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Epilepsy Seizure Prediction sing an SVM Algorithm

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Abstract

Epileptic seizures remain a real concern and a major medical challenge, simply because they strike unexpectedly and without warning, turning a patient's life upside down. Undoubtedly, the ability to detect an impending seizure well in advance is a lifeline, aiding physicians and completely transforming the course of treatment. However, there is a hurdle: while complex artificial intelligence models (such as deep learning) are highly accurate, they are resource-intensive and require powerful computers, making them difficult to run on small or portable devices. Therefore, in this study, we developed a smarter and lighter solution: a model based on the SVM algorithm. The idea behind this model is that it focuses specifically on the two minutes preceding a seizure, making it lightweight and easy to implement even on devices with limited capabilities. We analyzed brain signals and extracted the necessary data, and using this model, we were able to clearly distinguish between normal brain activity and the moments before a seizure. The results were very promising. We achieved an accuracy rate of nearly 80%, with the ability to provide warnings of an impending seizure 5 to 10 minutes before it occurs. We observed that delta and gamma waves were the most effective

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in detecting this threat. In short, what distinguishes this approach from others is its simplicity and low resource consumption compared to other complex systems, making it ideal for use on wearable devices (such as medical watches) and in real time. We plan to test this model on a larger scale, including data from adult patients at different centers, to ensure its effectiveness for all patients.

Keywords: Epilepsy, EEG, Seizure Prediction, Support Vector Machine, Frequency Domain, Wavelet Transform, Preictal Detection, Machine Learning.

1. INTRODUCTION

Epilepsy is one of the most popular neurological disorders within the global population, and it is characterized by stochastic, recurrent, seizure attacks. The causes of these seizures majorly include disregulation of neural communication involving unnecessary electrical disattentions within the cerebral cortex [1]. The statistics of seizure activity suggest that about 60 million people are affected by the seizure activity as collected by the World Health Organization (WHO). Also, a percentage of these patients are exposed to non-optimal or unsuitable therapeutic interventions, which can be mostly explained by the socioeconomic limitations [2]. Antiepileptic drugs (AEDs) are usually used as a first-line treatment of epilepsy; notwithstanding, the pharmacological methods can often be ineffective in treating refractory epilepsy. Accurate diagnosis and appropriate treatment are essential to enable people with epilepsy to avoid seizure triggers [3].

In a related study, researchers presented a prediction model for recurrent seizure [4]. They investigated health and environmental and genetic factors that could have significant impact on seizure prediction, such as brain injury and stroke. Studies suggest that the performance of predictive models may degrade significantly due to data limitations and technological constraints [5]. Machine learning technique is employed in many studies to monitor epileptic seizures by using predictive model [6]. Sucha a predictive model can be implemented by emerging technology, such as wearable devices. Extensive studies employed an electroencephalogram (EEG) signals for predicting seizure [7]. To make EEG signals useful and ready to use by ML algorithms, the frequency domain is applied to determine abnormal seizure wave patterns. Additionally, several ML algorithms are applied, such as the support vector machine (SVM) and common spatial patterns (CSPs) to analyze complex data [8]. However, several factors could affect the accuracy and reliability of seizure prediction, including impulses and biological rhythms [9, 10]. Implementing ML techniques in many studies has improved the reliability and accuracy of predictive models. Our study presented the significance of feature selection and frequency domain analysis used in our research which provides a pathway to develop technologies to enhance seizure prediction. The study is aiming to predict epilepsy using brain analysis signals and the SVM algorithm for feature extraction. Previous studies have adopted more complex algorithms to predict epilepsy within 1-2 seconds, implementing high-performance computing. However, our research focuses on a two-minute preictal prediction window using a simple SVM-based model. Hence, this study opens the way for its use in lightweight, accessible applications. The main contributions of this work are summarized as follows:

1. A lightweight and interpretable seizure prediction framework: We design and evaluate a computationally efficient EEG-based seizure prediction pipeline using classical machine learning

techniques, with a focus on real-time and wearable deployment rather than algorithmic novelty.

