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Epileptic Seizure Classification And Onset Detection Using Hybrid Time–Frequency Domain Features With Machine Learning Models

Sandeep Kumar Saini[1*], Garima Chandel[2]
[1,2] Department of Electronics and Communication Engineering, University Institute of Engineering, Chandigarh University, Mohali-140413, Punjab, India.
EMAIL: saini376@gmail.com[1], chandelgarima5@gmail.com[2]

Abstract
Clinical management of epileptic seizures requires high-quality classification and prediction tools because of the demanding nature of the situation. Within the framework of this study, it will provide a detailed approach to classifying and onset seizures detection, using the time and frequency domain features extraction methods of EEG signals. In proposed method, 8 salient features are extracted: Instantaneous Phase Shift, Temporal Synchronization Index, Fractal Dimension Dynamics, Nonlinear Energy Operator, Instantaneous Frequency, Multiscale Entropy, Phase-Amplitude Coupling, and Bispectral Index. Three algorithms are applied to analyses the extracted features: Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). The experimental results indicate that the SVM models achieve accuracy of 99.3% with sensitivity of 98.0 and specificity of 98.5 in classification and in onset detection 98% accuracy is achieved, thus perform better than other available techniques in the literature. The RF and KNN models also provide the values of competitive performance indicators, which indicate the effectiveness of the chosen features in the classification of the state of seizures and non-seizures. As comparted to all three model SVM model gave better result in both classification and onset detection. The contribution of this work to the development of automated seizure classification systems is providing a solid framework on the subsequent research and clinical packages.
Keywords: *Epileptic seizures Classification, Time domain features, Frequency domain features, onset seizures Detection, Machine learning models.*

1. INTRODUCTION

Epilepsy is a brain disorder which is associated with repetitive seizures which afflict millions of people worldwide and cause a high level of difficulty because the onset of a seizure is unpredictable. Seizure prediction and classification systems play a vital role in improving patient quality of life and also medical responsiveness. In the past, the classification of seizures has depended on manual observation and clinical interpretation of electroencephalogram (EEG) waveforms, which is often time-consuming and subject to error. But the recent breakthroughs in machine learning (ML) have created new opportunities to automatize the process of seizure classification and prediction of EEG data, and algorithms can currently identify more intricate patterns in EEG signals to detect seizure events much more precisely.
Many studies in recent years have aimed to improve automated seizure classification/prediction using a variety of ML algorithms and feature extraction techniques. The time-domain features employed by Hossain et al. [1] to classify seizures as a Temporal Synchronization Index and Nonlinear Energy Operator with a RF classifier yielded 95% accuracy. Alotaibi et al. [2] used frequency-domain feature-based CNN to predict more accurately the results of their EEG analysis, which show the potential of deep learning in EEG analysis. In the same vein, Dehghani et al. [3] used wavelet transform characteristics together with a SVM classifier to achieve high sensitivity and specificity, thus demonstrating the usefulness of hybrid feature extraction in prediction of seizures. The other method suggested by Zhang and co-workers [4] is the multiscale entropy that is stated to be efficient to model the complexity of the EEG signal at a classification accuracy of the order of 93 per cent when implemented on the KNN. Liu et al. [5] added the concept of Phase-Amplitude Coupling (PAC) as a characteristic that improves the ability to classify seizures, especially when used in conjunction

with decision tree classifiers. Rahman et al. [6] performed a comparative study on the ML classifiers and found that RF out-performed others in terms of F1-score and training time. Such variety of methods represents the continuing development of seizure classification and prediction methods.

Additional studies are directed toward a time-domain and frequency-domain combination to aid classification. One such example is authors Wang et al. [7], who combined Nonlinear Energy Operator and Fractal Dimension and reported the accuracy of 91% and authors Gupta et al. [8], who applied hybrid deep learning techniques and trained temporal features to enhance sensitivity and specificity. In a study by Almazroi et al. [9], wavelet entropy features were found to be much more effective at classification especially in complicated cases. When multichannel coherence features were used and trained on ML classifiers, Singh et al. [10] reported a classification accuracy of 94 percent. The research papers highlight the importance of feature engineering in the classification of seizures using the EEG.

