Effective electroencephalogram based epileptic seizure detection using support vector machine and statistical moment's features

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ABSTRACT

Epilepsy is one of the widespread disorders. It is a noncommunicable disease that affects the human nerve system. Seizures are abnormal patterns of behavior in the electricity of the brain which produce symptoms like losing consciousness, attention or convulsions in the whole body. This paper demonstrates an effective electroencephalogram (EEG) based seizure detection method using discrete wavelet transformation (DWT) for signal decomposition to extract features. An automatic channel selection method was proposed by the researcher to select the best channel from 23 channels based on maximum variance value. The records were segmented into a nonoverlapping segment with long 1-S. The support vector machine (SVM) model was used to automatically detect segments that contain seizures, using both frequency and time domain statistical moment features. The experimental result was obtained from 24 patients in CHB-MIT database. The average accuracy is 94.1, sensitivity is 93.5, specificity is 94.6 and the false positive rate average is 0.054.

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1. INTRODUCTION

Epilepsy is an illness characterized by epileptic seizures. It is one of the most general neurological diseases and it second most general neurological problem behind attack according to the World Health Organization (WHO). There are more than 50 million individuals (about 1%) worldwide suffering from epilepsy, making it the most widespread neurological disease in the world [1]. A lot of methods are used for detecting epilepsy seizures from effective electroencephalogram (EEG) signals but achieving high accuracy in time and frequency domain is difficult.

Currently, the illness is primarily treated with medicines and operations. Treatment with anti-epileptic drugs is not entirely efficacious for all cases [2]. Predominantly, patients cannot be aware of the seizure due to differentiation in the nature of human beings, and that may increase the physical injury [3]. Moreover, people with epilepsy suffer from social stigma and vocational obstacles. Another load for patients is the condition of continuous seizure activity without a recovery of consciousness between seizures, which is a life-threatening emergency [4]. The manual analysis of long-term EEG records by the EEG experts or doctors is the most active method of detecting seizures. This is a long and tedious task, particularly if there are a lot of EEG electrodes. Auto epileptic seizure detection methods can be useful for the EEG experts and doctors to assess long-term EEG signals. They could also be used with implantable deep brain stimulation devices [5].

Research on epilepsy was conducted over some years to aid the automated identification method and ease clinicians' burden [6]. Several studies have been produced in this regard. All these essays must be thoroughly reviewed. Therefore, the study was carried out on these shape detection methods for electroencephalogram (EEG) seizure detection. Many research papers were discussed in order to define epileptic seizure detection techniques. In addition, the literature review confirms that changes in the EEG datasets for various conditions are needed in the pattern identification techniques required to observe epileptic seizures [7]. This is largely because EEG has various characteristics detected under various circumstances.

In 1996 [8] a new algorithm was devised for seizure detection based on EEG records using 2-S window. Artificial neural network (ANN) has been used to classify the statistical features extracted from these epochs such as curvature, amplitude slop and frequency components [9]. Several attempts have been made to detect seizure using discrete wavelet transformation (DWT) to extract features from EEG records. In an investigation into epileptic seizure detection, the study [10] shows that seizure can be detected using fuzzy approximate entropy (FAE) as features. A recent estimation of an offline automatic seizure detection method using a massive test scalp EEG data-set (1,200 h with 146 seizures in 55 patients) showed an overall sensitivity of approximately 80% and a false detection rate of 0.1/h. The detection method is based on three measures: the pattern-match regularity statistics, the local maximum frequency and amplitude variation [11].

A novel method was used recently by Yuan *et al.* [12] to detect seizures automatically by using intracranial EEG. The records are segmented into 4 window size and decomposed into five levels using wavelet transform. Feature vector is generated using diffusion distances. A total of 193.75 h is classified using Bayesian linear discriminant analysis (BLDA). The average sensitivity was approximately 94% [12]. In 2018, Zhang *et al.* [13] proposed another seizure detection method based on Wavelet packet decomposition (WPD) to extract the *fDistEn* Kruskal-Wallis non-parametric one-way analysis of variance. The k-nearest neighbor (KNN) classifier has been used to classify features into either ictal or interictal [13].

