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K-SVM based advanced EEG Signal Classification Approach for Epileptic Seizure Detection

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The remarkable progress in human-computer interaction technology has yielded significant achievements across diverse scientific domains. Among these advancements, electroencephalogram (EEG) devices have played a crucial role in recording, analyzing, detecting, and categorizing brain signals, thereby facilitating the study of brain health and disorders. Support Vector Machines (SVM) have gained popularity as a reliable method for brain signal classification. However, for complex and non-linear signals like Electroencephalography (EEG), conventional SVM may not be sufficient to accurately classify different brain states associated with cognitive activities. To address this issue, a Kernel-based SVM (K-SVM) approach is employed in this study to classify EEG signals. K-SVM is well-known for its ability to handle non-linear classification tasks. This study highlights the potential of K-SVM as a robust classification approach for EEG analysis. The improved classification accuracy achieved by K-SVM provides valuable insights into the underlying neurophysiological processes of the brain. In this paper a comparative analysis is conducted to classify aplitic seizure classification using both SVM, K-SVM and KNN. This work focuses on the development of a system aimed at assisting clinicians through automated patient monitoring, reduced decision-making time, and improved determination of appropriate medical care. The Temple University Hospital Seizure Corpus (TUH), an extensively used open-source EEG database, is employed for this purpose. The dataset undergoes pre-processing techniques to ensure optimal outcomes, while feature extraction via Fast Fourier Transform (FFT) and Hjorth Descriptor is explored for EEG signal processing.
Keywords: SVM, K-SVM, KNN, FFT, EEG, Machine Learning.

1. Introduction

Machine intelligence has spearheaded revolutionary technological advancements aimed at enhancing the overall quality of life. In certain domains, MI has effectively replaced human involvement and yielded superior outcomes, offering advantages such as reduced time requirements and lower error rates. Particularly in the medical field, where time is often a critical factor determining lifestyle and well-being, numerous devices, techniques, and methodologies have been developed, seamlessly integrating with MI to optimize the human experience. Among these technologies, the EEG has gained as a important role that connects MI to address life's challenges, paving the way for numerous successful research endeavours and studies.

Epileptic seizures are sudden and unpredictable events that significantly impact the quality of life for individuals with epilepsy. Electroencephalography (EEG) signals have proven to be valuable in the detection and understanding of epilepsy. However, the manual analysis of EEG signals by clinicians is time-taking and subject to human error [1,2].

In this study, we propose an intelligent framework that leverages machine learning algorithms to classify epileptic seizures based on EEG signals which undergoes various stages from input signal to output. In the pre-processing stage, raw EEG signals are denoised, filtered, and segmented to extract meaningful information [3]. Next, a set of relevant features is extracted from the pre-processed EEG signals, capturing the distinctive characteristics of epileptic seizures. Final results of the study on the open dataset illustrated the superiority of the developed framework for accurately classifying the ES from the EEG signals [4-5]. The framework achieves competitive classification performance, outperforming traditional manual analysis methods. The selected features offer valuable insights into the underlying patterns and dynamics of epileptic seizures, aiding in the development of effective treatment strategies [6-11].

The proposed intelligent framework has the potential to assist healthcare professionals in the accurate and timely diagnosis of epileptic seizures. By automating the classification process, the framework can significantly reduce the burden on clinicians and improve the efficiency of epilepsy diagnosis. Furthermore, the framework's ability to capture subtle patterns in EEG signals opens avenues for personalized and targeted treatment approaches for individuals with epilepsy [12]. Future research should focus on incorporating real-time EEG monitoring and expanding the framework to handle diverse datasets, ultimately advancing the field of epilepsy diagnosis and treatment.

2. BACKGROUND

2.1 Seizure

Epilepsy, a chronic neurological disorder characterized by recurring seizures, affects millions of people worldwide. According to the World Health Organization (WHO), around 50 million people have epilepsy globally. Seizure incidence rates can vary significantly by country and region. Lower-income countries often have higher rates due to factors like limited access to healthcare, poor sanitation, higher rates of infectious diseases, and greater prevalence of risk factors such as birth injuries, head trauma, and central nervous system infections. The Global

Burden of Disease Study estimates that in 2016, there were approximately 12.9 million new cases of epilepsy worldwide. In India, epilepsy is a significant public health concern. According to the Indian Council of Medical Research (ICMR), there are an estimated 10-12 million people with epilepsy in the country.