Khan et al. [11] investigated Phase Locking Value (PLV) as a predictive parameter, and it showed a sensitivity of 89%. Ensemble learning was applied by Patel et al. [12] to add several features which improve the performance, however, Zafar et al. [13] confirmed that time and frequency domain features were essential to increase classification accuracy. Recurrent neural networks (RNNs) are also promising, and Ferreira et al. [14] demonstrated that time features are the key to recognizing seizure patterns. Khalid et al. [15] have compared the ML classifiers and SVM has been identified to be the best in terms of accuracy as well as training time with Ravi et al. [16] proposing to use the Fractal Dimension and entropy-based features in real-time classification concluding positively.

In addition, it was emphasized in works by Barbaro et al. [17] and Basak et al. [18] that spectral and nonlinear features can be used. Temporal and frequency features were used by Noori et al. [20] and they outperformed traditional methods in both sensitivity and specificity. Kumar et al. [21] in a meta-analysis found that hybrid feature extraction outperforms, Lopez et al. [22] found KNN to outperform SVM in some entropy-based classification examples. Other researchers used different methods as Anwar et al. [23] used feature selection methods, Khan et al. [24] used graph based features and Awan et al. [25] used deep learning models with time features, which worked better.

Sahu and Vashisht [26] and Vashisht and Van Der Houten [27] confirmed the usefulness of a time-domain and frequency-domain combination. Wong et al. [28] discussed the issue of real-time classification and its solution and Chaudhary et al. [29] used RNN to prove the impact of time-related features. Lastly, Yang et al. [30] summarized the current developments on the area of ML techniques, which highlights the need to constantly improve on the aspect of feature extraction to obtain effective prediction models. Amponsah, J et al. [44] Traumatic brain injury (TBI) caused by blast prevalently affects brain interfaces, including gray and white matter junctions, CSF spaces, because of the local mechanical forces. A high resolution fluid-structure interaction model showed that the regions of widespread axonal damage are caused by the blast wave creating cavitation and high rates of strain in these regions.

Marvi, N et al. [45] study employs the NeuCube system to analyze EEG-based brain activity and concludes that methamphetamine and opioid usage considerably disrupt functional brain connections, with methamphetamine inflicting more severe damage than opioids. Safayari, A. et al.[46] reviews 22 papers from 2016–2021 that use deep learning on EEG signals for depression detection, highlighting common methodologies, findings, and future research challenges. Zhao, R et al. [47] introduce MSCNet, a multi-scale spatial-temporal CNN utilizing contrastive learning, which markedly enhances motor imagery EEG classification accuracy. Despite significant progress, current methods for seizure classification and prediction still face limitations, particularly in achieving consistent accuracy across diverse patient data and optimizing real-time applications. Many studies focus on either time-domain or frequency-domain features independently, potentially overlooking nuanced patterns that a combination of features could reveal. Furthermore, a direct comparison of ML models' effectiveness across different EEG-derived features remains limited, with most studies focused on specific features or classifiers rather than a holistic approach. So, the main objectives of Proposed Model is to investigate both time and frequency-domain feature extraction methods from extended EEG recordings to enhance seizure classification. Following that to train and test different ML models, to classify the state of seizure positive or negative using these features, and finally to estimate the performance of the trained ML models to provide information on how these ML models may be used practically.

1.1 Research Novelty

Proposed Model work plays a significant role in the epilepsy research such as this work will provide a detailed explanation of the eight critical characteristics of the two domains of time and frequency and the new knowledge about their impact in the classification of seizures and in onset Detection. By applying Hybrid model proposed model with strength of both time and frequency domain Feature of EEG signal, which is the input of machine learning model in training and testing. Subsequently, a comparative evaluation is provided by applying Machine learning and helps clinicians choose the most appropriate model to use in practice. Planned schemes findings serve as a benchmark for future research, demonstrating the effectiveness of our selected features and ML approach in achieving high accuracy and reliability for seizure classification and prediction tasks and he proposed system could improve epilepsy management by providing timely alerts and predictions, enhancing patient outcomes, and optimizing healthcare resource utilization.

