# Comparison Machine Learning Algorithms for Recognition of Epileptic Seizures in EEG

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**Abstract.** The aim of this study is to diagnose epileptic seizures by using different machine learning algorithms. For this purpose, the frequency components of the EEG are extracted by using the discrete wavelet transform (DWT) and parametric methods based on autoregressive (AR) model. Both these two feature extraction methods are applied to the input of machine learning classification algorithms such as Artificial Neural Networks (ANN), Naive Bayesian, k-Nearest Neighbor (k-NN), Support Vector Machines (SVM) and k-Means. The results show that k-NN, ANN and SVM were the most efficient method according to test processing of both DWT and AR as feature extraction for recognition of epileptic seizures in EEG.

**Keywords:** Machine learning algorithms, epilepsy, electroencephalogram (EEG), discrete wavelet transform (DWT), auto regressive model.

## 1 Introduction

Epilepsy is a serious brain illness that is an endemic neurological disorder all over the world. It is a clinical result that occurs with abnormal neurological electrical discharging of brain. Epileptic seizures represent the most common positive signs and symptoms of brain disturbance, and epilepsy is one of the most common primary brain disorders [1]. Vascular causes, traumatic causes, infections and brain abscesses, brain tumors, nutritional deficiencies, pyridoxine deficiency, calcium metabolism disorders are lead causes for epilepsy. For in diagnosing epilepsy, research is needed for better understanding of mechanisms causing epileptic disorders. The evaluation and treatment of neurophysiologic disorders are diagnosed with the electroencephalogram [EEG]. EEG is crucial for accurate classification of different forms of epilepsy [2].

The parametric methods are used to adjust the EEG into the mathematical model, and the most utilized for the AR model, this reduces the spectral loss problems and gives better frequency resolution [3][4]. The EEG signals are non-stationary, so it shows only information in the domain of frequency; methods of time-frequency analysis information can be verified in the time and frequency domain for wavelet transform [5][6]. Extraction features by using discrete wavelet transform and auto regressive model transformed spectral components. These are applied to the input of machine learning classification algorithms.

Recognition of epileptic seizure is a complicated biomedical problem which has attracted substantial attention of computing by machine learning algorithms over the past two decades. A literature survey of the significant and recent studies that are concerned with effective detection of epileptic seizures using EEG signals are presented. Most of researchers have proposed recognition of epileptic seizure with different types of artificial neural network algorithms such as learning vector quantization [7], adaptive structure neural network [8], radial basis function [9], self-organizing maps [10], cellular neural networks [11], recurrent neural networks [12], and multilayered perceptron neural networks [13][14]. To solve this problem, several studies have been proposed in the literature in order to define different classifier systems such as support vector machine (SVM)[15][16], adaptive neuro-fuzzy inference system (ANFIS) [17], time-frequency analysis [18], adaptive learning [19], and variational Bayesian Gaussian mixture model [20].

In this study, coefficients of wavelet transform and auto regressive models are used for the recognition of epileptic seizures in EEG signals. Then these coefficients are applied as inputs for different machine learning algorithms such as Multi-layered neural networks with Back-propagation, Naive Bayesian, k-Nearest Neighbor (k-NN), Support Vector Machines (SVM), and k-Means algorithms. Moreover, classification performance of different machine learning algorithms are compared for two feature extraction methods.

## 2 Theoretical Background

The aim of this study is to contribute to the diagnosis of epilepsy by taking advantage of the engineering. So, for diagnosing of epileptic seizures from EEG signals are transformed discrete wavelet and auto regressive models. After these transformations, extract data is applied input for Back-propagation, Naive Bayesian, k-Nearest Neighbor (k-NN), Support Vector Machines (SVM) and k-Means algorithms. There is one possible outcome of the detection of epileptic seizure logically. If a person has epileptic seizure problem, the output is logic 0, otherwise logic 1.