San-Segundo [14] proposed to use a deep neural network for epileptic EEG signal classification. They used two convolutional layers for feature extraction and three fully-connected layers for classification. They evaluate several EEG signals transforms for generating, the inputs to the deep neural network: Fourier, wavelet and empirical mode decomposition. They used two datasets Bern-Barcelona EEG and Epileptic seizure recognition. For the first dataset, the obtained accuracy increased from 92.3% to 98.9% when classifying between focal and non-focal signals using the empirical mode decomposition. And the second dataset was obtaining the best results when using the Fourier transform. The accuracy between 99.0% and 99.5% for classifying seizure vs. non-seizure, from 91.7% to 96.5% when differentiating between healthy, non-focal and seizure recordings, and from 89.0% to 95.7% when considering healthy, focal and seizure recordings.

In the review of literature, it was found that most researchers extract the features from all channels. This process is costly both in terms of time and memory. The channel selection process, however, yields more reliable results. Moreover, most of the research has been reviewed using complicated and expensive work. In this paper the support vector machine (SVM) is used to classify these features. Recent evidence about seizures suggests that a combined algorithm can be employed for seizure onset/offset detection. It is based on triadic wavelet decomposition features such as variance, standard deviation and high order moments. Two classifiers were used in this study: linear discernment analysis (LDA) and KNN [15]. In contrast, automatic channel selection and statistical moment's features have not been used in most studies on epileptic seizure detection from EEG records. They rather use either all channels or the first channel. However, channel selection before feature extraction has recently been utilized in some other research areas like motor imagery [16]. The rest of the paper involves research methodology in section 2 which include subsections such as EEG dataset, pre-processing and data processing. The results and discussions are presented in section 3. Finally, conclusion of our finding consequence in section 4.

2. METHOD

The main idea of this work is to propose a relevant, fast and precise EEG based seizure detection system. The input of the proposed system is an EEG signal generated as a human brain signal, and the output is the detected seizure clips in the generated signal that contains seizures. The approach used in this study is adopted in fast algorithms employed to extract discriminative features to accomplish high detection accuracy and keep the required computational complexity as low as possible.

2.1. EEG dataset

The EEG data used in this paper is obtained from (Children's Hospital Boston CHB-MIT scalp EEG database [17], which is public and available at [18]. The database contains 24 children (male and female) suffering from epilepsy. Each subject has between 9-42 *continuous.edf* (European Data Format) files that contain original raw data of the brain signals. The signals were sampled at 256 sample per second with 16 bit-resolution. Most of the dataset files contain 23 channels (in some cases 24 or 26 channels). The records are based on electrodes placed according to the International 10–20 system.

The dataset contains annotation files for all 24 cases. For each case, the annotation file includes the number of channels, sample rate, number of seizures, seizure start time and seizure end time. For more information on the dataset as shown in Table 1. The whole dataset (24 patients) was tested on our methodology. Therefore, two thirds of the data for each patient was used for training the classifier and one third of it was used to test and validate the classifier.

Table 1. Description of the CHB-MIT EEG dataset

Subject (patient)	Gender	Age (years)	# of seizure	Duration of Recordings (hh:mm:ss)
Chb01	F	11	7	40:33:08
Chb02	M	11	3	35:15:59
Chb03	F	14	7	38:00:06
Chb04	M	22	4	156:03:54
Chb05	F	7	5	39:00:10
Chb06	F	1.5	10	66:44:06
Chb07	F	14.5	3	67:03:08
Chb08	M	3.5	5	20:00:23
Chb09	F	10	4	67:52:18
Chb10	M	3	7	50:01:24
Chb11	F	12	3	34:47:37
Chb12	F	2	27	20:41:40
Chb13	F	3	12	33:00:00
Chb14	F	9	8	26:00:00
Chb15	M	16	20	40:00:36
Chb16	F	7	10	19:00:00
Chb17	F	12	3	21:00:24
Chb18	F	18	6	35:38:05
Chb19	F	19	3	29:55:46
Chb20	F	6	8	27:36:06
Chb21	F	13	4	32:49:49
Chb22	F	9	3	31:00:11
Chb23	F	6	7	26:33:30
Chb24	-	-	16	21:17:47
Total			185	979:56:07