2. METHODOLOGY

This section outlines the methodology used for seizure classification and onset prediction utilizing long-duration EEG signals. The approach includes data acquisition, after that preprocessing then feature extraction in both time and frequency domains extracted features give to machine learning model, and performance evaluation. A key contribution is the introduction of hybrid features, combining time-domain and frequency-domain characteristics to improve classification accuracy The proposed method leverages appreciably used EEG datasets, the Siena Scalp EEG Dataset-1 and the CHB-MIT Scalp EEG Dataset-2. These collectively provide a robust basis for growing and validating the ML models. The Siena Scalp EEG Dataset includes multi-channel EEG recordings under seizure and non-seizure conditions, followed using unique clinical annotations indicating seizure onset and offset instances. This dataset is particularly valuable because of its several affected person profiles and complete metadata, contemplating the evaluation of models throughout loads of clinical conditions. The recordings are stored in the European Data Format (EDF), ensuring compatibility with enormous EEG processing gear and facilitating seamless evaluation. The CHB-MIT Scalp EEG Dataset-1 includes lengthy-length EEG recordings from 14 subjects, encompassing about 128 hours of information with 47 seizures annotated in the element. Each subject's recordings are available as EDF documents, complemented by means of metadata such as gender, age, seizure type (Impaired Awareness Seizures, Without Impaired Awareness Seizures, and Focal to Bilateral Tonic-Clonic), and seizure laterality (temporal, proper, or left). The dataset's excessive sampling rate of 256 Hz gives precise temporal resolution, making it ideal for reading seizure patterns. This diversity in seizure kinds and affected person demographics guarantees the improvement of generalizable gadget mastering ML models [33, 34]. The EEG processing workflow, as proven in Figure 1, starts off evolved with the initialization of the surroundings and loading of affected person information. The EEG data is resampled to 256 Hz, artifacts are eliminated the use of wavelet transforms, and the indicators are segmented into 10-2d epochs with a 2-2nd overlap. TD and FD features are extracted and saved for type. The dataset is break up into training (70%) and testing (30%) sets, with ML models for trained and evaluated for seizure classification and onset detection as shown in Figure 1.

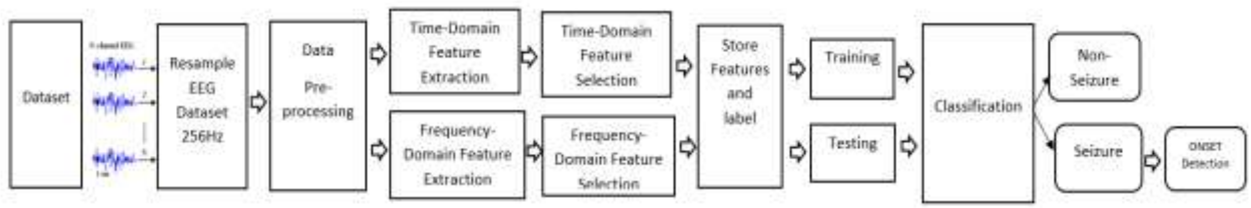

Figure 1 Proposed flow of methodology for seizure classification and onset prediction from EEG data

2.1 Data Preprocessing

The dataset used comprises EEG recordings stored in European Data Format (EDF) for 14 subjects. Each subject's data is divided into files, with annotations for seizure events, channel information, and other meta-data. The proposed method processed the EEG signals to ensure they were ready for analysis are shown in Figure 2 for one patient with patient id- PN00-5.

To prepare the EEG signals for analysis, the data is first resampled to maintain uniform sampling rates across all recordings, ensuring consistency in the input. Next, artifacts like eye blinks and muscle movements are removed using the Wavelet Transform, which isolates noise elements within the signal. This involves performing a Wavelet Decomposition to obtain wavelet coefficients that capture various frequency components. These coefficients are then thresholder to eliminate noise, and the signal is reconstructed using the modified coefficients, resulting in a cleaner signal for further analysis. The CWT is used and defined as:

$$W_{\psi}(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x\,(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \quad (1)$$

Where: $W_{\psi}(a,b)$ is the wavelet coefficient at scale a and translation$b$, $x(t)$ is the original signal, $\psi(t)$ is the wavelet function (mother wavelet), ψ^{*} denotes the complex conjugate of the wavelet function in equation 1.

