International Journal of Grid and Distributed Computing
Vol. 14, No. 1, (2020), pp. 1093-1100

Seizure and Sleeping Disorder Detection for identification of Angelman Syndrome from EEG Using Machine Learning

Swati G. Gawhale[1], Dr. Dhananjay E. Upasani[2], Dr. Anupama Deshpande[3]
[1]Research Scholar, Shri Jagadish Prasad Jhabarmal Tibrewala University, Jhunjhunu Rajasthan, India.
[2]Associate Professor, MIT School of Engg., MIT ADT University, Pune, India.
[3]Professor, Shri Jagadish Prasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan, India.
gawhaleswati@gmail.com[1], upasanide@gmail.com[2]

Abstract

Angelman syndrome (AS) is distinguished by extreme developmental delay or learning disability, gait ataxia, severe speech disorder, and/or tremulousness of the limbs, and distinct activity characterized by repeated laughter, joking, and excitability. Seizures and sleeping disorder are also very common. The earliest signs of developmental delays appear at the age of six months, but the distinctive clinical characteristics of AS do not appear until after one year. A seizure is an electrical disruption in the brain that occurs suddenly and without warning. It may affect the behaviour, growth, and emotions of epileptic patients, as well as their state of consciousness. The ability to anticipate epileptic seizures quickly will save an epileptic patient a lot of trouble, such as slipping, drowning, crashes, and maternity complications. The function extraction stage and the classification stage are the two primary stages of seizure identification. In this article, a new algorithm is introduced for detecting seizures in as little as 10 seconds. To describe the actions of EEG operations, a variety of features are derived from the signal. The classifiers are fed these characteristics. SVM, KNN, and decision tree are the classifiers in question. The findings reveal that SVM is the most accurate and sensitive classifier for predicting the occurrence of seizures.

Keywords: *Angelman syndrome, Seizure Classification, Sleeping Disorder Electroencephalography (EEG), Machine Learning, Support Vector Machine (SVM), Healthcare*

1. Introduction

Angelman syndrome is a complex genetic disorder that primarily affects the nervous system. Characteristic features of this condition include delayed development, intellectual disability, Epilepsy, severe speech impairment, and problems with movement and balance (ataxia). Epilepsy is now regarded as one of the most common long-term neurological conditions [1]. Epilepsy has an effect on the lives of epilepsy patients and their families [1]. It causes shivering and abrupt movements in patients, and it may also result in death [2]. As a result, effective automated diagnosis of epileptic seizures is extremely important. This led to the creation of a reliable and accurate strategy for predicting seizure occurrences in order to make the lives of patients easier [3]. Electroencephalography (EEG) is a simple procedure for determining electrical activity in the brain [4]. It is most often used to recognize and investigate epileptic seizures, with electrodes connected to the head recording brain activity [5]. The ictal condition, which is essentially the length of time of the seizure itself, can be separated into four stages by EEG signs, which are characterized by epilepsy patients [6]: The preictal condition refers to the time period before the onset of a seizure.

The postictal condition is the period of time after the seizure where the cerebrum recovers from the seizure. The natural state is assumed to be the interictal state. The function extraction and classification phases of a seizure exploration system can be divided into two parts [7].

The features extraction phase is most likely the most important step in the EEG signal processing process, as it allows you to maximize the classification level capacity [8]. A second

ISSN: 2005-4262 IJGDC

goal of the degree is to use the mechanism to compact the statistics without losing valuable details, allowing it to operate in real-time [9]. To derive different features from EEG, different techniques are used.

For function extraction, the auto regressive (AR) model is combined with sample entropy [10]. To remove characteristics, both wavelet energy and spectral power are used [11]. Another method for FE is the semi supervised intense energy ratio (SEER) [12]. In addition, CDBNs (Convolutional Deep Belief Networks) are used [13]. The characteristics are extracted using a combination of PCA and WT [14]. The methods used are empirical mode decomposition (EMD) [15] and a typical spatial pattern (CSP) [16]. The proposed model extracted features using the statistical features methodology [17].