2. Clear and reproducible methodological formulation: The study provides explicit definitions of the preictal window, seizure prediction horizon, and validation protocol, enabling transparent interpretation and reproducibility of seizure prediction experiments.

3. Practical evaluation on a public clinical dataset: The proposed framework is evaluated on the CHB-MIT EEG dataset, allowing direct comparison with existing studies and demonstrating the feasibility of classical approaches under realistic constraints.

2. RELATED WORK

In recent years Machine learning (ML) techniques are widely used in different sectors, including the health sectorshelping people who suffering from epile. The technique has been used to design a prediction model for seizure prediction, helping people who suffer from epilepsy to prepare before it occurs [11]. Many algorithms have been employed to analysis EEG signals, such as the support vector machine (SVM) due to its features in analyzing large data. For instance, Savadkoohi et al. (2020) [12], proposed prediction model for seizure prediction by implemented SVM and K-nearest neighbor (KNN) algorithm to evaluate EEG data in particular domain of time and frequency [12]. In the same vein, Tamanna et al. (2021) applied SVM and the discrete wavelet transform (DWT) to design a model for prediction. , achieving 96% accuracy and 26.1 minute difference in recurrence [13]. In another study, Messaoud and Chavez (2021) employed forest classifier (RF) which has more efficiency than a single decision tree [6]. The proposed predictive model attained 82.07% accuracy.

Aslam et al. (2022) achieved high level of accuracy for seizure prediction using several ML algorithms, including long short-term memory (LSTM), the signal to noise ratio (SNR), and CNN techniques. The designed system achieved 90% accuracy [14]. Ali et al. (2019) proposed a predictive model by implementing LSTM algorithm. It attained remarkable accuracy by classifying preictal and interictal EEG clips [15]. Usman et al. (2017) applied ML technique for analyzing complex EEG signals data, achieving 92.23% actual positive rate. Convolutional Neural Networks (CNNs) is used to classify epileptic conditions to attain reliable accuracy for predictive model by calculating theses conditions at intervals time of up to 60 minutes [16]. This method is working by alters EEG data signals into visual representation. The findings also achieved average prediction time is 23.6 minutes [17]. The hybrid learning techniques are offering more reliable and efficacy for predictive model, attaining 95% accuracy. LSTM and residual neural networks (RNNs) are employing for extract features form EEG signals [18].

To address the limitations of EEG data, Generative Adversarial Networks (GANs) are employed to generate artificial EEG signals, thus enhancing the accuracy of the analysis [19]. Bekbalanova et al. (2019) implemented several ML techniques for seizure prediction, including SVM, K-nearest neighbors (KNN), and a decision tree to analyze EEG signals. The study has achieved a maximum accuracy of 100% [20]. Nevertheless, several studies have criticized the results due to many challenges and limitations in data quality.

Missing and unclear data will affect ML algorithms' performance, which imposes obstacles to regulating this approach in clinical applications [21]. CHB-MIT datasets are used to solve missing data, but they do not offer a diverse patient population [22]. Hence, when the model is developed, it is challenging to achieve efficient prediction across diverse epileptic etiologies. Even modified models offer high reliability, they need patient-specific comprehensive data [23]. Wearable and computational devices that have been used to predict seizures produce low spatial frequency and resolution in real time applications [24]. Moreover, false alarms may pose challenges for the predictive model, resulting in unnecessary patient stress. It is also difficult to evaluate false alarms as a result of variations in seizure prediction horizons [25].

These issues provide the understanding of the need to have a more reliable predictive model to make predictions based on the seizures. The proposed methods have various pitfalls although numerous studies have been conducted on the application of ML techniques to measure seizures. In this study, the researcher has used the SVM model to overcome these challenges in the process of measuring and predicting epileptic seizures.

3. METHODDOLOGY

This paper will present an epileptic seizure forecasting system based on machine learning and Support Vector Machines (SVM) on scalp EEG signals. The methodology will be constructed in such a way that it will be clinically relevant, reproducible, and safeguard data leakage by the tight temporal definition and validation procedures.