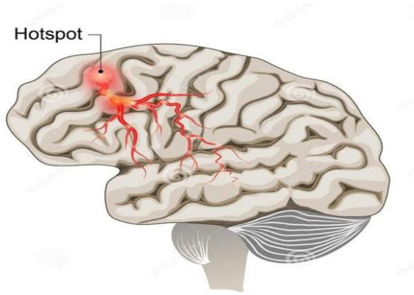


Figure 1: Brain with Aplitic

Epilepsy is a basic neurological disorder (NLD) (Figure 1) which is categorized by irregular electrical motion in the human brain. Seizures are temporary disruptions of brain activity that can cause changes in behaviour, sensations, and consciousness. Epilepsy affects people of all ages and can significantly impact their quality of life. However, in individuals with epilepsy, this electrical activity becomes abnormal, resulting in recurrent seizures. During a seizure, individuals may experience a variety of symptoms, which can vary depending on the type of seizure and the specific areas of the brain affected [12-15]. Some common signs and symptoms of seizures include:

- Temporary confusion or loss of awareness: The person may appear dazed, have a blank stare, or be unresponsive for a short period.

- Uncontrolled jerking movements: This can involve the arms, legs, or other parts of the body. These movements are often repetitive and involuntary.

- Sensory disturbances: Some individuals may experience abnormal sensations such as tingling, numbness, or a "pins and needles" sensation.

- Changes in consciousness or behaviour: Seizures can lead to altered behaviour, emotions, or thoughts. Some individuals may exhibit strange behaviours, engage in repetitive actions, or have emotional outbursts.

- Loss of muscle tone: The person may suddenly go limp, causing them to fall or slump.

- Autonomic symptoms: Seizures can also affect the autonomic nervous system, resulting in changes in heart rate, breathing, sweating, or digestion.

2.2 EEG Data

EEG data plays a crucial role in clinical neurophysiology, neuroscience research, and understanding brain function and dysfunction [16]. It provides valuable insights into the electrical activity of the brain and aids in diagnosing and monitoring neurological conditions.

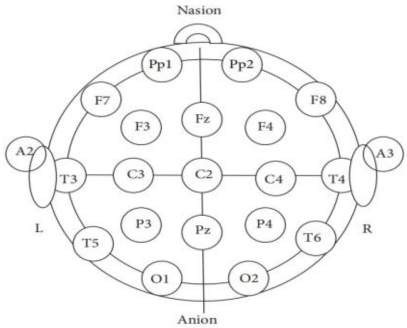


Figure 2: The International Electrodes Distributed System

The procedure for recording an electroencephalogram (EEG) involves the following steps:

- Preparation: The patient is prepared for the EEG recording. This typically involves ensuring that the patient's hair and scalp are clean and free from any products or substances that may interfere with the electrode placement or signal quality.

- Electrode Placement: Electrodes are attached to the patient's scalp using a conductive gel or paste (Figure 2, 3). The number and placement of electrodes can vary depending on the specific recording setup and the purpose of the EEG. Standard electrode placements include those based on the International 10-20 system, which provides a consistent and standardized method for electrode placement across individuals.

- Impedance Checking: Once the electrodes are placed, the impedance or resistance between each electrode and the scalp is checked. This step ensures good contact between the electrodes and the scalp, as poor contact can result in artifacts or poor signal quality. If necessary, the electrodes are adjusted or repositioned to improve contact.

- Recording: The EEG recording begins once the electrodes are properly placed and the impedance levels are satisfactory. The patient is typically instructed to remain still and relax during the recording to minimize artifacts and allow for a clear representation of brain activity. The recording can last for a specific duration, which can vary depending on the clinical or research needs.

- Data Analysis: After the recording is complete, the EEG data is analyzed. This analysis involves examining the patterns and characteristics of the recorded brain activity. The data can be reviewed visually, and various signal processing techniques can be applied to extract relevant information or identify specific abnormalities.