The classification process is used to distinguish between seizure and non-seizure patients. The classification step's key goal is to accomplish this. Several classification strategies have been established, and we will discuss a few of them briefly. The most widely used classifier technique is the support vector machine (SVM), which achieves better precision than other techniques [18]. [19] An artificial neural network (ANN) is capable of making very good decisions about groups. A different kind of classifier is the Gaussian Mixture Model (GMM) [20]. Electrophysiological signals such as ECG and EEG signals have been analyzed using the visibility graph (VG) system [21]. LDA (Linear Discriminant Analysis) [22] is a form of discriminant analysis that looks for patterns in data. Classifier based on deep learning [23].

2. Related Work

Physiologists may use machine learning techniques to help them predict and diagnose epileptic seizures. In this way, NN, SVM, DT, fuzzy logic, and other techniques alternate the focus of study. Welch FFT was used for feature extraction, Principal Component Analysis (PCA) was used for dimensioning reduction, and Artificial Immune Recognition System (AIRS) with Fuzzy resource distribution function was used by Polat and Günes [24]. Convolutional neural networks (CNNs) were used to study EEG recordings by Acharya et al. [25]. Hosseini and colleagues [26] suggested a three-tiered structure. In the first tier, data is collected from the patient using an intracranial EEG (iEEG) sensor attached to a mobile computer. Function extraction and classification was performed in the second tier by a group of notebooks or home gateways.

Finally, in the third category, data for big data collection and decision-making is stored on a cloud server. Wavelet Transform (WT) is used to filter the signal, Infinite Independent Component Analysis (I-ICA) is used to minimize dimensionality, and SVM is used to classify the data. Cooman et al. [27] suggested an algorithm based on ECG data to detect Heart Rate Increase (HRI) in order to detect epilepsy. This method considered ECG because it is easier to obtain than EEG for patients outside of hospital facilities. The HRI algorithm for feature extraction was paired with SVM for epilepsy classification in this study. Vandercasteele et al. [28] compared the sensitivity of ECG and Photoplethysmography (PPG) sensors for epilepsy identification and associated the findings with a hospital system's sensitivity. The precision and simplicity of using wearable devices as a long-term replacement for hospital equipment are the emphasis of this strategy. The function collection in the study works is often alternated between the time and frequency domains. The EEG morphological features were converted to the frequency domain using the Fast Fourier Transform (FFT) by Polat and Günes [24]. However, performing the transformation added additional computational complexity and necessitated dimensionality reduction prior to classification. The function extraction protocol was simplified by Acharya et al. [25], who normalized the EEG signal with Z-score. The neural network training protocol is accelerated by normalization, and the computational complexity is minimized by running it in the time domain. Li et al. [29] suggested a time-frequency approach as an alternative. When we compare the findings of similar studies, we find that the domain has little effect on the algorithms' classification accuracy, but that operating in the time domain results in less complex architectures.

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The findings of the associated job study show that it is extremely accurate. However, neither the computational complexity nor the possible applicability of the proposed architectures in-device or at the edge is discussed in the research papers. Furthermore, the existing designs for epilepsy diagnosis do not meet the low complexity criteria for wearable interface applications. Because of the computer's restricted processing, storage space, and battery life, program for epilepsy diagnosis running on the wearable device includes a simple algorithm. Additionally, architectures that propose data transfer to cloud servers are vulnerable to security threats that must be addressed.

3. Proposed Methodology

In this article, an algorithm is suggested for automatically detecting epilepsy from short-term EEG recordings. The following diagram depicts how the algorithm is constructed.