### 2.1 EEG Data Recording

EEG signals are separated into α, β, δ and θ spectral components and provide a wide range of frequency components. EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands as follows: δ(0.5-4 Hz), θ(4-8 Hz), α(8-13 Hz), and β (13- 30 Hz) [21].

EEG data set has acquired different age groups in this study. They are known epileptic with uncontrolled seizures and are admitted to the neurology department of the Medical Faculty Hospital of Dicle University[1]. For this system LabView programming language has been used [3] and the EEG data used in 400 people who received 200 of them are epilepsy and with 200 of them are normal. Data set represents of signals belong to several healthy and epileptic patients. The EEG signals that are contained by PCI-MIO 16E DAQ card system that provides real time processing and is a data bus of computer, signal processor and personal computer. Fig. 2 shows that how to acquire EEG data from a patient [1]. EEG signals are to ensure the accuracy of diagnosing disease that usually is taken 8-10 hours in the form of records. EEG signals are used in section and 23.6 seconds, 173 Hz sampling frequency is illustrated with. International 10–20 electrode placement system according to the data collected, 12-bit analog-digital conversion after the samples are recorded subsequently. Data can be passed through the filter 0.53–40 Hz band–pass, the EEG in the presence of clinical interest for focusing range is provided. The EEG data used in our study were downloaded from 24-h EEG recorded from both epileptic patients and normal subjects. The following bipolar EEG channels were selected for analysis: F7-C3, F8-C4, T5-O1 and T6-O2. In order to assess the performance of the classifier, we selected 500 EEG segments containing spike and wave complex, artifacts and background normal EEG [6].

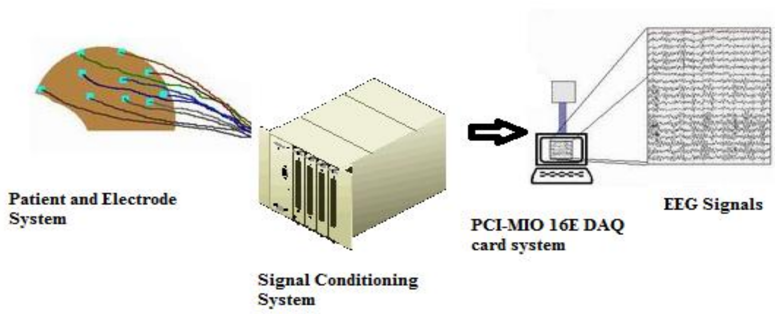


**Fig. 1.** Acquisition of EEG Data from a Patient[1]

### 2.2 Discrete Wavelet Transform

Wavelet transform is more advantageous spectral analyze method than other spectral analyze methods on non-stationary signals. Because the wavelet transform method changes large low-frequency, high frequency that is narrow for the window size. So, the entire frequency range can be achieved in the optimum time-frequency resolution [22] Continuous and discrete wavelet transform is analyzed in the scale and variation of parameters due to the continuous wavelet coefficients for each scale is difficult and time consuming. For this reason, discrete wavelet transform is used more

[1] We would like to thank to Prof. Abdulhamit Subasi who supports us giving his EEG data.

often than these non-stationary signals. Wavelet scale is divided into a number of points for x[n] process as seen in Fig. 2 that is called multi resolution decomposition. It is important that is selected appropriate wavelet decomposition level, the number of detection and wavelet transform analysis of signals. Because of classification accuracy is dependent on type of wavelet, dominant frequency components of signals are determined according to the number of decomposition levels.
Wavelet coefficients contain important information about EEG signal that provide extraction of feature vector. Statistical-time frequency of EEG signals sequences are:

1. The average of the absolute value of coefficients in each sub-band.
2. The maximum absolute value of coefficients in each sub-band.
3. The mean force coefficients of each sub-band.
4. Standard deviation of coefficients in each sub-band.
5. The average absolute value of the ratio of adjacent bands.
6. Distribution of breakdown coefficients in each sub-band.

1-3 sequence is signal characteristic; 4-6 sequence is that amount of frequency change. This feature vector, of EEG signals that are used as inputs for multi-layer neural network classification.