2.2. Preprocessing

There are some reasons why preprocessing is required for EEG recordings. Firstly, the signals that are picked up from the brain are not necessarily the accurate representation of those signals arising from the brain, as that spatial knowledge becomes lost [19]. Secondly, EEG information tends to contain a lot of noise which may hide weaker EEG signals. Artifacts like eye blinking, breathing or muscle motion will contaminate the data and distort the image. Lastly, we need to separate the relevant system signals from random neural activity that happens within EEG recordings.

As EEG preprocessing is still an active field of research, there is no universally embraced EEG preprocessing line. This implies that investigators have some liberty at selecting how to change the raw data. In order to achieve the best results in seizure detection, EEG recording is comprised of numerous different kinds of signals, each having a different frequency range [20]. Digital filtering is used to retain only the frequency components of interest and to remove any other data. We applied the Band-Pass Filter (BPF) [21] as shown in Figure 1 to eliminate the artifacts by suppressing the frequencies below 0.4 Hz. and above 40 Hz, to improve the quality of our EEG recordings.

The upper cut-off frequency and lower cut-off frequency are calculated as (1):

$$fc = \frac{1}{2\pi RC}\ Hz \tag{1}$$

where *fc* is the cut-off frequency and *RC* is resistance capacity.

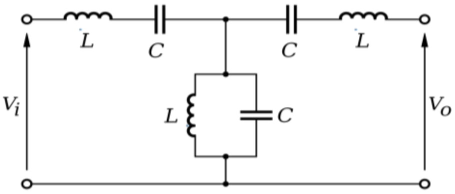

Figure 1. A medium-complexity example of a band-pass filter [22]

2.3. Data processing

Mostly, seizure detection can be translated into the multiple classification issues: Ictal (the seizure stage) and interictal EEG (the seizure-free stage). Although the underlying physiological activity is multi class, it is neither simple nor useful for the individual to determine and label the sub classes of the seizure and seizure-free stages. Additionally, dividing the EEG recording into two encompassing classes (seizure-free and seizure) is also consistent with basic objective practices. In the data, EEG recordings were regarded as “seizure” by experts at all recordings from seizure beginning to finish. EEG records out of the end of “seizure” were considered as “seizure-free.”

2.3.1. Channel selection

EEG recordings generally have multiple channels for signals from different human brain locations. Decreasing the number of channels is of utmost significance, for instance, in developing mobile medical aid devices for patients with epilepsy. Reducing algorithmic computational complexity will contribute to quicker real-time reaction and reduced power consumption to keep shorter operating time.

Moreover, the lower the number of channels, the greater the patient’s convenience and the shorter the setup time needed to fix gel-based EEG electrodes. Another aspect to be closely regarded in seizure detection is the overfitting impact of using a big number of redundant electrodes. Channel choice can be used to decrease the pattern size of features and reduce the costs of feature extraction and computational classification. In what follows, the channel choice method is used to detect seizures and rank them according to the variance value of the channel. It is based on max variance between all channels.

In this study, channel selection is done by calculating the variance of all seizure segments for all channels (18 electrodes) and choosing the channel with the highest variance value. In fact, the highest variance value in selected channel represents the brain area injured with seizure as shown in (2):

$$\sigma^2 = \frac{\sum_{i=0}^{N-1}(x_i-\mu)^2}{N} \tag{2}$$

where x is the samples of signal, μ is the mean of signal and N is the length of the signal.