3.1 Data Collection

The EEG data used in this study were obtained from the publicly available CHB-MIT Scalp EEG Database [26, 27], collected at the Children's Hospital Boston . The dataset contains long-term scalp EEG recordings from 24 pediatric epilepsy patients (male and female), each with 9 to 42 continuous EEG sessions.

All EEG signals were recorded using the international 10–20 electrode placement system, sampled at 256 Hz with 16-bit resolution. Recordings consist of 23 EEG channels, providing sufficient spatial coverage for seizure-related brain activity. Expert neurologists annotated seizure onset and offset times, which were used as temporal ground truth for labeling. To support seizure prediction rather than detection, EEG recordings were later segmented into fixed-length temporal windows. The precise definition of preictal and interictal intervals, and their temporal relationship to seizure onset, is formally described in Section 3.4. The workflow of the proposed SVM-based prediction system is illustrated in Figure 1.

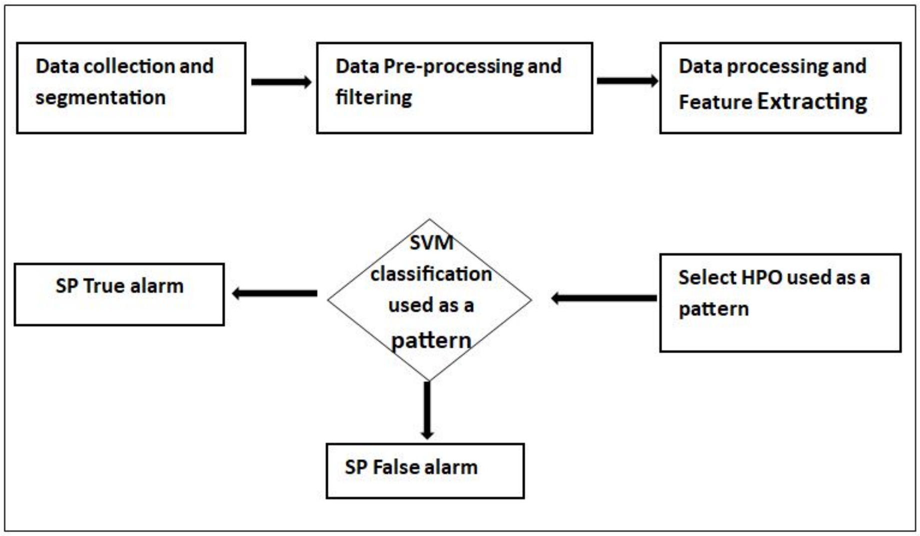

Figure 1: Workflow of the proposed SVM-based prediction system

3.2 Data Preprocessing

Raw EEG recordings contain various noise sources, including power-line interference, baseline drift, and physiological artifacts[28]. To mitigate these effects, a sequence of digital preprocessing steps was applied.

A conventional IIR notch filter was used to suppress power-line interference at 50 Hz, consistent with standard clinical EEG acquisition practices [29]. In addition, a high-pass filter with a cutoff frequency of 0.4 Hz was applied using the filtfilt function in the MATLAB Signal Processing Toolbox. This technique utilizes zero-phase digital filtering, processing the signal in both forward and reverse directions. This approach effectively eliminates phase distortion while preserving the morphological features of the EEG waveform.

To generalize the model and mitigate overfitting in the process of training, five-fold cross-validation was used as part of the hyperparameter optimization framework[30]. The grid search method was employed to identify the best values of radial basis function (RBF) kernel parameters of the SVM classifier. Accuracy, sensitivity, specificity, precision and F1-score were used as the performance measures to compare the model performance against the actual performance.

3.3 EEG Preprocessing

Raw EEG records include several noise sources such as power-line interference, base line drift and physiological artifacts. In order to counteract these effects, a series of digital preprocessing was used before the extraction of features.