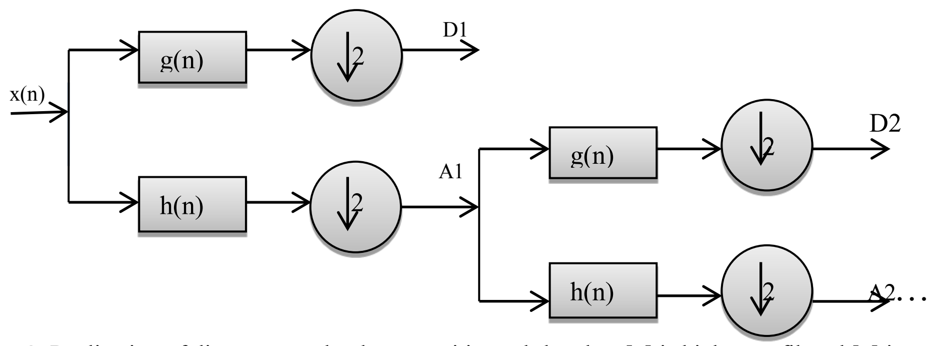


**Fig. 2.** Realization of discrete wavelet decomposition sub-bands; g[n] is high-pass filter, h[n] is low pass filter [22]

### 2.3 Auto Regressive (AR) Model

AR method is the most frequently used parametric method for spectral analysis. By a rational system, the model-based parametric methods are established on modeling the data sequence $x(n)$ as the output of a linear system characterized and the spectrum estimation procedure consists of two steps. The parameters of the method are calculated given data sequence $x(n)$ that is $0 \leq n \leq N-1$. Then from these approximates, the PSD estimate is computed. Because estimation of the AR parameters can be done easily by solving linear equations [23][3]. Data can be modeled as output of a causal, all-pole, discrete filter whose input is white noise in the AR method.

Some factors must be taken into consideration for obtaining stable and high performance. AR method such as selection of the optimum estimation method, selection of the model order, the length of the signal which will be modeled, and the level of stationary of the data[3][24]. Estimated AR parameters or the reflection coefficient AR is based on spectral estimation methods. The method developed by Burg for AR parameter estimation based on the minimization of the forward and backward prediction errors and on estimation of the reflection coefficient as shown Fig. 3.

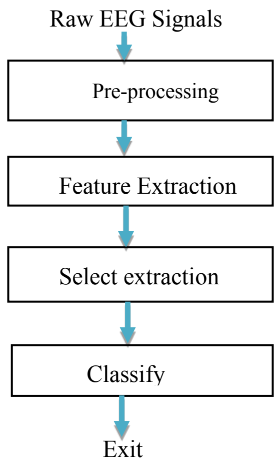


**Fig. 3.** Operations Performed in the Diagnostic Systems [24]

Aim of using these two feature extraction methods are applied to the input of machine learning classification algorithms such as Artificial Neural Networks (ANN), Naive Bayesian, k-Nearest Neighbor (k-NN), Support Vector Machines (SVM) and k-Means. To be applied EEG data set as input for classification, we should use mathematical approaches to characterize the EEG signals with discrete wavelet transform (DWT) and parametric methods based on autoregressive (AR) model.

## 3 Used Machine Learning Algorithms

As mentioned previously, EEG data is extracted with auto regressive and wavelet transforms. This result of this extraction is obtained machine learning algorithms input data. Wavelet transformation data set is 129 and auto regressive data set is 15.We have total 400 record of people that 200 of them are epilepsy the other 200 are normal. And so, for wavelet transform vector size is 400x129 and auto regressive extraction input vector size is 400x15. Cross validation is used for testing and training process that estimates the generalization error of a predictive model. In k-fold cross-validation a training set is divided into k equal-sized subsets. Then the following procedure is repeated for each subset: a model is built using the other k-1 subsets as the training set[25]. We have two classes that are epilepsy and normal. Accuracy result is given according to Rapid Miner Studio data miner tool [25].

