extracted by the proposed feature extraction methods (WPD, GAFDS). Then, the preprocessed data will be passed by the PCA feature selection method. Finally, the selected features will be applied to the proposed ML algorithms (SVM, CNN), and the results will be evaluated and compared. The following sections will go through all the phases mentioned in the proposed methodology in detail.

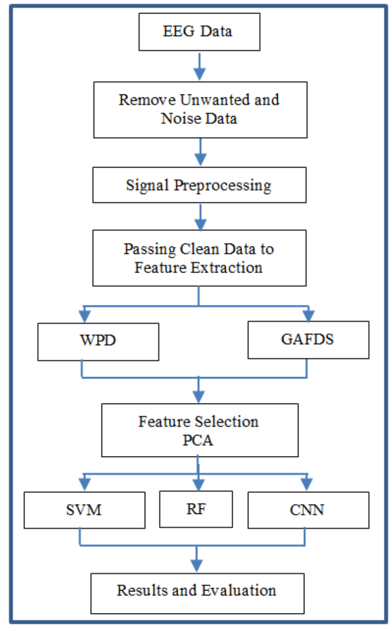


Fig. 1. The proposed methodology.

## III. EEG DATASET DESCRIPTION

EEG data have been collected from the Children's Hospital Boston [16], consisting of EEG recordings from pediatric subjects with intractable seizures. Recordings, grouped into 23 cases, were collected from 22 subjects (5 males, with ages from 3 to 22 and 17 females, with ages from 1.5 to19). Each case in the data files contains between 9 and 40 continuous .edf files from a single subject. In most cases, the .edf files contain 1 hour of digitized EEG signals, although those belonging to some cases are 2 and 4 hours long. Occasionally, files in which seizures are recorded are shorter. All signals were sampled at 256 samples per second with 16-bit resolution. Most files contain 23 EEG signals (24 or 26 in a few cases). One file in the dataset called RECORED contains a list of all 664 .edf files included in this collection, and the file RECORDS-WITH-SEIZURES lists the 129 of those files that contain one or more seizures. In all, these records include 198 seizures (182 in the original set of 23 cases) [16].

## IV. SIGNAL PREPARATION AND PRE-PROCESSING

In this paper, the preparation phase is used to clean the data by denoising the signals, removing the noise, and selecting the channels and signals that will be used. Denoising will be based on signal filters to remove the artifacts and EEG noise from the device and brain signals. The particles are isolated from the signal during the pre-processing phase to observe the artifact-free EEG signals. This method is achieved by filtering the data using the EEG signals acquired from multiple electrodes using a belt pass filter, a Common Spatial Pattern (CSP) filter, a broad Laplacian filter, and an Optimized Spatial Pattern (OSP) filter, which can then be transformed into the surrogate channel. With the use of a Finite Impulse Response (FIR) filter, the pure channel data will be small after artifact elimination. In the categorization process, obtaining relevant information is the main issue, and the epilepsy seizure data will be utilized and the whole bio-physical data will be transformed using Matlab.

During the pre-processing phase, the noise will be eliminated from the original signal to acquire the noise-free signal.

## V. FEATURE EXTRACTION

Feature extraction is a process that removes the corresponding information or functions from the signal to easily explain the features. Therefore, the perception of an input signal is a significant operation. The extract of knowledge describes the physiology and pathology of the brain. It includes many variables which involve a huge memory or a strong data processing algorithm [17]. A function extraction method is required for this context to overwhelm these variables or to read the data accurately. The feature collection reduces the dimension of feature space, making it simpler to train and implement results. In this study, two feature extraction methods will be applied to the EEG dataset, WPD and GAFDS.

### *A. Wavelet Packet Decomposition (WPD)*

WPD is a wavelet transition under which more filters than other methods are utilized. Wavelet packets constitute a peculiar linear wavelet mixture. They form bases that maintain much of their parent wavelets' orthogonality, smoothness, and positions. The linear combination coefficients are determined with a recursive algorithm that allows the study tree's root in each newly computed wavelet packet chain [5].

### *B. Genetic Algorithm –Based Frequency-Domain Feature Search (GAFDS)*

The Genetic Algorithm (GA) uses the chance optimization approach for the analysis and demonstrates global optimization strength. The frequency domain is a coordinate system in signal processing, which defines the frequency characteristics of the signal. A frequency spectrogram represents the relationship between the frequency and the amplitude of the signals, often used for the study of signals. The GAFDS system adopts GA to look for the proper description of frequency spectrum characteristics [18].