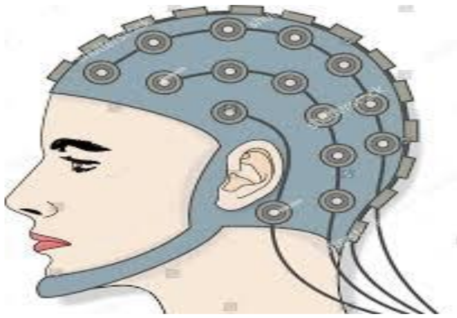


Figure 3: EEG Head Cap

EEG data refers to the recorded electrical activity of the brain captured by an electroencephalogram (EEG). The brain generates electrical signals through the activity of neurons, and these signals can be detected and measured using electrodes placed on the scalp. EEG data consists of voltage measurements over time, reflecting the electrical fluctuations in different regions of the brain. The data is typically recorded as a series of waveforms or traces, with each trace corresponding to the electrical activity captured by a specific electrode [1-2]. The EEG data provides valuable information about brain function and can be used to assess various aspects of brain activity, such as:

- Brainwave Patterns: EEG data reveals different types of brainwave patterns, such as delta, theta, alpha, beta, and gamma waves. These patterns are associated with different mental states, such as deep sleep, relaxation, alertness, and cognitive processing.

- Seizure Activity: EEG is particularly useful in detecting and characterizing seizure activity. Specific patterns in the EEG data can indicate the presence, type, and location of seizures, helping in the diagnosis and treatment of epilepsy.

- Brain Disorders: EEG data can provide insights into various neurological conditions and disorders, such as epilepsy, sleep disorders, brain tumors, and brain injuries. Abnormal patterns or deviations from the normal EEG activity can aid in diagnosing and monitoring these conditions.

- Cognitive and Mental States: EEG data can be used to study cognitive processes, such as attention, memory, and emotional responses. It helps researchers investigate brain dynamics associated with specific tasks, mental states, or disorders like attention-deficit/hyperactivity disorder (ADHD) or Alzheimer's disease.

EEG is a non-invasive technique used to measure and record the electrical activity of the brain. It involves placing electrodes on the scalp, which detect and amplify the tiny electrical signals generated by the neurons in the brain. EEG data provides valuable insights into the brain's electrical patterns and can be used to study various aspects of brain function [7-10]. It is particularly useful in the diagnosis and monitoring of neurological disorders, including epilepsy, sleep disorders, brain tumors, and cognitive impairments. These signals are characterized by different frequency components, which correspond to different brain states and activities. The main frequency bands observed in EEG signals are delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz).

2.3 Dataset

The data utilized in this study was obtained from the largest open-source repository of EEG data, known as the TUH (Temple University Hospital) Groups 288]. The TUH Groups have curated and organized EEG information into multiple file formats, with one of the main file formats being the European Data Format (EDF). The EDF files contain the EEG data samples used in this work. The datasets available in the TUH Groups repository offer a wide range of seizure types along with their corresponding characteristics. It is crucial to carefully select and accurately measure the input data to ensure the effectiveness of the classification technique and to develop a model that meets the specific requirements of the study.

2.4 Performance Evaluation Metrics

- ROC: To evaluate the performance and validate the accuracy of the classification model, five parameters were employed. These parameters include sensitivity, specificity, confusion matrix, classification accuracy, and the Receiver Operating Characteristic (ROC) curve. Sensitivity measures the ability of the model to correctly identify positive cases, while specificity measures the ability to correctly identify negative cases. The confusion matrix provides a comprehensive view of the model's classification results across different classes. Classification accuracy represents the overall accuracy of the model's predictions. The ROC curve visually represents the trade-off between the true positive rate and the false positive rate for different classification thresholds.

- Confusion Matrix: The confusion matrix is a tabular representation that includes four different values based on the predicted and actual data values. It consists of two classes: the actual values (True/False) and the predicted values (Positive/Negative). These options are considered when calculating the confusion matrix, resulting in four possible outcomes: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). By considering these four outcomes, the confusion matrix provides a comprehensive understanding of the model's performance, including the identification of true and false predictions (Figure 4). It allows for the evaluation of both the model's ability to correctly classify instances (TP and TN) and its errors (FP and FN).