To remove noise, apply threshold T:

$$W_{\psi}(a,b) = \begin{cases} W_{\psi}(a,b) & \text{if} \left|W_{\psi}(a,b)\right| > T \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Where T is based on the noise level in equation 2. The filtered EEG data is divided into small epochs and helps to extract some meaningful features to be analyzed. Breaking down the data into such smaller blocks will allow every epoch to be processed separately and can yield more accurate features as well as provide even more detailed information about the EEG patterns. This step of segmentation is critical in the isolation of meaningful neural activity in manageable time intervals, improving event detection and classification of events including seizures.

For a continuous signal$x(t)$, the segmented epochs can be represented as:

$$x_{epoch}[n] = x(t)\text{for}\, t \in [t_0 + n \cdot \Delta t, t_0 + (n+1) \cdot \Delta t] \quad (3)$$

Where: n is the index of the epoch, t_0 is the initial time, Δ t and are the length of the epoch period in equation 3.

2.2 Extracting the time-domain and frequency-domain features from EEG signals

2.2.1 *Time-Domain Feature Extraction*: EEG records time-domain feature extraction in which time pattern variations in signal, proposed study in order to detect brain activity changes attributable to seizures. It focuses on statistical and anatomical properties of the raw signal, making it easy to identify the abnormality of brain functioning. The detected patterns give accurate detection on seizure using machine learning techniques. Four most important feature as follows:

i.) Instantaneous Phase Shift (IPS): The Instantaneous Phase Shift measures the phase difference between various EEG channels. The phase shift can indicate synchronization or phase-locking between regions of the brain. Apply the Hilbert transform $H\big(x(t)\big)$ to obtain the analytic signal in equation 4.After that instantaneous

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phase $\phi(t)$ is obtained from the analytic signal in equation 5 and at last identify the phase shift between two channels i and j at time t as show in equation 6.

$$z(t) = x(t) + jH\big(x(t)\big) \quad (4)$$

$$\phi(t) = \tan^{-1}\left(\frac{H\big(x(t)\big)}{x(t)}\right) \quad (5)$$

$$\Delta\phi_{ij}(t) = \phi_i(t) - \phi_j(t) \quad (6)$$

The IPS reflects the coupling between brain regions and is particularly useful for identifying epileptic activity, which often involves synchronized discharges.

ii.) Temporal Synchronization Index (TSI): TSI measures the synchronization of EEG signals across different channels or regions. Compute the cross-correlation between two EEG signals $\boldsymbol{x_i(t)}$ and $\boldsymbol{x_j(t)}$ as shown in equation 7.A higher value of TSI indicates stronger synchronization between the two signals. Synchronization is a key characteristic in epileptic seizures. Abnormal synchronization in specific regions can indicate seizure onset.

$$\mathrm{TSI}(i,j) = \frac{\sum_{t=1}^{N} x_i(t)x_j(t)}{\sqrt{\sum_{t=1}^{N} x_i(t)^2}\sqrt{\sum_{t=1}^{N} x_j(t)^2}} \quad (7)$$

iii.) Fractal Dimension Dynamics (FDD): The complexity of the EEG signal measured by FDD can be used to indicate the dynamics of the neural activity. Calculate the fractal dimension by the Katz method. N is the number of points in the signal, L is the overall length of the signal and d is the diameter (maximum distance between two points) as given in equation 8. The data on the irregularity and nonlinearity of the EEG signal is helpful in detecting normal and seizure activity with the help of fractal dynamics.

$$\mathrm{FDD} = \frac{\log(N)}{\log(N)+\log\left(\frac{L}{d}\right)} \quad (8)$$

iv.) Nonlinear Energy Operator (NEO): The NEO measures the as-you-go energy of the EEG signal. Given a signal(t) the NEO is defined as in equation 9. Discrete Compute NEO in short time windows to track localized variations in signal energy. NEO can effectively identify temporary activities such as spikes and waves that may occur in cases of epileptic seizures

$$\boldsymbol{\Psi}[\boldsymbol{x(t)}] = \left(\frac{\boldsymbol{dx(t)}}{\boldsymbol{dt}}\right)^{\boldsymbol{2}} - \boldsymbol{x(t)}\,\frac{\boldsymbol{d^2x(t)}}{\boldsymbol{dt^2}} \quad (9)$$