## VI. MACHINE LEARNING ALGORITHMS

Supervised ML algorithms are the best classification technique to find whether the data are classified as a seizure or not. In ML, the classification of EEG signals deals with the categorizing a set of classes to which a new reading belongs, based on a training set of EEG feature sets containing occurrences whose class relationship is identified [19]. Classification will be done to segment the data that will be tested with obtained data from several classifiers. Due to this, it is likely to identify if the information is of seizure or not. SVM, RF, and CNNs will be implemented in this paper. For software setup, Anaconda Python 3.7 was used for the experimental work. Keras has added due to its success and broad support for various learning styles, design features, and hypermeters. Libraries such as Panda's data storage, NumPy for multidimensional arrays, and Scikit Learn for data analysis were enabled. The ML classifiers have been trained, tested, and classified via the Sklearn machine libraries.

### *A. Support Vector Machine (SVM)*

SVM is an ML technique used for classification and regression. SVM is effective in high-dimensional spaces and in cases where the number of dimensions is greater than the number of samples. SVM includes a separating hyperplane used to differentiate between the plots or classes. The selection of the hyperplane is done according to the best separating area [20]. The classification method used in SVM (Figure 2) distinguishes a collection of binary labeled workout data and a maximum distance hyperplane and shows the seizure, non-seizure, and support vector points. The extracted confusion matrix from performing the SVM classifier and the comparison of the 2 feature extraction methods can be seen in Table I. GAFDS showed better results with accuracy near 94.5% compared with the WPD which showed a lower accuracy of 92.95%.

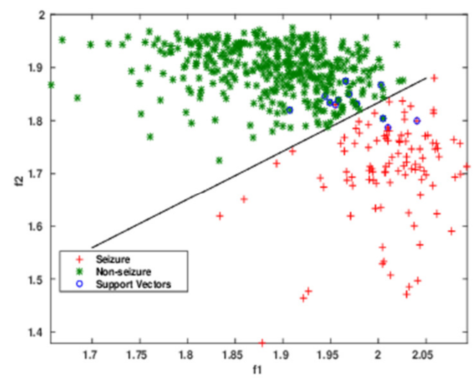


Fig. 2. SVM algorithm for EEG data.

TABLE I. SVM CLASSIFIER CONFUSION MATRIX

| Feature extraction | Number of artifacts | Accuracy % | Precision % | Recall % | f1-score % |
|---|---|---|---|---|---|
| GAFDS | 64,512 | 94.49 | 97 | 98 | 97 |
| WPD | 64,512 | 92.95 | 96 | 97 | 96 |

TABLE II. RF CLASSIFIER CONFUSION MATRIX

| Feature extraction | Number of artifacts | Accuracy % | Precision % | Recall % | f1-score % |
|---|---|---|---|---|---|
| GAFDS | 64,512 | 88.03 | 88 | 98 | 93 |
| WPD | 64,512 | 87.07 | 88 | 97 | 92 |

### *B. Random Forest (RF)*

RF is a popular supervised ML technique used in classification and regression problems. It creates decision trees on various instances and takes their vote for classification and average in the case of regression. RF can handle datasets containing continuous variables as in the case of regression and categorical variables as in the case of classification. It performs better in classification problems [21]. With the RF classifier, the data need to be segmented into different sets. We start from calling the Sklearn's ensemble library to call the RF classifier. The function will load the data and split them into training and testing sets. The labeled data will start to train using the maximum iteration number that can be reached. This threshold has been set to 80%. Different types of feature extractions have been used to support the classifier. A total of 150 trees, with max depth = 12, and 50 nodes were used. The extracted confusion matrix from the RF classifier and the comparison of the 2 feature extraction methods can be seen in Table II. The

RF confusion matrix shows the metric values for both feature extraction methods. GAFDS showed better results with accuracy of 88.03% whereas WPD showed a lower accuracy of 87.07%.

### C. Conventional Neural Networks (CNNs)

This paper utilizes a simple CNN to classify epileptic seizures [22, 23]. The diagnosis of epileptic seizure affects the identification and different characteristic of the EEG signals as discussed above. Furthermore, it needs a method for classifying epileptic seizures. Figure 3 shows the EEG signals classifications using CNN.

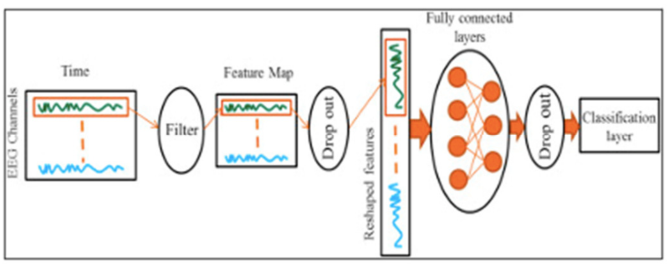


Fig. 3. EEG signal classifications using CNN.

Table III shows the CNN parameters that have been used for testing the proposed method. All layers have been chosen based on the dataset size without affecting the performance, run time, and accuracy results. The extracted confusion matrix from the CNN classifier and the comparison of the 2 feature extraction methods can be seen in Table IV. The CNN confusion matrix and the used parameters show the metric values for both feature extraction methods used in this paper. GAFDS showed better accuracy results.