Power-line interference at 50 Hz was suppressed using a conventional IIR notch filter, which is in line with typical practices of acquiring EEG in clinics [31]. Moreover, the filtfilt function of the MATLAB Signal Processing Toolbox was used with a high-pass filter and cutoff frequency of 0.4 Hz. This is a zero-phase digital filtering technique which makes the signal run in forward and backward directions, which avoids phase distortion, and maintains the morphological features of the EEG signal [32].

To make all EEG channels and recording sessions consistent and reproducible, all preprocessing steps were equally applied to all channels. The raw EEG signals were preprocessed and then, the feature extraction and classification steps were carried out as explained in the subsequent sections.

3.4 Feature Extraction

EEG signals are non-stationary and multi-resolution and time-frequency analysis is therefore especially appropriate in tasks of seizure prediction. In order to extract these properties, the Discrete Wavelet Transform (DWT) was used to extract features; this is because the localization of the DWT is better in time and frequency domain [31, 32].

A five-level wavelet decomposition was used to decompose each EEG segment into several frequency subbands. The Daubechies db8 wavelet was chosen because of its effectiveness in the analysis of physiological signals and the studies related to epilepsy [33, 34]. This breakup provided the detail coefficients (D1-D5) and a final approximation coefficient (A5), which represent clinically significant EEG rhythms, such as, gamma, beta, alpha, theta, and delta bands[35, 36]. The frequency contents higher than 50 Hz were excluded because they do not play a vital part in the analysis of seizure related EEG (table 1). Based on the subbands statistical and energy-based features were obtained to create an initial feature vector consisting of the temporal and spectral properties of the EEG signals. These characteristics give a concise description of signal aspects linked with signal generation of seizures[37, 38].

Table 1: Frequencies with decomposition levels

Decomposition Level	Frequency Bandwidth (Hz)	Frequency Bands
D2	32 - 50	Gamma
D3	16 - 32	Beta
D4	8 - 16	Alpha
D5	3 - 8	Theta
A5	0.5 - 3	Delta

The wavelet coefficients provided a compact representation showing the energy distribution of the EEG signal in the frequency and time domains. The coefficients were used to reduce dimensionality and obtain feature vectors for gamma, beta, alpha, theta, and delta bands, which are related to seizure liability [39]. Figure 2 shows that each stage comprises two digital filters and two down samplers by 2

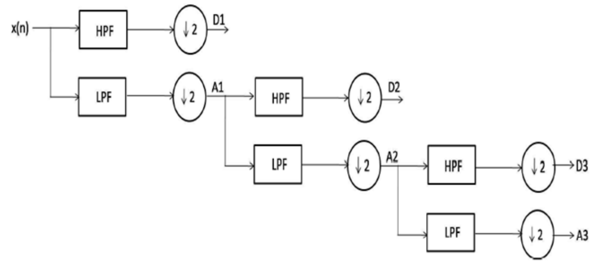

Figure 2: Sub-band decomposition of DWT implementation [35]

3.5 Feature Selection

Fourier based analysis was used to further define frequency-domain behavior and increase discriminative ability. Fast Fourier Transform (FFT) algorithm has been used to calculate the Discrete Fourier Transform (DFT) to do spectral analysis efficiently [40, 41]. According to the results of the FFT, Power Spectral Density (PSD) characteristics were computed to describe the amount of energy in each band of frequency [42].Since the extracted feature set is high-dimensional, when combined in many channels of EEG, High-Order Spectra (HOS) was utilized to represent the final feature representation, and capture nonlinear interaction, as well as minimize feature redundancy and still maintain seizure-relevant information. It is an efficient and robust feature selection method that uses the most informative spectral and statistical features of every EEG epoch of epileptic activity.

3.6 Labeling and Pattern Classification

At this step, EEG segments that are preprocessed were labeled and categorized to be used in predicting seizures. The events of seizure of each patient were marked by expert annotations, EEG segments were divided into two classes: preictal (the state of target seizure prediction) and interictal (the state of the normal baseline). Classification was done using features derived on all channels using two-minute EEG segments.