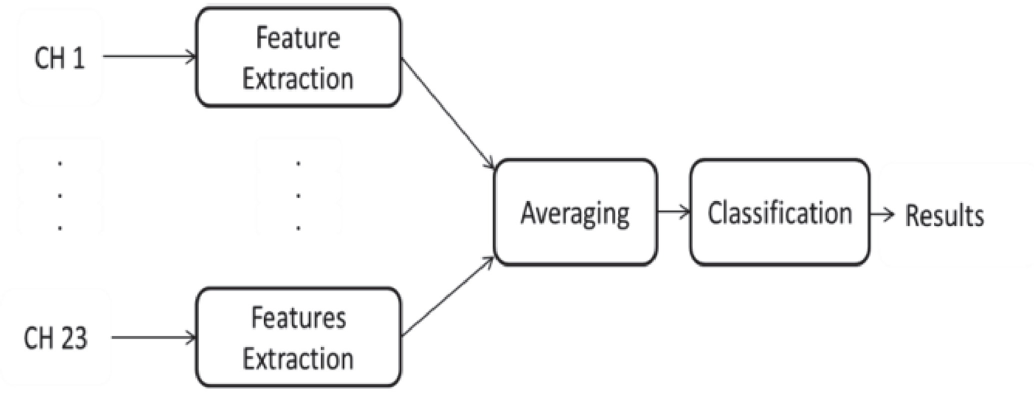

Figure 1. Block Diagram of Proposed Methodology

The work is divided into two phases: preparation and testing. The proposed algorithm employs all 23 channels during the training process for each event. The features are then extracted over a 10-second cycle. After that, for mathematical elimination, averaging is estimated. To train the classification model, the extracted features are used. Finally, the learned model is checked against other cases to ensure that it performs as anticipated.

The EEG signal is used to retrieve a series of functions. Standard Deviation, Mean, Variance, Median, Kurtosis, Skewness, Entropy, Moment, Maximum of the EEG signal, Minimum of the EEG signal, and Power of the EEG signal are all derived for each 10 second EEG recording[8][24]. Classifiers are fed the extracted features. This research employs five different classifiers. Support Vector Machine (SVM), K-nearest neighbors (KNN), and decision tree are three of the classifiers available.

A total of 50 samples are used to train the classifier (containing seizures and normal cases). The consistency validation is done using the K-fold process for 5 subsampled samples. Half of the findings are shown in the diagram below.

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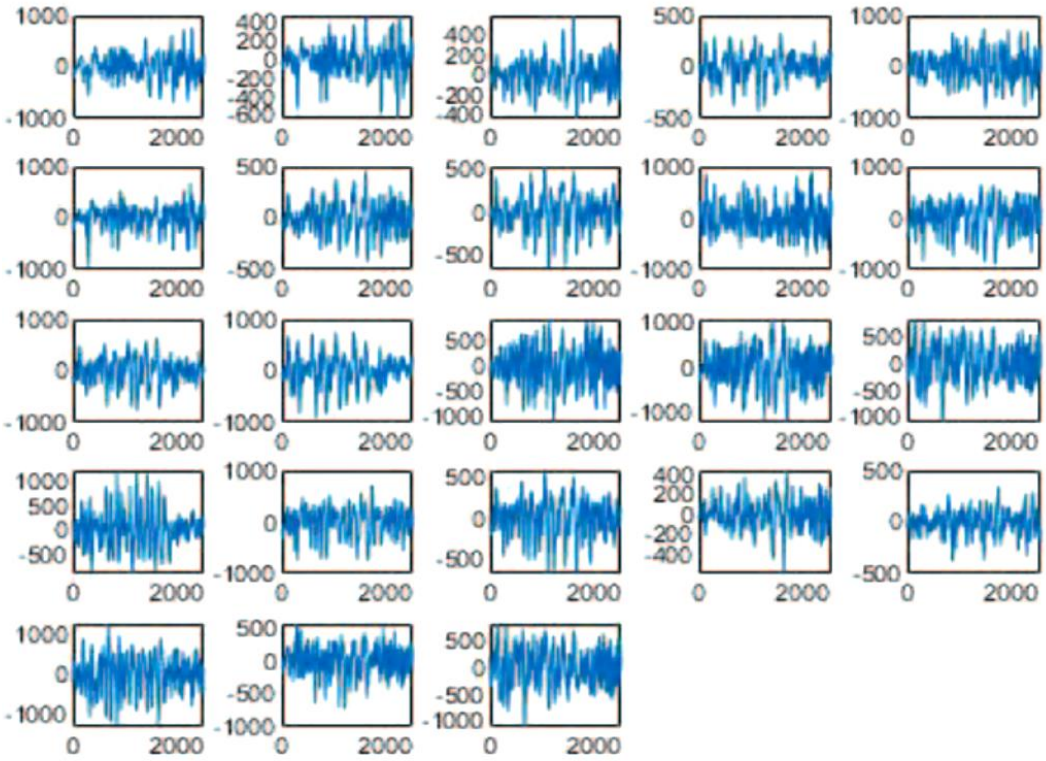