Predicted Values

Actual Values

	Positive	**Negative**	
True	True Positive (TP)	False Negative (FN) **Type 2 Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
False	False Positive (FP) **Type 1 Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
	Percision $\frac{TP}{(TP+FP)}$	**Negative Predictaive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

Figure 4: Confusion Matrix Table Values

- K-fold cross-validation: The validation dataset plays a crucial role in K-Fold Cross Validation as it helps in selecting the best parameters for the model. There are various ways to divide the data into folds, such as 90%-10%, 80%-20%, or 70%-30% splits. The number of folds, represented as K, determines how many times the process of training and testing is repeated. The advantage of this method is that it allows us to define the size of the testing data and the number of iterations required [15]. By utilizing K-Fold Cross Validation, we can make use of the entire dataset for both training and testing, leading to a more comprehensive evaluation of the model's performance. Additionally, this method provides a wider range of evaluation metrics, offering a clearer understanding of the data. K-Fold Cross Validation is a valuable technique that allows for better utilization of data and provides a more comprehensive evaluation of machine learning models. It enables the selection of optimal parameters and offers a range of metrics to assess model performance.

3 LITERATURE SURVEY

Seizure detection and classification have gained significant attention in recent years, as they hold promise for paving the way towards seizure prediction [16]. Researchers have extensively studied the components of neurons and transporters to analyze, understand, and detect the underlying causes of seizures. Spike-wave and sharp wave patterns have been identified as common features in seizure analysis [17-19]. However, these patterns are often difficult to detect during epileptic seizures, as patients are usually asleep. To overcome this challenge and the diverse shapes of seizures, numerous techniques has developed for automatic seizure identification using EEG signals [20-21]. It is important to note that seizures may not necessarily be indicative of epilepsy, thus requiring additional tests such as blood and cerebrospinal fluid analysis, as well as CT scans to rule out any brain abnormalities. Adeli et al. [22] utilized wavelet-transforms (WT) to analyze epileptic seizure values, particularly focusing on absence seizures. Paivinen et al.[23] explored seizure recognition through mathematical methods, calculating a group of features from small time windows, including time domain, frequency domain, and nonlinear features. Combining these features demonstrated improved results. Furthermore, Osorio et al. [24] investigated the of seizure detection (SD) based on seizure strength and developed a real-time plan for direct brain stimulation [25]. Various studies emphasize the diverse requirements of seizure detection techniques, which are influenced by different dataset characteristics and circumstances. Pattern recognition techniques have emerged as one approach, focusing on enhancing classification accuracy through feature mining and classification techniques [26]. Mormann et al. (27) uses particularly Hjorth parameters for detect the preliminary stage.

4 PROPOSED FRAMEWORK

The human brain continuously produces electrical indicators that represent the body's various states, whether normal or abnormal. Electroencephalography (EEG) is widely regarded as an important tool for capturing brains even small and weak brain signals. To maximize the benefits of EEG characteristics, it is crucial to carefully select appropriate data, employ suitable pre-processing techniques, and apply effective analysis methods aligned with our objectives. This section focuses on the methodology employed for signal collection using EEG. Subsequently, we delve into the strategies employed for pre-processing, aiming to transform the original data into a suitable domain compatible with the chosen classification technique. Original brain signals to contain unwanted artifacts, which can lead to misdiagnosis. Therefore, pre-processing techniques are implemented to enhance data quality by minimizing the presence of artifacts. Furthermore, we explore the methods utilized for feature extraction, enabling us to obtain the most suitable data that aligns with our model and facilitates achieving the highest accuracy rate. Lastly, we employ machine learning algorithms, specifically Kernel -Support Vector Machine (K-SVM) straightforward classifiers in the final phase of our work. Figure 5 provides a visual representation of the EEG classification techniques approach adopted in this study.

4.1 EEG Data Acquisition

The continuous generation of electrical signals in the brain represents various states, both normal and abnormal. Electroencephalography (EEG) is a widely recognized tool in neurology due to its ability to capture even weak brain signals. To maximize the benefits of EEG data, careful selection of appropriate data, suitable pre-processing techniques, and effective analysis methods are essential. The methodology begins with signal collection using EEG, which involves distributing channels on the scalp and utilizing a system for accurate channel placement. The data size for each class and the frequency rate of the recorded data are also considered. These factors ensure the availability of sufficient and representative EEG data for analysis.