A Support Vector Machine (SVM) classifier was used because it is very strong in dealing with high-dimensional biomedical data and also because it was able to maximize the distance between classes [43]. The RBF kernel was used because it was determined suitable to model nonlinear decision boundaries. The grid search with five-fold cross-validation on the training data was used to optimize model hyperparameters (C and γ). The data were separated into two-thirds training and one-third testing to ensure that there was a strict separation between the training and the testing sets to avoid cases of leakage of data.

$$\mathrm{SVMStruct} = \mathrm{svmtrain}(\mathrm{K}, \mathrm{label\_class}); \tag{1}$$

$$\mathrm{Result} = \mathrm{svmclassify}(\mathrm{SVMStruct}, \mathrm{F}); \tag{2}$$

Where K is the training pattern matrix, label_class is seizure/non-seizure labels, and F is the test dataset.

The performance of the classification was then measured by conventional measures, such as accuracy, sensitivity, specificity, precision, and F1-score, which is an effective measure of the predictive power of the model on the segment level.

3.7 EEG Segmentation and Seizure Prediction Framework

Accurate temporal labeling and validation are critical in seizure prediction studies to ensure clinical realism and to prevent optimistic bias .

***Preictal and Interictal Definition*:** The time of seizure onset of every patient was determined by expert annotations. A preictal window was a period of time that was set to take place before the occurrence of a seizure. EEG segments obtained in this range were identified as preictal, which is the target class of seizure prediction. EEG segments that were far enough out of seizures and were not coinciding with either preictal or postictal periods were termed interictal. In order to prevent inter-class contamination, the safety margin was added to the seizure events whereby interictal data was not subjected to any transitional brain dynamics that are related to seizure generation.

***Seizure Prediction Horizon and Seizure Occurrence Period*:** The seizure prediction problem was developed based on the Seizure Prediction Horizon (SPH) and Seizure Occurrence Period (SOP) model. The SPH determines the lowest possible duration between a prediction alarm and the quickest potential onset of the seizure, which guarantees effective early warning. The SOP indicates the time slot within which a positive prediction should be followed by a seizure. Despite the fact that the classifier works on EEG segment basis, a series of subsequently occurring preictal predictions inside the established SPH-SOP range are understood as signs of an impending seizure event, which allows clinically meaningful analysis.

3.8 Classification Using Support Vector Machines

The Support Vector Machine (SVM) was used to classify between preictal and interictal EEG segments. The high dimensionality of the biomedical data is well-suited to SVMs, and the margin between classes is maximized, which ensures the robust performance of SVMs. RBF kernel has been chosen because of its capacity to capture nonlinear decision boundaries. Model parameters χ and γ [44].

γ were optimized using grid search with five-fold cross-validation on the training data. The dataset was divided such that two-thirds of the data were used for training and one-third for testing, with strict temporal separation [45].

3.9 Validation Protocol and Data Leakage Prevention

To ensure unbiased performance estimation, a patient-wise and seizure-wise validation protocol was adopted. Training and testing segments originated from different seizure events, and no temporal overlap existed between them. Feature normalization and hyperparameter tuning were conducted exclusively on the training set and subsequently applied unchanged to the test data. This strict separation prevents the model from exploiting subject- or event-specific information unavailable in real-world deployment, ensuring that reported results reflect realistic seizure prediction behavior rather than segment-level memorization .

3.10 Performance Evaluation

Standard classification metrics such as accuracy, sensitivity, specificity, and precision, and F1-score were used to evaluate the prediction performance. Whereas the classification is done on the basis of the segment level, the results are viewed at the level of the seizure-event level summarizing series of positive predictions in the SOP window. The frequency of false alarms is examined with reference to the frequency of their occurrence over time and clinical implications.

4. RESULTS

4.1 Performance Evaluation and Interpretation

The suggested framework is tested based on standard classification measures, such as accuracy, sensitivity, specificity, and F1-score, which are calculated on an EEG segment level. These measures are indicators of the model predictive capacity to distinguish between preictal and interictal EEG episodes and are common in seizure prediction research that utilizes classical machine learning methods.