### 3.1 Artificial Neural Networks (ANN)

Generally, Artificial Neural Networks (ANN) classifier is simulating working principle of the human brain. ANN algorithm is powerful about calculation and data mining takes its ability to learn and generalization that encountered in the process of training or learning is defined as the inputs of ANN to produce appropriate responses [26]. Back-Propagation (BP) is a specific technique for implementing weight for a multilayered perceptron (MLP). The basic idea is to efficiently compute partial derivatives of an approximating function realized by the network with respect to all the processing element (or neuron) of the adjustable weight vector for a given value of input vector. Owing to nonlinear activation functions, it can be easily classify nonlinear data [26]. Since MLP structure with BP algorithm an appropriate method for classification, it can be used for epileptic seizure recognition. For Wavelet transform coefficients, number of neurons of input layer is 129, for auto regressive parameter, number of neurons of input layers is 15. Wavelet transform MLP structures number of neurons of hidden layer is selected as 129, hidden layer neuron number is selected 15 for AR method and both of them neuron number of output layer is 2 which are classified as epilepsy and normal.

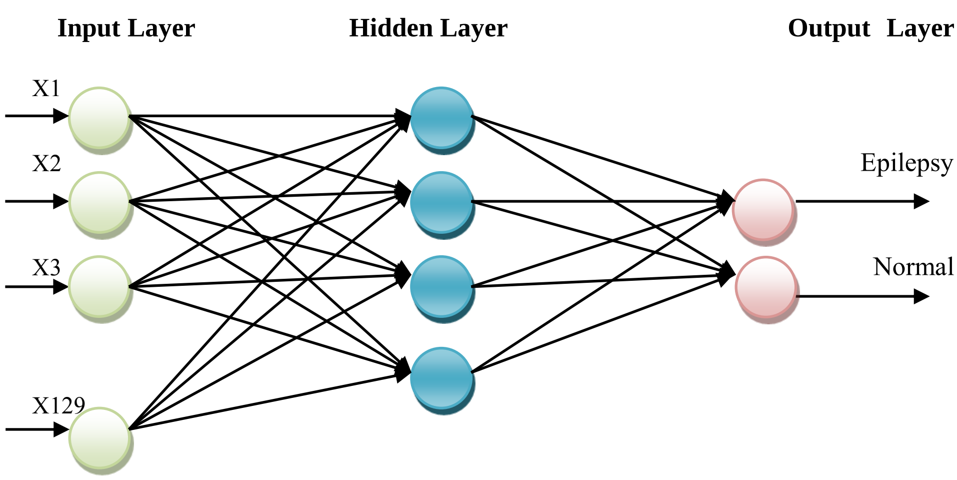


**Fig. 4.** Back Propagation Algorithm Layer Architecture for Wavelet Transform

### 3.2 Support Vector Machines(SVM)

Vapnik has been developed to support vector machines algorithm[27] that is given optimal results in signal processing, artificial learning and data mining fields[28]. Basically, SVM interested in 2 classes problems. Knerr and his friends have been suggested one-against-one method for classifying multi-class data [29]. In this method, n(n−1)/2 classifiers are generated with n class and each of data is trained with two classes. By this method, the problem of multi-class problem gets converted into two classes. Another method is for multi-class data classification [30] that is specified for n and so, SVM become for n classes. i.th SVM, as the data i own class using the class data, all of the data from the other classes as if they belonged to the second class agrees. So +1 label to, data, while all the data belonging to other classes and training. This way n gives -1 the label makes for a SVM. In this study, SVM algorithm, two classes C-SVM algorithm is used by applications on the performance analysis with cross validation.