4.2 Data Pre-processing

Pre-processing techniques, including feature reduction and extraction, play a vital role in EEG data analysis. They help in noise reduction, improving data quality, and enhancing the efficiency and accuracy of classification algorithms. By selecting and combining appropriate pre-processing techniques, valuable insights can be extracted from EEG signals, leading to better understanding and interpretation of brain activity (Figure 6).

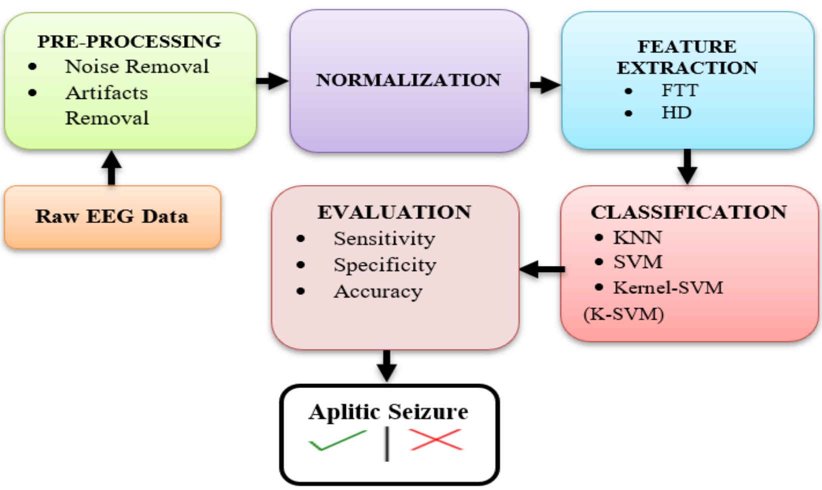


Figure 5: Proposed system architecture

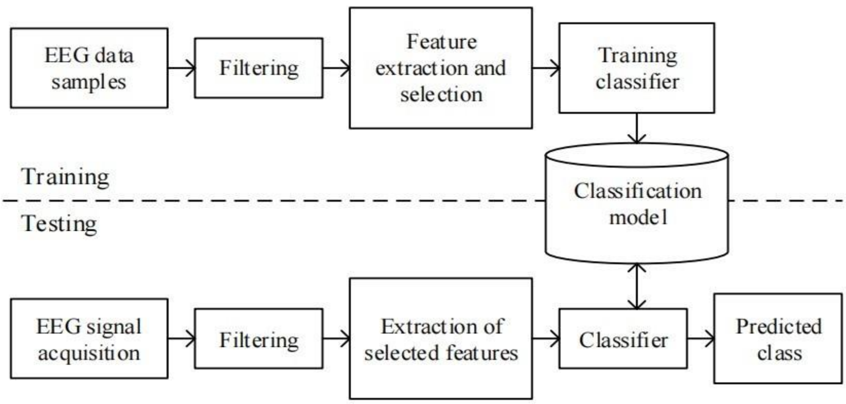


Figure 6: EEG signal processing phases

4.3 Feature Extraction

Feature extraction methods are then applied to extract the most relevant and informative data for the classification model. These techniques aim to capture the distinctive characteristics of EEG signals associated with different classes or states [28]. Extracting meaningful features enables the model to achieve higher accuracy rates and better discrimination between classes.

- Wavelet Transformation: Wavelet transformation is a widely used technique for feature extraction in EEG data analysis, particularly in machine learning-based seizure detection. The wavelet transform allows for the decomposition of EEG signals into different frequency sub-bands, providing a time-frequency representation that captures both temporal and spectral information. One of the key advantages of wavelet transformation is its ability to adapt to different scales or frequencies present in EEG signals. By applying wavelet decomposition, the time series EEG signal can be represented as a set of wavelet coefficients at different scales or resolutions. This decomposition helps identify local changes in the EEG signal across both time and frequency domains.