Segment-level predictions are further interpreted in an event based framework of seizure prediction to improve clinical interpretability. Sequential positive preictal forecasts within the specified seizure occurrence period (SOP) are considered to be an indication of an impending incidence of a seizure. This method of aggregation allows an approximate calculation of the level performance at events with a saving on the computational efficiency.

The frequency of false alarms is examined with regards to the time of the day in the interictal interval. Instead of basing our discussion on raw classification measures only, we also talk about false prediction behavior in the context of continuous EEG monitoring situations, where there is a trade-off between early warning of seizures and reliability of alarms. The view offers clinically relevant understanding of the usability of the system beyond the levels of accuracy of segments.

Table 2 presents the average of all channels for each band in the SVM training set with known status type, where 1 represents the data of a preictal seizure and 0 represents the non-seizure data. The majority of patients signify preictal seizures with a higher average of gamma frequency compared to others. However, the delta frequency is adequate due to its suitable range of (0–3 Hz).

The model was then tested using approximately one-third of the total dataset, and the data were provided without labeling. The SVM algorithm achieved a classification accuracy of 80%, considering all features from all channels after calculating the average for each frequency band (delta, theta, alpha, beta, and gamma). The values 1 and 0 represent seizure and non-seizure signals in the SVM

Table 2: Training data

Patient No.	Avg of Delta	Avg of Theta	Avg of Alpha	Avg of Beta	Avg of Gamma	Status Type
103	**1.198883**	**5.746552**	**12.59417**	**17.1241**	**36.02604**	**0**
104	**1.21228**	**5.505622**	**13.09162**	**16.3542**	**33.73154**	**1**
115	**1.141633**	**5.072661**	**11.33369**	**17.41322**	**43.6457**	**1**
116	**1.003244**	**5.465044**	**11.82678**	**17.96067**	**44.18335**	**0**
118	**0.951062**	**5.077365**	**12.09383**	**17.37192**	**44.6993**	**1**
121	**1.089825**	**5.363961**	**12.1391**	**17.5806**	**41.21606**	**1**
126	**1.036208**	**5.451991**	**11.45035**	**17.63458**	**40.33205**	**1**
301	**0.958673**	**5.087874**	**9.984087**	**22.61629**	**41.85769**	**0**
1031	**0.984752**	**5.38533**	**12.93327**	**17.30924**	**35.82423**	**1**
1041	**0.80432**	**4.997661**	**15.0709**	**17.39076**	**33.39025**	**0**
1151	**0.994173**	**5.159987**	**9.930822**	**17.02519**	**44.17613**	**0**
1161	**0.960849**	**4.984978**	**10.39822**	**17.94219**	**42.4421**	**1**
1181	**1.020978**	**5.103461**	**12.14633**	**17.12482**	**40.35051**	**0**
1211	**1.256477**	**5.365783**	**12.28475**	**17.85125**	**40.00091**	**0**
1261	**0.457959**	**5.145844**	**10.3888**	**16.35782**	**34.4337**	**0**
3011	**0.70686**	**5.08063**	**9.754761**	**22.05798**	**42.44609**	**1**

model. T and F refer to true and false predictions of seizure alarms. These results demonstrate the model's ability to predict a seizure 5 to 10 minutes prior to onset (during the preictal state)

Several factors have been used to evaluate performance, including accuracy, sensitivity, specificity, precision, and F1-score. The result of the confusion matrix (table 3) has shown that high true positive detection and a low false alarm rate, as well as strong separability between preictal and interictal classes. The SVM model correctly identified 4 preictal cases and 4 normal cases, with 1 false positive and 1 false negative. These results correspond to an overall accuracy of 80%, sensitivity of 80%, specificity of 80%, precision of 80%, and an F1-score of 0.80.