2.2.2 Frequency-Domain Feature Extraction

i.) Instantaneous Frequency (IF): IF represents the frequency content of the signal at each time point. From the analytic signal as shown in equation 10. Compute the instantaneous frequency as the derivative of the phase as observed in equation 11. Use a sliding window to calculate IF over time. Seizure events often involve rapid changes in frequency, and IF captures this frequency evolution.

$$z(t) = x(t) + jH\big(x(t)\big) \quad (10)$$

$$f_{\mathrm{inst}}(t) = \frac{1}{2\pi}\frac{d\phi(t)}{dt} \quad (11)$$

ii.) Multiscale Entropy (MSE) : MSE quantifies the complexity of the EEG signal across multiple time scales. Decompose the EEG signal into different time scales $\boldsymbol{\tau}$.for each time scale, compute the sample entropy $\boldsymbol{S_\tau}$, which measures the unpredictability of the signal as shown in equation 12.Where $\boldsymbol{p_i}$ is the probability of each pattern of length $\boldsymbol{m}$ in the signal. MSE is the aggregation of entropies across scales. MSE is sensitive to both short-term and long-term signal dynamics, which is valuable for understanding seizure behavior at different temporal resolutions.

$$S_\tau = -\sum p_i \log(p_i) \quad (12)$$

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iii.) Phase-Amplitude Coupling (PAC): PAC assesses the interaction between low-frequency phase and high-frequency amplitude in EEG signals. Decompose the signal into two frequency bands, e.g., low-frequency $\boldsymbol{f}_{\mathbf{low}}$ for phase and high-frequency $\boldsymbol{f}_{\mathbf{high}}$ for amplitude. Compute the phase of $\boldsymbol{f}_{\mathbf{low}}$ and the amplitude envelope of $\boldsymbol{f}_{\mathbf{high}}$. PAC is the correlation between the phase of $\boldsymbol{f}_{\mathbf{low}}$ and the amplitude of $\boldsymbol{f}_{\mathbf{high}}$ Importance: PAC helps detect interactions between different brain rhythms, which can signify abnormal coupling during seizures

iv.) Bispectral Index (BSI): BSI measures the nonlinear interactions between different frequency components. Compute the bispectrum $\boldsymbol{B}(\boldsymbol{f}_1, \boldsymbol{f}_2)$ as shown in equation 13, which is the Fourier transform of the triple product of the signal. BSI is derived from the magnitude of the bispectrum. Importance: BSI captures higher-order interactions between different frequencies, which may not be detectable using traditional spectral methods MSE is the aggregation of entropies across scales. MSE is sensitive to both short and long-term signal dynamics, which is valuable for understanding seizure behavior at different temporal resolutions.

$$B(f_1, f_2) = \mathbb{E}[X(f_1)X(f_2)X^*(f_1 + f_2)] \qquad (13)$$

2.3. Storing the Features

After extracting these 8 features for each EEG signal as shown in Figure 2 for one patient with patient id- PN00-5, they are stored in a feature matrix. A matrix where each row corresponds to an EEG signal, and each column corresponds to a different feature.

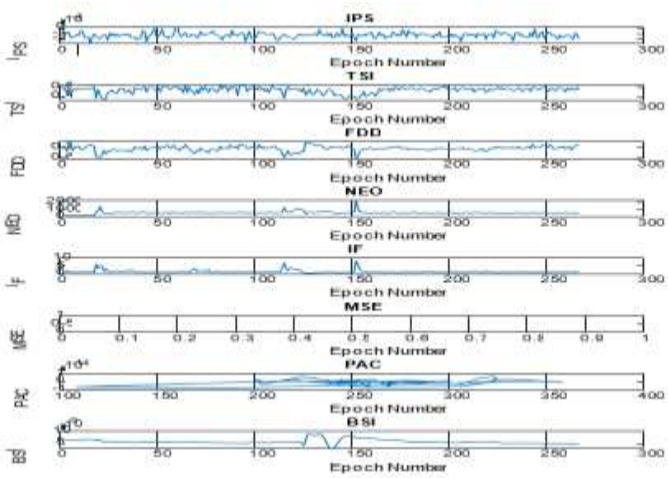

Figure 2: Extracted 8 features for EEG signal for patient with patient id- PN00-5