2.3.2. Data segmentation

A sliding window analysis is ordinarily performed to segment the raw EEG data into portions of smaller length. These segments are utilized for the feature extraction process. The signals for each patient were segmented into 1-S long segment (this value was selected on the basis of several trials) without overlapping the successive segments, for example as shown in Figure 2.

Each segment is attached to an ictal class according to the annotation files included in the CHBMIT database. The interictal were randomly chosen from signals between two seizures. The segments of ictal and interictal are balanced and have the same length to make them ready for the feature extraction stage.

2.3.3. Feature extraction

Feature extraction means extracting the most relevant information as the data without this step is very large and is not valid for the classification process [23], [24]. Therefore, the extracted features will serve as a pattern to classify each frame as either ictal or interictal. In this research, two types of features have been performed. The first are time-domain features obtained from data without transformation into a frequency-domain, whereas the second are the frequency-domain features attained by transforming the data into a frequency domain using DWT.

a. Time domain features

In the time domain, features are extracted from the segment with respect to time directly without transforming it into other domains. The energy, log-energy and statistical moments were calculated for each segment using (3) to (5):

$$energy = \frac{1}{N}\sum_{i=0}^{N-1} x_i^2 \tag{3}$$

$$log - energy = log(energy) \tag{4}$$

$$\mu_i' = \frac{1}{N}\sum_{i=0}^{N-1}(x_i - \mu)^o \tag{5}$$

where μ_o is the statistical moment, X is the samples of signal, μ is the mean of signal, o is the order of moment (ex: 1,2,3,4) and N is the length of the signal. The normal and epileptic EEG data are classified where the features are computed by using the log energy entropies that are not experienced in seizure.