- Hjorth Descriptor (HD): HD act as an effective feature extraction method for EEG signal analysis in the context of epileptic seizure detection. The Hjorth Descriptor, a set of three parameters that characterize the signal's activity, mobility, and complexity, has been widely utilized in various neurophysiological studies. In this study, the Hjorth Descriptor is employed to extract informative features from EEG signals obtained from patients with epilepsy. These features are then used to train and evaluate machine learning algorithms for seizure detection. The results demonstrate the effectiveness of the Hjorth Descriptor in capturing important characteristics of EEG signals related to epileptic seizures, leading to improved classification performance.

4.4 Normalization

Normalization and standardization are widely used feature scaling techniques in machine learning. Normalization is a crucial step in data preparation, particularly when employing Fast Fourier Transform (FFT) for signal processing. It ensures that all data points are brought to the same range, making them ready for classification. Various methods can be used for data normalization, including Z-score, T-score, MinMax, Logistic, LogNormal, and TanH transformations. Linear transformations like z-score or t-score, also known as standardization, are commonly employed for data normalization.

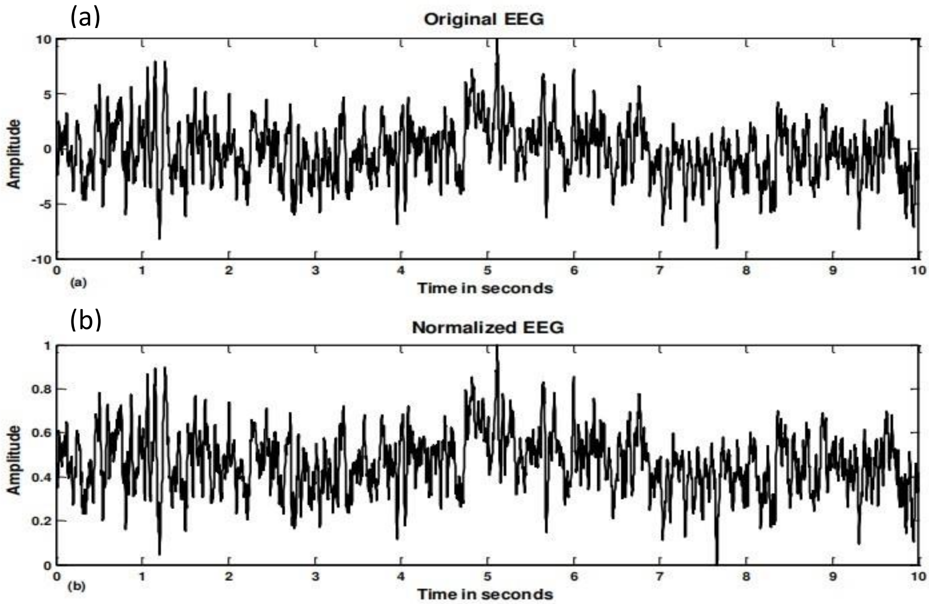


Figure 7: (a) Normal EEG Signals (b) Normalized EEG Signals

These techniques rescale the features, bringing them to a similar range, typically between 0 and 1. Normalized data facilitates easier comparison and serves as input for subsequent classification steps, leading to improved accuracy. It is important to note that data normalization is typically applied individually to each method, and some algorithms may have their own data normalization or scaling techniques. Figure 7, illustrates two types of EEG signals: normal EEG signals and normalized EEG signals.

Next, data preparation techniques are employed to transform the original data into a format compatible with the chosen classification technique. This step aims to address unwanted artifacts that may be present in the original brain signals, which can potentially lead to misdiagnosis. Pre-processing techniques are utilized to enhance data quality by reducing the impact of artifacts.

4.5 Classification

The classification of EEG (Electroencephalogram) data has emerged as a crucial area of research with significant implications for understanding brain functioning, diagnosing neurological disorders, and developing advanced brain-computer interface systems. EEG signals, which reflect the electrical activity of the brain, offer a rich source of information about various cognitive states, such as attention, relaxation, sleep stages, and even pathological conditions like epilepsy. To overcome these challenges, various classification techniques have been explored, ranging from traditional machine learning algorithms, such as Support Vector

Machines (SVM). Kernel-SVM, and K-Nearest Neighbors (KNN) are used in this paper.