Table 3: Confusion matrix of the SVM classifier

Actual \Predicted	Preictal (1)	Normal (0)
Preictal (1)	4 (TP)	1 (FN)
Normal (0)	1 (FP)	4 (TN)

4.2 Frequency-Domain Analysis

The analysis in frequency domain demonstrated that the delta (0.53-3 Hz) and gamma (32-50 Hz) bands had the most significant changes in energy in preictal and interictal states (Figure 3). Preictal periods had high levels of delta and gamma energies, which were very strong discriminating elements. As Table 2 indicates, the delta and gamma frequency bands had a good discriminative ability which is consistent with the literature that relates the beginning of a seizure to low-frequency synchronization of activity and high-frequency bursts of energy.

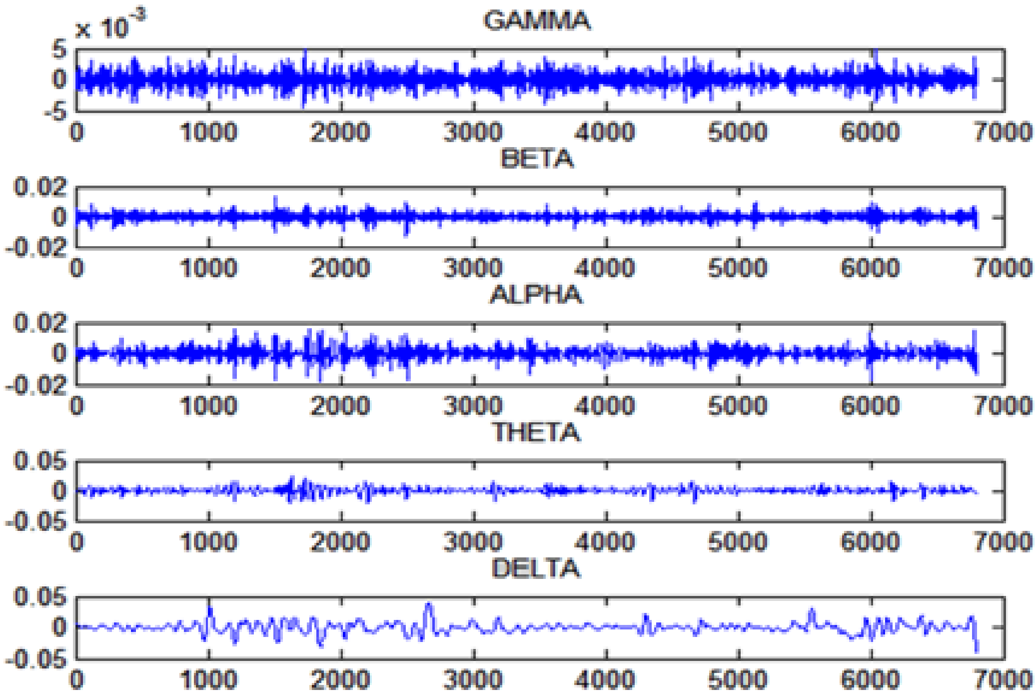

Figure 3: Feature Vectors of the Main Five Bands

4.3 Comparative Analysis

Although the deep learning-based seizure prediction models usually boast of a better classification results, the models require enormous calculation resources, massive training data, and they are also not very transparent in their decision making. Conversely, the suggested framework has interpretability, minimal computational complexity, and easy deployment as its priorities. The obtained performance indicates that classical machine learning methods can be a feasible and effective alternative in the situation when the need to use real-time performance and explainability is paramount.

4.4 Statistical Validation

Cross validation method is used to evaluate the model ‘s stability and deviation in accuracy. The findings of this evaluation have confirmed the stability of our model and deviation in accuracy below 3%. At the same time, the SVM is tested by a Wilcoxon signed-rank test ($p < 0.05$) which confirmed our model surpassed baseline linear classifier with significant statistical difference. To test the predictive model in terms of reliability and efficacy for seizure prediction, computational complexity evolution has been implemented. The findings revealed that SVM computation runs in O(d) time per feature vector (d is the number of fused features), and DWT runs in O(N) per window. The analysis of our data suggested that the predictive model required less than 150 ms to classify and run every 2 minute EEG window in standard hardware. The findings of low latency illustrated the possibility of deploying the proposed model on a wearable device or embedded platforms.