TABLE III. CNN PARAMETERS

| Input Layer | Hidden layer | Neurons | Epochs | Output layer |
|---|---|---|---|---|
| Based features | 10 | 50 | 30 | Based features |
| Based features | 20 | 100 | 30 | Based features |
| Based features | 30 | 150 | 30 | Based features |
| Based features | 40 | 200 | 30 | Based features |
| Based features | 50 | 300 | 30 | Based features |

TABLE IV. CNN CLASSIFIER CONFUSION MATRIX

| Feature extraction | Number of artifacts | Accuracy % | Precision % | Recall % | f1-score % |
|---|---|---|---|---|---|
| GAFDS | 10 | 94.8 | 97 | 96 | 96 |
| | 20 | 95.34 | 97 | 97 | 97 |
| | 30 | 96.52 | 97 | 98 | 98 |
| | 40 | 96.88 | 97 | 99 | 98 |
| | 50 | 97.93 | 97 | 100 | 99 |
| WPD | 10 | 94.34 | 97 | 95 | 96 |
| | 20 | 95.07 | 97 | 96 | 97 |
| | 30 | 95.41 | 97 | 97 | 97 |
| | 40 | 96.3 | 97 | 98 | 97 |
| | 50 | 97.6 | 97 | 99 | 98 |

## VII. Results and Evaluation

In this paper, EEG signals were used as the data source. The proposed method used and compare different ML techniques. The experiment uses Python programming language and an Intel i7 processor. The data were split into two sets, the first set (70%) for training and the second (30%) for testing. Table V and Figure 4 show the obtained results, which show that CNN had the best results for both feature extraction methods, followed by the SVM. RF had the lowest accuracy compared with the other ML algorithms in both feature extraction methods.

TABLE V. COMPREHENSIVE RESULTS

| Feature extraction | Number of artifacts | Accuracy % | Precision % | Recall % | f1-score % |
|---|---|---|---|---|---|
| SVM | GAFDS | 94.49 | 97 | 98 | 97 |
| | WPD | 92.95 | 96 | 97 | 96 |
| RF | GAFDS | 88.03 | 88 | 98 | 93 |
| | WPD | 87.07 | 88 | 97 | 92 |
| CNN | GAFDS | 97.93 | 97 | 100 | 99 |
| | WPD | 97.6 | 97 | 99 | 98 |

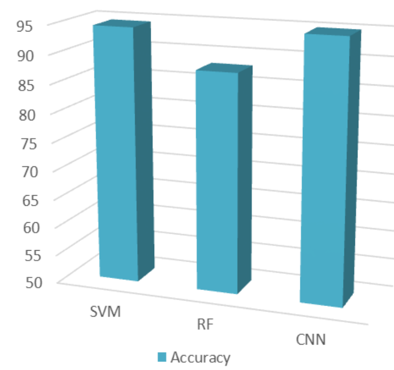


Fig. 4. Accuracy results for 70% training and 30% testing of EEG signals.

According to the obtained results for classifying EEG data for different size datasets using different ML algorithms, there are considerable differences among the results: some had low and some high accuracy. There are various reasons for such results, such as the use of different EEG data collection and screening methods, the selection of different EEG data features, the use of different EEG data formatting methods, and finally the different classification techniques and their parameters. EEG data classification accuracy is commonly relatively below. The reason behind that is the bulk of noise and artifacts which appear in the EEG signals and are not easy to avoid and hence make their analysis difficult. There are certain methods available to remove the artifacts from the EEG data as discussed above. However, this may cause losing some valuable data and affect the classification accuracy results.

## VIII. Conclusions and Future Work

In this paper, different methods of pre-processing for the EEG signals and two feature extraction methods were applied to extract the main features from the EEG signal. PCA was used to select the most useful features needed for the classification phase. The goal of this study was to test various ML techniques for the classification of EEG data. Three ML algorithms, i.e. SVM, RF, and CNN were used in the experiments. The chosen methods were analyzed using EEG data obtained from a children's hospital in Boston, including

EEG reports from children with intractable seizures. The chosen algorithms were built, and the results were compared in terms of accuracy and other evaluation methods, and the best classifier among all methods was selected for EEG signal diagnosis.

The CNN gave the best results in EEG data classification with. It should be noted that the findings are fully disparate when it comes to classifying EEG data separately for each subject. This means that the specific participants have major variations. Another important finding is that centered brain activities for a particular target will lead to greater accuracy than various brain activities for multiple targets. For future work, the use of other methods such as fuzzy logic [24], decision tree algorithm [25], and other supervised ML methods such as k-NN, Naïve Bayes, and logistic regression [26-28] is recommended.

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