- Support Vector Machines (SVM): SVM is a commonly used algorithm. Support Vector Machines (SVM) is a popular machine learning algorithm used for classification and regression tasks. SVMs are effective in handling both linear and non-linear data by finding an optimal hyperplane or decision boundary that maximally separates different classes in the feature space. The key idea behind SVM is to map the input data into a higher-dimensional space, where it becomes easier to find a hyperplane that separates the classes. SVM aims to find the hyperplane that maximizes the margin, i.e., the distance between the hyperplane and the closest data points from each class. This margin maximization leads to better generalization and robustness of the model.

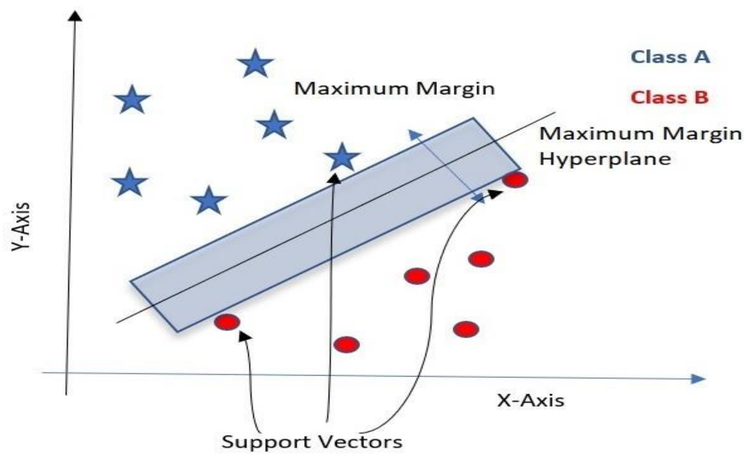


Figure 8: Kernel-Support Vector Machine (K-SVM) Classifier

- Kernel-SVM: K-SVM also known as Kernel-based Support Vector Machines, is an extension of the standard Support Vector Machine (SVM) algorithm that allows for non-linear classification tasks (Figure 8). While traditional SVMs work well for linearly separable data, they may struggle with complex, non-linear datasets where a linear decision boundary is insufficient to accurately separate classes. Kernel SVM addresses this limitation by utilizing a kernel function to implicitly map the input data into a higher-dimensional feature space, where it becomes linearly separable. The kernel function calculates the similarity or distance between pairs of data points in the original feature space and transforms them into a new space. This transformation allows for the discovery of non-linear relationships between the data points.

- K-Nearest Neighbors (KNN): KNN is another MLA commonly applied in seizure detection. In a study [28], KNN was used to separate EEG signals into health and no-healthy seizure classes. The KNN algorithm achieved a classification accuracy and demonstrated its ability to effectively identify seizure patterns in EEG data.

5 RESULTS AND ANALYSIS

In this study, three classification techniques, namely KNN, SVM and K-SVM, were implemented to classify epileptic seizures. These algorithms were chosen for their computational efficiency and speed. The frequency data used in the study had a sampling rate of 250 Hz, with each sample representing a 1-second interval. To mitigate the risk of overfitting, a 5-fold cross-validation technique was employed.

Table 1: Value of Avg Spec, Avg Sen and Accuracy using FFT

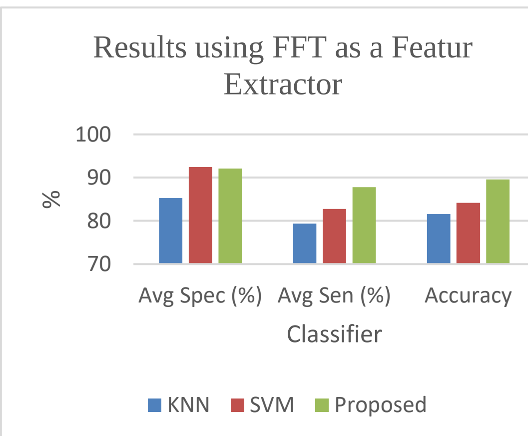
Classifier Model	Avg Spec (%)	Avg Sen (%)	Accuracy	Prediction Time
KNN	85.3	79.4	81.6	4 Minutes
SVM	92.5	82.8	84.2	3 Minutes
K-SVM	92.1	87.8	89.6	2.5 Minutes