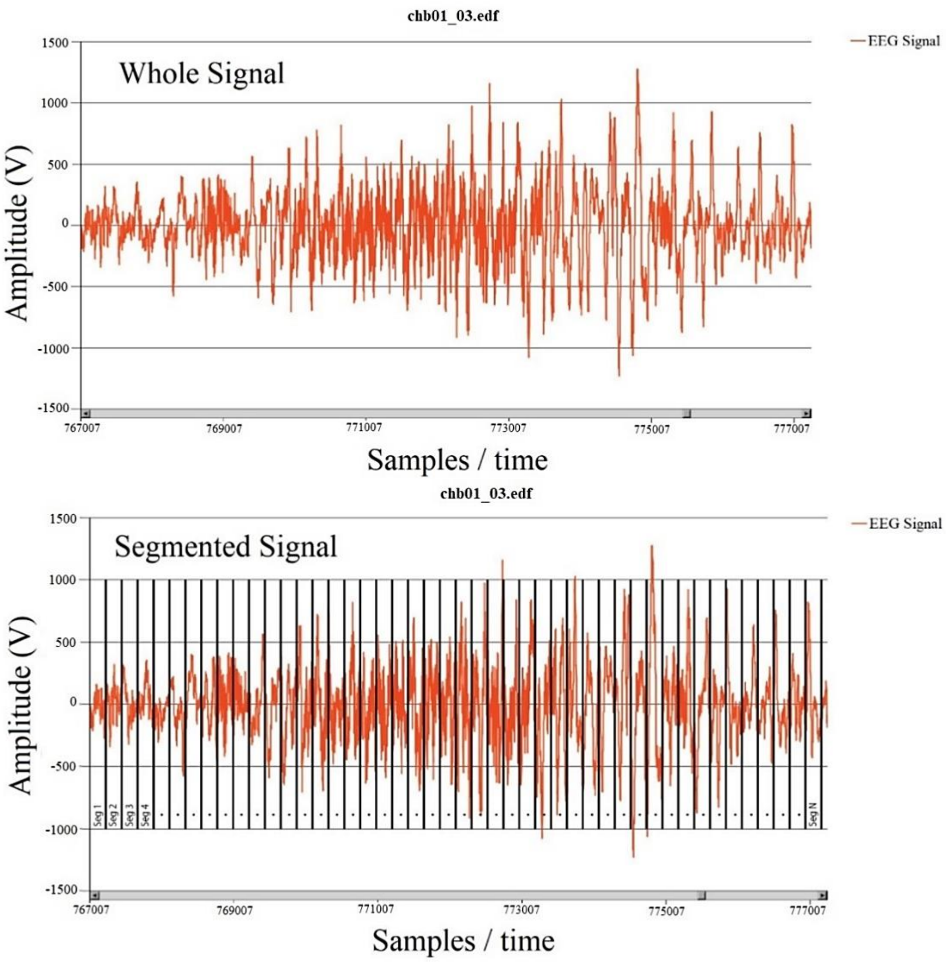

Figure 2. Segmentation of a 40-second ictal signal into 40 segments for the subject chb01_03

b. Frequency domain features

In the frequency domain, the signals are analyzed with regard to frequency as fast fourier transform (FFT), discrete fourier transform (DFT), continuous wavelet transform (CWT) and DWT [25]. In our methodology, we use DWT of mother db4 to convert the EEG signals from the time-domain into the frequency-domain.

$$DWT(i,j) = \frac{1}{\sqrt{|2^j|}}\int_{-\infty}^{\infty} x(t)\psi(\frac{t-2^j k}{2^j})dt \tag{6}$$

The DWT are commonly used in neuroscience data to decompose digital signals into signal sub bands. We noted that Daubechies order 4 wavelet transformation (db4) mother wavelets were very extensive and were deployed to fix actual issues in biomedical engineering. The frequency bands (gamma, beta, alpha, theta and delta) are extracted by way of a 5-level decomposition [26] see in Figure 3 from each segment to transform it into a frequency-domain. The seven statistical moment (5) features are calculated for each sub-band. In the result, the features vector dimensions become $(44*1)$ features for each segment: 9 features in the time-domain and 35 features in the frequency-domain for each segment.

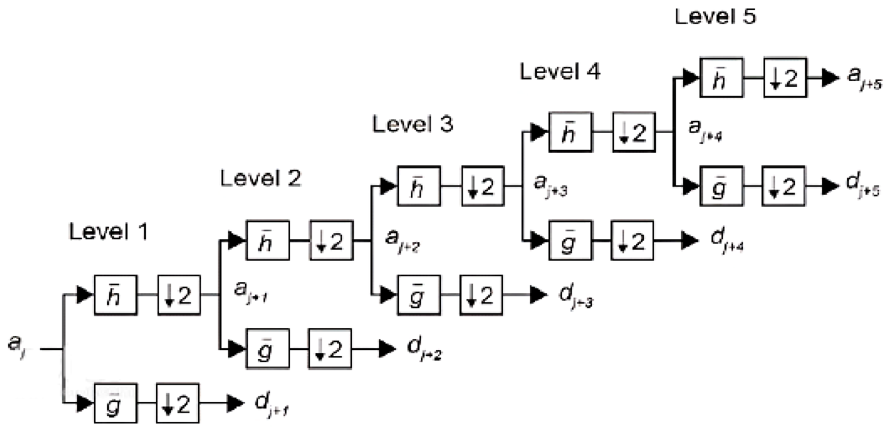

Figure 3. Five-level DWT decomposition [27]

2.3.4. Feature analysis and selection

The feature selection step is a combination of search techniques for suggesting new discriminating feature subsets along with an evaluation measure which scores the various feature subsets [28]. The selection of features has an advantage over dimensions reduction methods due to its capability to choose the best discriminatory features from the features vector [29]. Feature analysis is achieved by determining the intra-distance (within-distance). The within-distance (WD) gives an indication about the correlations strength of the class samples features to discard uncorrelated features.

$$WD(c,f) = \frac{\sigma_{cf}}{\mu_{cf}} \tag{7}$$

Where σ is the standard deviation, μ is the mean, c is the class number and f is the feature number.

This study used the wrapper method in feature selection to select the best subset of features. The first step of the wrapper method is the combination of relevant features as a subset of two features with the highest classification accuracy. Next, another feature with the best subset is chosen and so on until all features are tested or accuracy achieves the optimal rate.