Figure 2. The results of the proposed model

4. Experimental Setup and Evaluation Metrices

4.1. Dataset

The database of EEG recordings from Bonn University is used in this experiment. The Bonn EEG data, defined by Andrzejak et al. [30], is divided into five sets (designated A-E), each containing 100 single channel EEG segments of 23.6 s length, sampled at 173.6 samples per sec with 12 bit resolution and classified into three groups: regular, inter-ictal, and ictal. A total of 4096 samples are used in each data segment. The bandpass filter was set to 0.53 - 40 Hz (12 dB/octave) in this experiment. Each collection was recorded in a separate set of circumstances. After excluding any objects, such as muscle action or eye motions, these segments were chosen from continuous multi-channel EEG recordings to ensure that they met stationary criteria. There are 500 EEGs in total so each section is handled as a separate EEG signal. The same 128-channel amplifier system was used to record all of the EEG signals, with an average common comparison. The statistical validity of the findings can be improved by using a broad data set. Sets A and B contain segments extracted from surface EEG recordings made on five healthy volunteers using a typical electrode positioning scheme of 10 to 20 electrodes. For set A, the subjects were awake and asleep, and for set B, they were awake and relaxed with their eyes closed. Five epileptic patients who were undergoing pre-surgical diagnosis provided the segments for sets C, D, and E. The epilepsy was diagnosed as temporal lobe epilepsy (epileptogenic focus: hippocampal formation). Only behaviour measured at seizure-free periods (interictal epileptiform activity) was included in sets C and D, with segments in set C collected from the hippocampal formation of the opposite hemisphere of the brain and segments in set D recorded from inside the epileptogenic field. Set E, on the other hand, only included seizure activity (ictal intervals), with all segments obtained from ictal activity-prone sites.

4.2. Evaluation Parameters

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After finishing the training of different classifier, each classifier is tested using 30 samples (containing both seizures and normal). The results are evaluated using Accuracy, F1-Score, Precision, and recall. The following are formulas used for the evaluation.

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

$$Precision = \frac{TP}{TP + FP} \quad \text{.............(2)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{.............(3)}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad \text{.............(4)}$$

Where,

TP is True Positive

TN is True Negavtive

FP is False Positive

FN is False Negative

4.3 Evaluation Result

The evaluation results for the three classifiers used in the proposed method are described in the table below.

Table 1.Results of the Evaluation Parameters of the Proposed System

Metric	Classifier	Baseline	Seizure	Accuracy	Macro avg	Weighted Avg
f1-score	Decision Tree	0.985507	0.962963	0.929167	0.974235	0.979402
	K-Nearest Neighbors	0.958904	0.869565	0.9375	0.914235	0.934708
	Support Vector Machine	0.970588	0.928571	0.958333	0.94958	0.959209
precision	Decision Tree	1	0.928571	0.929167	0.964286	0.980655
	K-Nearest Neighbors	0.921053	1	0.9375	0.960526	0.942434
	Support Vector Machine	1	0.866667	0.958333	0.933333	0.963889
recall	Decision Tree	0.971429	1	0.929167	0.985714	0.979167
	K-Nearest Neighbors	1	0.769231	0.9375	0.884615	0.9375
	Support Vector Machine	0.942857	1	0.958333	0.971429	0.958333

The confusion matrix generated in the above experiment are shown in following figure 3.

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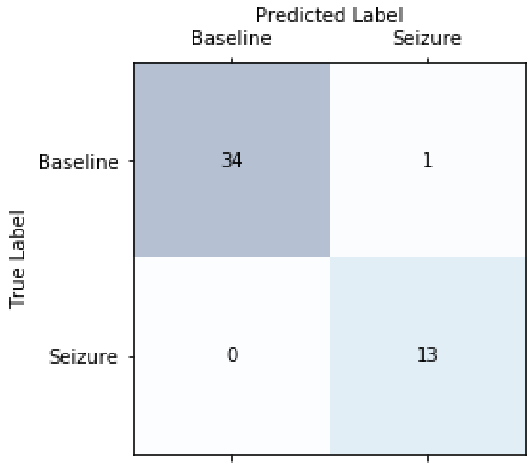
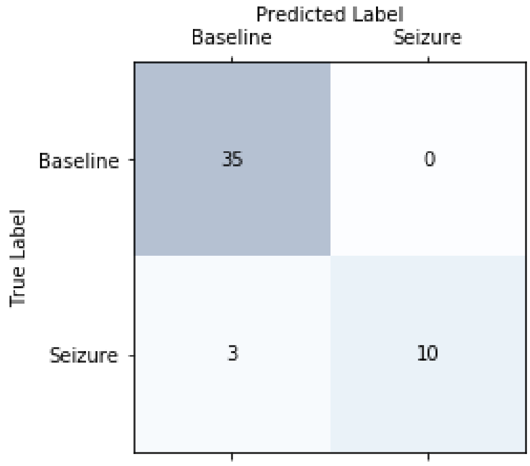
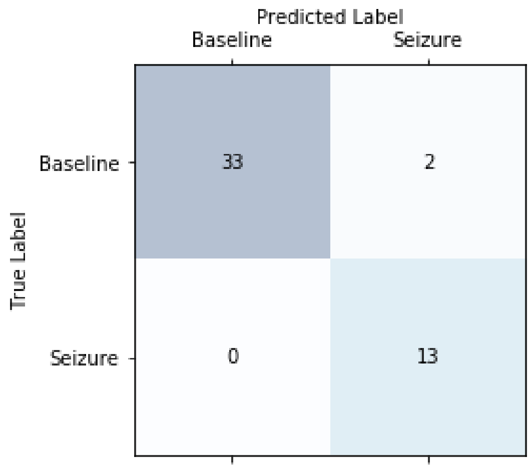