Table 2: Value of Avg Spec, Avg Sen and Accuracy using Hjorth Descriptor

Classifier Model	Avg Spec (%)	Avg Sen (%)	Accuracy	Prediction Time
KNN	83.1	77.4	79.3	4 Minutes
SVM	90.6	80.7	82.1	3 Minutes
K-SVM	90.1	85.8	87.6	2.5 Minutes

he results presented in the table showcase the performance of three different classifier models: KNN (K-Nearest Neighbors), SVM (Support Vector Machine), and K-SVM (Kernel-based Support Vector Machine). These models were evaluated based on their average specificity, average sensitivity, and overall accuracy in a classification task (Figure 9 (a) & (b)).

Specificity refers to the ability of the model to correctly identify negative instances or the true negatives. It measures the proportion of actual negative cases that are correctly classified as negative. In the given results, the KNN model achieved an average specificity of 85.3%, while SVM and K-SVM outperformed it with values of 92.5% and 92.1%, respectively. This indicates that SVM and K-SVM exhibited higher accuracy in correctly classifying instances as negative.



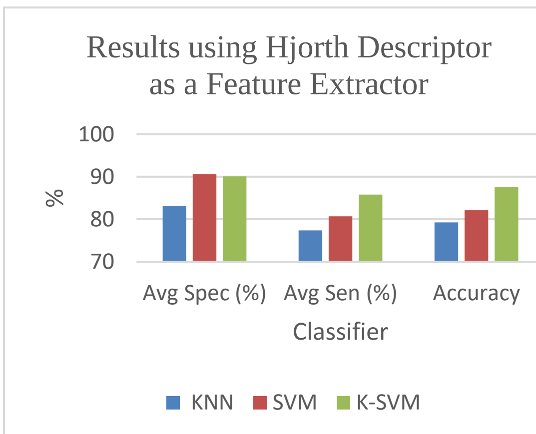


Figure 9 (a): Classification using FFT (b) Classification using HD

Sensitivity, also known as recall or true positive rate, represents the model's ability to correctly identify positive instances or the true positives. It measures the proportion of actual positive cases that are correctly classified as positive. In the results, KNN achieved an average sensitivity of 79.4%, while SVM and K-SVM demonstrated higher performance with sensitivities of 82.8% and 87.8%, respectively. This indicates that SVM and K-SVM had better accuracy in correctly classifying instances as positive.

Accuracy represents the overall performance of the model in correctly classifying both positive and negative instances. It measures the proportion of all instances that are correctly classified. In the given results, KNN achieved an accuracy of 81.6%, while SVM showed improved accuracy at 84.2%. However, K-SVM exhibited the highest accuracy of 89.6%, surpassing both KNN and SVM. This suggests that K-SVM achieved the best overall performance in accurately classifying instances.

Based on the results obtained, it can be concluded that utilizing the FFT feature in conjunction with KNN, SVM and K-SVM classifier, along with the THU dataset, is an effective approach for classifying EEG data. The combination of FFT and these classifiers has demonstrated promising results in accurately identifying epileptic seizures comparative to HD (Table 1 & 2).

6. CONCLUSION

Overall, the results demonstrate that K-SVM outperformed both KNN and SVM in terms of accuracy, specificity, and sensitivity. It highlights the effectiveness of using a kernel-based approach for handling non-linear classification tasks, as K-SVM leverages the power of kernel functions to capture complex relationships between data points. These findings have important implications for applications that require accurate classification, such as medical diagnosis, where the higher accuracy achieved by K-SVM can lead to improved determination of appropriate medical care and decision-making support for clinicians. The work presented in this study is expected to make a significant contribution to the field of EEG signal classification. The models were thoroughly tested under various conditions to achieve the best possible results. Building upon the success of this work, there are several potential future directions that can be explored:

- Testing on Different Datasets: It would be valuable to apply the developed classification techniques to other datasets, possibly involving different neurological disorders. This would help to assess the generalizability of the models and their performance in diverse contexts.

- Improving Classifier Performance: There are several avenues for enhancing the performance of the classifiers. This can be achieved by increasing the amount of available data, addressing issues related to missing data, and exploring advanced feature engineering techniques. Fine-tuning the selection of features and optimizing their representation can also contribute to improved classification accuracy.

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