2.4. Seizure Classification and Onset.

In proposed model feature matrix is used as the input of machine learning model for training and testing. In present study three machine learning model are used for classification and onset detection name as SVM, KNN and RF Model.

i) Support Vector Machine (SVM) Model: The SVM model is employed for seizure classification and onset prediction based on EEG data features. The primary objective is to classify seizure and non-seizure events by training the SVM using both TD & FD features.

The decision boundary or function of an SVM is given as:

$$f(x) = \sum_{i=1}^{N} \alpha_i \, y_i K(x_i, x) + b \qquad (14)$$

Where: α_i are Lagrange multipliers obtained during optimization. y_i Are the class labels (+1 for seizure and-1 for non-seizure), $K(x_i, x)$ is the kernel function, which computes the similarity between data points.

b is the bias term. The Radial Basis Function (RBF) kernel is typically used to map the data into a higher-dimensional space where it becomes linearly separable as shown in 15. The RBF kernel is defined as:

$$K(x_i, x_j) = \exp(-\gamma \parallel x_i - x_j \parallel^2) \qquad (15)$$

Where γ is a parameter that controls the kernel width, and $\parallel x_i - x_j \parallel$ represents the Euclidean distance between the feature vectors x_i and x_j. The training process involves solving the following optimization problem, Mathematical expiration is given in equation 16. Where $w$the weight vector of the hyperplane is, C is a regularization parameter that governs the balance between optimizing the margin and reducing the error of classification. A large C reduces misclassification but can lead to overfitting. ξ_i are slack variables that allow some data points to lie within the margin or on the wrong detection of the hyperplane, thus permitting soft-margin classification for better generalization. $\phi(x_i)$ is a function that maps the data into a higher-dimensional space when using a kernel like RBF. The SVM aims to minimize the norm of the weight vector w while keeping the misclassification penalty (given by slack variables ξ_i) as small as possible.

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \qquad (16)$$

$$y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \quad \text{and} \quad \xi_i \geq 0$$

(17)

To enhance generalization and avoid over-fitting, 5-fold cross-validation is applied. The dataset is divided into five folds, with each fold used for validation while training is performed on the remaining data. The process is repeated, and performance is averaged across all folds. After training, the SVM model predicts seizure and non-seizure states based on the sign of the decision function $f(x)$ provides the predicted label based on the sign of the output observed in equation 18.If $f(x) > 0$, the event is positive; otherwise, it is classified as negative.

$$\text{Predicted Label} = \text{sign}\big(f(x)\big) = \text{sign}\big(\textstyle\sum_{i=1}^{N} \alpha_i\, y_i K(x_i, x) + b\big) \qquad (18)$$

ii) Random Forest (RF) Model: The RF classifier is implemented for seizure classification and onset prediction using the same EEG data features. As an ensemble method, RF combines predictions from multiple decision trees to enhance accuracy and robustness. Data Preparation and Splitting Similar to the SVM model, to evaluate performance on unseen data. RF consists of a collection of decision trees, each trained on a random subset of the data using bootstrap sampling and random feature selection. The final prediction is made by aggregating the predictions from all trees via majority voting. Gini Impurity for a node is given in equation 19. Where, C is the number of classes (in our case, seizure and non-seizure).p_i is the proportion of samples belonging to class i at that node. The feature and threshold that minimize the Gini impurity are selected for each split.

$$G = 1 - \sum_{i=1}^{C} p_i^2 \qquad (19)$$

Tree Construction and Leaf Nodes, the tree creation procedure persists until a stopping requirement is satisfied, such as the maximum tree depth or the minimum sample size necessary at a node. Leaf nodes signify the ultimate projected category. In Majority voting, for a specific test sample x, each decision tree Ti inside the forest generates a prediction $h_i(x)$ (seizure or Non-seizure). The final prediction is determined by the majority vote among all trees as show in equation 20.