2.3.5. Classification

The SVM is one of the most widely used supervised machine learning algorithm for classification problems [30], [31]. SVM basically adopts a nonlinear kernel function to convert the input data into a high dimension function space, which makes it easier to separate the data instead of the initial input space. The SVM iterative learning processes will, depending on input data, lastly develop an ideal hyperplane in a high-dimensional feature space with maximum margin between classes. Therefore, choosing boundaries for the separation of distinct data classes will be the maximum margin of hyperplanes. The wider distance between hyperplanes and group data will thus improve the efficiency of classification.

$$g(\bar{X}) = \bar{W}^{T}\bar{X} + b \tag{8}$$

Assume that the training data is a set of M training samples $\{X_m\}$ and their dependent variable $\{y_m\}$ where, y_m is -1 or $+1$. Where the decision rule is: *IF g(X)>0 THEN C1 else C2*.

The final feature vector contains $(44*N*1)$ features, where N is the length of ictal and interictal segments for each subject. The features vector has been divided into a training set and a test set (2/3 for training and 1/3 for testing) [32]. The proposed method is characterized by high classification accuracy and can be applied in real-time seizure monitoring and detection systems.

3. RESULTS AND DISCUSSION

Our proposed method is experimented on CHB-MIT dataset as shown in Table 1. Each patient in the dataset was tested and evaluated using the confusion matrix outcomes. True positive (TP) is defined by the count of segments that are correctly classified as ictal segments. True negative (TN), on the other hand, is defined by the count of segments that are correctly classified as interictal segments. False positive (FP) is defined by the count of segments that are incorrectly classified as ictal segments. Finally, false negative (FN) is defined by the count of segments that are incorrectly classified as interictal segments. Table 2 shows the results in detail, while Figures 4 and 5 represent the accuracy, sensitivity, specificity and error rate respectively for all cases on CHB-MIT database.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

$$Specificity(TNR) = \frac{TN}{TN+TP} \tag{10}$$

$$Sensitivity(Recall) = \frac{TP}{TP+FN} \tag{11}$$

$$Precision = \frac{TP}{TP+FP} \tag{12}$$

$$F\ score = \frac{(1+\beta^2)(Precision*Sensitivity)}{(\beta^2*Precision+Sensitivity)} \tag{13}$$

F-score is a harmonic mean of precision and recall. β is commonly 0.5,1 or 2.

$$FPR = 1 - Specificity \tag{14}$$

$$ERR = 1 - Accuracy \tag{15}$$

It can be obviously observed that the average of the results was high for all features (accuracy, specificity, and sensitivity), ranging between 93 and 94 percent. Comparing these percentages with the outcomes of other publications in the same area of epilepsy seizure detection, it could be noted that this method proved to be able to detect seizures with very acceptable accuracy. It should also be taken into account that the researchers used the fewest possible channels compared to the other methods. The research can be developed to reduce the error rate to its lowest levels by applying some filters on the data before processing it. This can be done in future work.

Table 2. Seizure detection results for the 24 cases of the CHB-MIT EEG database. FPR=false positive rate