(a)



(b)



(c)

Figure 4. Confusion Matrix for (a) Decision Tree (b) K-Nearest Neighbors and (c) Support Vector Machine

The accuracy of the three algorithm in the experiment is found to be 92.91 % for Decision Tree, 93.75 for KNN and 95.83% for Support vector machine. The comparative analysis for the proposed methodology is shown in figure 5.

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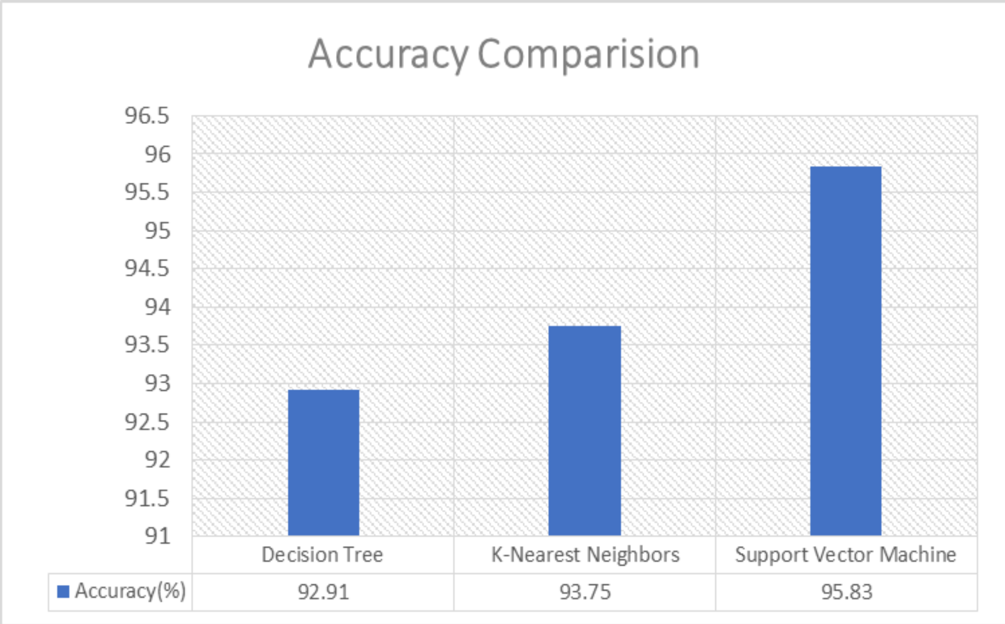

Figure 5. Comparitive of Accuracy for DT, KNN and SVM

4.4 Conclusion

In this study, detection model is designed for training EEG data. The proposed algorithm is able to characterize the characteristics as natural or neurologically affected perfectly. The model is planned as receiving features from EEG platforms. Then averaging is taking to refer to various classifiers. The obtained outcomes showed that the SVM is the best performance to achieve a good accuracy of 95.83 percent , and sensitivity of 100 percent . Upon these results SVM is proposed for epilepsy detection algorithm. The useful argument in this work, the suggested methodology is able to assess the frequency of seizure through just 10 seconds, which is really necessary for the epilepsy patient to prevent any symptoms or disorders.

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ISSN: 2005-4262 IJGDC