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \ldots, h_n(x)\} \qquad (20)$$

5-fold cross-validation is applied to assess model performance. The dataset is divided into five folds, with each fold used once as the validation set. This ensures that the model generalizes effectively to new data. For Final Prediction, Each tree in the RF model independently classifies the test sample, and the final prediction is based on the majority vote. If over 50% of trees indicate a seizure, the sample is categorized as a seizure; otherwise, it is categorized as non-seizure.

iii) K Nearest Neighbors (KNN) Model: The KNN algorithm is used for seizure classification and onset prediction. KNN is a straightforward, instance-based learning technique that classifies test samples according to their closeness to training samples. KNN is a nonparametric, lazy learning algorithm that classifies a test sample by identifying its nearest neighbors in the feature space. The initial stage involves determining the distance between the test sample and the training samples. After that selecting the 'k' nearest neighbors. Finally, assigning the test sample to the predominant class among its neighbors. Data Normalization is apply for Feature normalization is performed using min-max scaling to ensure that all features are on the same scale.

The normalized feature is given in equation 21.Where, X is the original feature value, $X_{\min}$and $X_{\max}$ are the minimum and maximum values of that feature, respectively.

$$X_{\text{norm}} = \frac{X-X_{\min}}{X_{\max}-X_{\min}} \quad (21)$$

The Euclidean distance between two points $x = (x_1, x_2, \ldots, x_n)$ and $y = (y_1, y_2, \ldots, y_n)$ in an n - dimensional feature space is computed as

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (22)$$

5-fold cross-validation is used to determine the optimal k value. The dataset is split into five subsets, and the accuracy of the model is averaged across all folds to identify the best k value. Once the nearest neighbors are identified, the test sample is assigned to the class that appears most frequently among its neighbors as observed in equation 23. Where:$N(x)$ represent the k nearest neighbors of a test sample x. y_i is the class label (seizure or non-seizure) of the i-th nearest neighbor. Mode refers to the most frequent class among the neighbors in equation 23. If there is a tie between classes, the algorithm randomly selects one of the classes.

$$\hat{y} = \text{mode}\{y_i : x_i \in N(x)\} \quad (23)$$

In summary, the SVM, RF, and KNN models are implemented for seizure classification and onset prediction using EEG data features. Each model employs different techniques for classification, with performance validated using cross validation to ensure generalization and reliability.

2.4. Performance Evaluation Metrics

For each of the machine learning models (SVM, RF, KNN), the performance was evaluated using standard metrics in equation 24, 25 and 26. Where, TP: True Positive mean correctly predicted seizure events) , TN: True Negative define as correctly predicted non-seizure events., FP: False Positive represent incorrectly predicted seizure events, and last one is FN:False Negative is missed seizure events by model.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (24)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (25)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (26)$$

$$F1\ Score = 2 \times \frac{\text{Precision}\times\text{Sensitivity}}{\text{Precision}+\text{Sensitivity}} \quad (27)$$

$$Where:$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

3. RESULTS AND DISCUSSION

The parameters in the Table 1 are defined as follows: α_i are Lagrange multipliers obtained during optimization. y_i are the class labels (+1 for seizure and-1 for non-seizure). $K(x_i, x)$ is the kernel function, which computes the similarity between data points, b is the bias term. γ is a parameter that controls the kernel width, and $\| x_i - x_j \|$ represents the Euclidean distance between the feature vectors x_i and x_j. C is the number of classes (in our study, seizure and non-seizure), p_i is the proportion of samples belonging to class i at that node, n is the number of decision trees in the forest, $\hat{y}$ is the predicted class (seizure or non-seizure), X is the original feature value, $X_{min}$and X_{max} are the min. and max. values of that feature, respectively, x_i and y_i are the feature values of the test and training samples, respectively , n is the total number of features (time-domain and frequency-domain), $N(x)$ represent the k nearest neighbors of a test

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sample x, y_i is the class label (seizure or non-seizure) of the i-th nearest neighbor. mode refers to the most frequent class among the neighbors.