Subject(patient)	Accuracy	Sensitivity	Specificity	F-Score	FPR	Precision	Error
Chb01	96.622	95.27	97.973	96.575	0.02	97.917	0.034
Chb02	98.276	98.276	98.276	98.276	0.017	98.276	0.017
Chb03	94.776	96.269	93.284	94.853	0.067	93.478	0.052
Chb04	92.46	97.619	87.302	92.83	0.127	88.489	0.075
Chb05	95.699	98.925	92.473	95.833	0.075	92.929	0.043
Chb06	92.157	98.039	86.275	92.593	0.137	87.719	0.078
Chb07	96.789	96.33	97.248	96.774	0.028	97.222	0.032
Chb08	97.557	98.371	96.743	97.577	0.033	96.795	0.024
Chb09	99.457	100	98.913	99.459	0.011	98.925	0.005
Chb10	95.973	98.658	93.289	96.078	0.067	93.631	0.04
Chb11	96.84	99.628	94.052	96.926	0.059	94.366	0.032
Chb12	91.768	97.764	85.772	92.234	0.142	87.296	0.082
Chb13	94.413	91.061	97.765	94.22	0.022	97.605	0.056
Chb14	94.737	96.491	92.982	94.828	0.07	93.22	0.053
Chb15	98.042	99.699	96.386	98.074	0.036	96.501	0.02
Chb16	98.214	96.429	100	98.182	0	100	0.018
Chb17	97.959	97.959	97.959	97.959	0.02	97.959	0.02
Chb18	95.283	92.453	98.113	95.146	0.019	98	0.047
Chb19	96.203	93.671	98.734	96.104	0.013	98.667	0.038
Chb20	86.224	86.735	85.714	86.294	0.143	85.859	0.138
Chb21	94.03	95.522	92.537	94.118	0.075	92.754	0.06
Chb22	99.265	98.529	100	99.259	0	100	0.007
Chb23	90.493	89.437	91.549	90.391	0.085	91.367	0.095
Chb24	93.86	95.906	91.813	93.983	0.082	92.135	0.061
Total	**94.103**	**93.571**	**94.634**	**94.081**	**0.054**	**94.643**	**0.059**

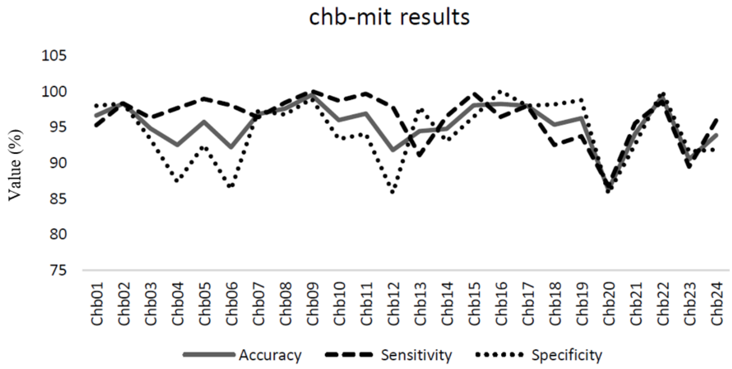

Figure 4. Accuracy, sensitivity and specificity for all 24 cases on CHB-MIT database respectively

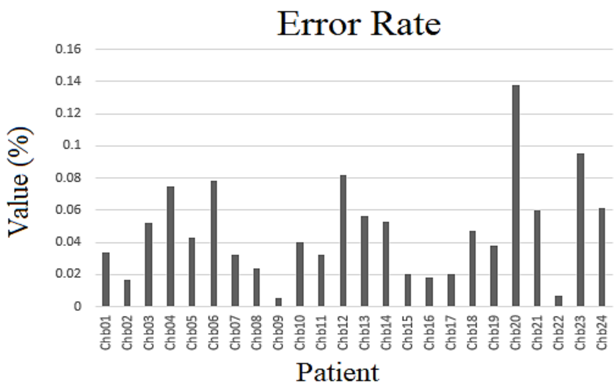

Figure 5. Error rate for all 24 cases on CHB-MIT database

4. CONCLUSION

The researchers use SVM and DWT to identify epilepsy seizures in raw EEG signals (They use one channel only because if all channels are used in EEG recording analysis, this complicates the system. Therefore, the channel selection method based on maximum variance for ictal epochs has been proposed to obtain the minimum number of channels, that represent the best option in epileptic seizure detection) by segmenting the EEG signals into 1-S long segment, extracting features using DWT and classifying these features using SVM. Good results were attained on CHB-MIT dataset and the proposed method can be evaluated on very long-term EEG data. Reaching this result with high accuracy was due to using artificial intelligence algorithms with the statistical analysis of the data. Because the CHB-MIT dataset contains children only, future work will focus on adults with epilepsy EEG data and use more than one channel.

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