5. DISCUSSION

The employment of DWT and SVM methods provide a reasonable trade-off between efficiency and accuracy of predictive model. The data analysis revealed that the short preictal window enhances the ability of early detection while minimizing false positive. The findings also suggested that our model can work with minimum data and run efficiently on standard hardware. The study also illustrated that both delta and gamma bands generated robust discriminative features in distinguishing preictal from interictal EEG states. The findings of the SVM algorithm attained 80% accuracy within interval time 5 to 10 minutes prior to seizure onset. Even though other studies offered high level of accuracy employing hybrid deep learning techniques, these approaches need large datasets and substantial computational resources. On the other hand, our proposed model is more practical, low cost, suitable for wearable devices and embedded systems. There are several challenges that we have faced in this study. Firstly, the CHB-MIT public dataset employed in this study was limited in terms of diversity where most of EEGs belong to children. Algorithmic performance can be reduced when dealing with missing and unclear data. This imposes challenges in deploying ML approaches in clinical applications. Another challenge is predicting different types of seizures among patients that place limitation on model development. Individual models could offer high level of performance, but it needs to comprehensive data of the patients. When the prediction model runs on wearable devices and computational systems produce low frequency and resolution in real time applications. False positive alarms also remain a major issue in ML-based prediction models, causing unnecessary patient stress and reducing clinical reliability. These limitations highlight the need for more effective predictive ML models in epilepsy diagnostic approaches.

5.1 Limitations

Although the findings are encouraging, there are a number of limitations that should be mentioned. To begin with, the experimental assessment is carried out only through the CHB-MIT EEG dataset, which is mostly composed of pediatric measurements of one medical facility. Therefore, the applicability of the results to adult populations and to multi-center clinical settings is low. Second, the performance of seizure prediction is basically evaluated at the EEG segment level. In spite of interpretation at the segment-levels, an event-level more thoroughly prospective assessment with readily available rates of false-prediction per hour and the predictive range of seizures would be better clinically validated. Third, specific variability of patients is not thoroughly studied in this paper. Although a patient-wise validation procedure is utilized in order to reduce the data leakage, additional research on personalized models and adaptive thresholds can be more robust. Fourth, even though the suggested framework was developed to be deployed in real-time and on wearable devices, experimental validation on embedded or wearable hardware platforms has not been covered in the current study and is another significant direction of future research. Lastly, the existing system uses only the EEG signals. Reliable predictors of seizures and false alarms could be further enhanced by the addition of other physiological modalities, including electrocardiography or oxygenation.

5.2 Future Work

As for our next steps, our ambitions are high. We will focus our efforts on developing this framework to enable proactive, event-based verification, and most importantly, to port it to operate efficiently on small, energy-efficient chips and devices. We will not be content with the current data alone. We aim to test the model on larger datasets from multiple medical centers to ensure the accuracy and comprehensiveness of the results. We also see a very promising opportunity in integrating other vital signs from the body (in addition to EEG) and making the system intelligent enough to adapt to each patient's unique physiology, thus transforming it into a powerful and effective medical tool in practice.

6. CONCLUSION

The study proposed prediction model using ML approaches for seizure prediction. It employed the SVM technique for data brain analysis and employing a frequency-domain approach across several bands to extract features two minutes before the occurrence of an epileptic event. In contrast to other techniques that employed sophisticated complex model for seizures prediction with high accuracy, our proposed model provides lower computational solution, making it suitable for wearable applications. The findings have shown that a high-quality feature extraction due to the employing of the SVM and DWT. The study also provide insight into the importance role of gamma and delta frequency bands in predicting seizure variability. Finally, the study highlights that incorporating physiological parameters, such as heart rate and oxygen saturation, could further enhance the model's predictive accuracy.

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