### 3.3 Naive Bayes Algorithm

Naive Bayes classifier is an independent model that is simple probabilistic classifier based on applying from Bayes statistic independence assumptions. Classifier assumes that the presence or absence of a particular feature of a class is unrelated to the presence of any other feature. Because of this method features depend on each other, classifier considers all of properties to independently contribute to the probability. Naive Bayes is advantageous for small size of training data to estimate the means and variances of the variables necessary for classification [31]. In this study, to classify epileptic seizure input data set obtains AR and wavelet transform data with cross validation and laplace correction is used for parameters that prevent high influence of zero probabilities.

### 3.4 k-Nearest Neighbors Algorithm

k-Nearest Neighbors algorithm (k-NN) is a non-parametric classification method that calculates class memberships based on k-closest training examples. k-NN is the simplest and a type of lazy learning method. Classification continues approximated locally and all computation is deferred until classification. So, for this study, EEG data is classified with cross validation by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors [32]. In this study following process steps are:

- k is specified with EEG samples(k=2)
- Selection of k entries for input(for DWT = [400X129], for AR= [400X15])
- The most common classification of model is found. This study model contains 400 examples with 15 dimensions of the following classes are epilepsy and normal for DWT data. The model 400 examples with 129 dimensions of classes.

### 3.5 k-Means Algorithm

k-Means clustering solves the problem by unsupervised learning that is the simplest method. Algorithm's general logic is as the input parameter to divide the k-cluster through data object of a data set consists of n. The aim of this algorithm is obtained at the end of the partitioning process, intra-cluster similarity is to ensure that the maximum and minimum inter-cluster similarity. The performance of the method is effected the number of clusters k, the initial cluster centers are selected as the criteria for the measurement of values and similarities [33]. Method's steps are showed in following with cross validation:

**Step 1**: Before clustering, to determine initial cluster centroid value for number of k cluster. c = $\{c_1, c_2, \ldots, c_k\}$. For this, objects are selected between random point (k=2).

**Step 2**: Training set in the each data, $x_k = \{x_1, x_2, \ldots, x_k\}$ are included in the nearest or similar cluster with selected initial cluster centers. To calculate cluster that is used similarity formula (p = 129 for wavelet transform, p = 15 for auto regressive).

$$\cos((x_i, \text{center}(c_j)) = \frac{x_i}{||x_i||} * \frac{center(c_j)}{||center\ c_j\ ||}$$

$$i=\{1,2,3...n\}, j=\{1,2,3...k\} \tag{1}$$

**Step 3:** It is composed of a cluster center points of clusters are changed with the average values of all the objects.

$$\text{center}(c_j) = \frac{{}_{i=1}^{n_j}(X_i)}{n_j} \tag{2}$$

**Step 4**: Repeat Step 2 and Step 3 while unchanging cluster centers for identification.

## 4 Experimental Studies

In our study, we present EEG data of 400 patients that 200 EEG data belong to epileptic seizure other 200 EEG data is normal. So, we have two classes including normal and epilepsy for algorithms. We have two different forms of extraction methods which are wavelet and AR. Wavelet transformation vector size is 400x129 and AR method vector size is 400x15. Training and testing data has been selected according to cross validation Extracted of these data is applied to machine learning algorithms (ANN, SVM, Naive Bayes, k-Means and k-NN) in Rapid Miner Tool. In conclusion, classification methods accuracies are given according to two extraction methods.

**Table 1.** Training Data Set Accuracy Rates of Used Classifiers for two Feature Extractions

| Classifiers | Wavelet | AR Model |
|---|---|---|
| ANN | %99.75 | %99.50 |
| SVM | %99.5 | %99.50 |
| Naïve Bayes | %99.5 | %98.00 |
| k-Means | %58.5 | %96.50 |
| k-NN | %100 | %99.75 |

In the experimental study, ANN and SVM algorithms in wavelet transform, k-Means algorithm in AR have been received from the best classification success as it is indicated in Table 1. According to EEG data size precision values are applied according to 400 records belongings to patience in Table 2 and Table 3 k-Means algorithm has been observed to give the lowest performing in terms of experiment classification in wavelet.

**Table 2.** According to Wavelet Transform Vector Size Precision Values(Testing)

| **ANN** | **Accuracy:%99.75** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 200 | 1 | %99.5 |
| Prediction Normal | 0 | 199 | %100 |
| Class Recall | %100 | %99.5 | |

| **Naive Bayes** | **Accuracy:%99.5** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 200 | 2 | %99.01 |
| Prediction Normal | 0 | 198 | %100 |
| Class Recall | %100 | %99 | |

| **SVM** | **Accuracy:%99.5** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 200 | 2 | %99.01 |
| Prediction Normal | 0 | 198 | %100 |
| Class Recall | %100 | %99 | |

| **k-NN** | **Accuracy:%100** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 200 | 0 | %100 |
| Prediction Normal | 0 | 200 | %100 |
| Class Recall | %100 | %10 | |

Experimental calculating results are given according to specificity and sensitivity values as given below:

Artificial Neural Network algorithm: hidden layer neuron number is 129, training cycles is 1000, learning rate is 0.3, momentum is 0.2, and error epsilon value 1.0E-5 is used for wavelet transform vector size precision values. SVM: kernel type is dot kernel type, C value is 0.5, convergence epsilon is 0.001, and epsilon is 0.0 is used for wavelet transform vector size precision values. Laplace correction is used for Naive Bayes. Laplace correction is suitable for high influence zero probabilities. k-NN algorithm: class number k is 2, mixed measure types and Euclidean distance is used for wavelet transform vector size precision values.

**Table 3.** According to Auto Regressive Performance Vector Values(Testing)

| **ANN** | **Accuracy:%99.5** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 199 | 1 | %99.5 |
| Prediction Normal | 1 | 199 | %99.5 |
| Class Recall | %99.5 | %99.5 | |

| **Naïve Bayes** | **Accuracy:%98** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 200 | 4 | %98.04 |
| Prediction Normal | 0 | 196 | %100 |
| Class Recall | %100 | %98 | |

| **SVM** | **Accuracy:%99.5** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 200 | 2 | %99.01 |
| Prediction Normal | 0 | 198 | %100 |
| Class Recall | %100 | %99 | |

| **k-NN** | **Accuracy:%99.75** | | |
|---|---|---|---|
| | True Epilepsy | True Normal | Class Precision |
| Prediction Epilepsy | 200 | 1 | %99.5 |
| Prediction Normal | 0 | 199 | %100 |
| Class Recall | %100 | %99.5 | |

Artificial Neural Network algorithm: hidden layer neuron number is 15, training cycles is 1000, learning rate is 0.3, momentum is 0.2, and error epsilon value 1.0E-5 is taken for AR vector size precision values. SVM: kernel type is dot kernel type, C value is 0.5, convergence epsilon is 0.001, and epsilon is 0.0 is used for AR vector size precision values. Laplace correction is used for Naive Bayes. k-NN algorithm: class number k is 2, mixed measure types and Euclidean distance is used for wavelet transform vector size precision values.

## 5 Conclusion

The aim of this study is to detect epileptic seizure using two different feature extraction methods and comparison performance of various machine learning algorithms. For this purpose we used effective well-known supervised learning algorithms. Except ANN, the others are statistical machine learning algorithms. In conclusion, on the empirical result of the wavelet transform method is achieved with k-NN. Because, k-NN is more effective algorithms than the others for less number of class. According to results of feature extraction methods, we can say that wavelet transform is better than the AR method for EEG signals. Moreover, these results show that proposed recognition of the epileptic seizure by using k-NN and ANN are faster and have better accuracy than literature studies. On the other hand, k-means algorithm has been observed to give the lowest performing in terms of our results. Although ANN needs more iteration time for training, it doesn't need any iteration for testing. But k-NN needs less iteration for both training and testing.

EEG data is close to each other that affect the performance of clustering. Practicing, in medicine have been the most difficult in differencing between the abnormal and normal EEG. In this study, in the diagnosis of the epilepsy disease faster and more effective results than previous studies for early diagnosing.

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