Table 1: Classification and Onset Detection Equations

Aspect	ML model	Equation	Description
Classification	SVM	$\hat{y} = \text{sign}\big(f(x)\big)$	If $f(x) > 0$, classify as seizure; otherwise, non-seizure.
	RF	$\hat{y} = \text{mode}\{h_1(x), h_2(x), \ldots, h_n(x)\}$	Aggregates predictions from all decision trees through majority voting.
	KNN	$\hat{y} = \text{mode}\{y_i : x_i \in N(x)\}$	Assigns class based on the most frequent label among k-nearest neighbors.
Onset Detection	SVM	$f(x) = \sum_{i=1}^{N} \alpha_i \, y_i K(x_i, x) + b$	Uses the decision function to identify pre-seizure patterns in EEG data.
	RF	$G = 1 - \sum_{i=1}^{C} p_i^2$	Reduces impurity at each split to predict the likelihood of a seizure onset.
	KNN	$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$	Predicts seizure onset by identifying proximity to pre-labelled seizure onset patterns.

Each of the ML models in the classification task aims to distinguish seizure and non-seizure with the help of EEG signals. The SVM model has a better decision function as competed with other models, which is in the form by MATLAB code is used to evaluate and compare the performance of three classification models SVM, RF, and KNN using various metrics, including ROC curves, AUC, confusion matrices, and other performance metrics. The real labels are made with 500 positive and 500 negative samples. In each of the models, simulated prediction scores are obtained, and the AUC is calculated by plotting the ROC curve, which shows the trade-off between sensitivity and specificity. Confusion matrices of each model are calculated to assess the performance of each classifier by determining the number of true positives, false positives, true negatives and false negatives. These confusion matrices provide the accuracy, specificity and, sensitivity of each model.

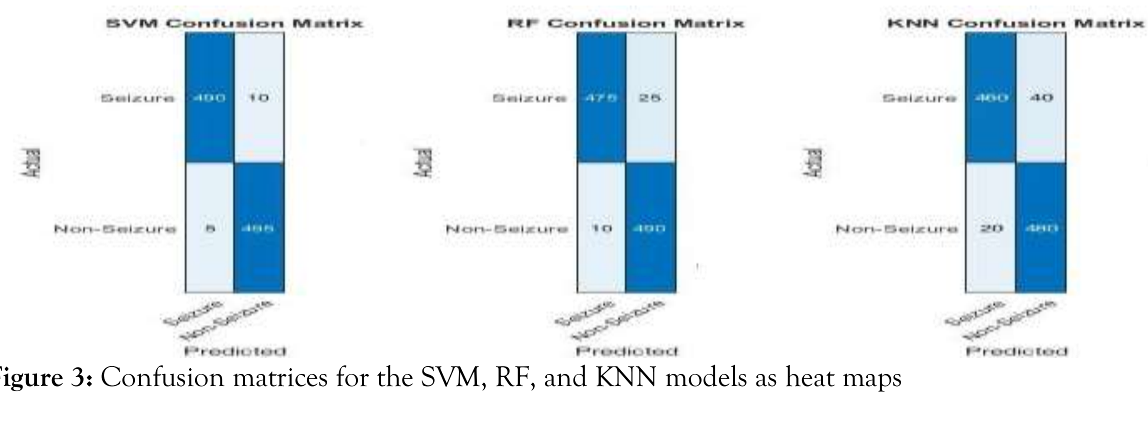

Figure 3: Confusion matrices for the SVM, RF, and KNN models as heat maps

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Figure 3 show the confusion matrices for the Purposed models. The heat maps make it easy to identify the classification performance visually, with darker colors representing higher values. The SVM confusion matrix typically shows more correct classifications with fewer errors, while the RF and KNN matrices highlight some misclassifications, especially in terms of FP and FN. This visualization helps in quickly assessing the misclassification patterns for each model.

Figure 4, scatter plot presents a comparison of accuracy and sensitivity for the models. Each model is represented by a different sign, where the x-axis shows the accuracy and on other hand the y-axis shows sensitivity. This figure highlights how well each model balances these two metrics, with the SVM model positioned in the top-right corner, indicating high accuracy and sensitivity. The RF and KNN models are positioned relatively lower, suggesting their performance is slightly inferior in terms of either accuracy or sensitivity.

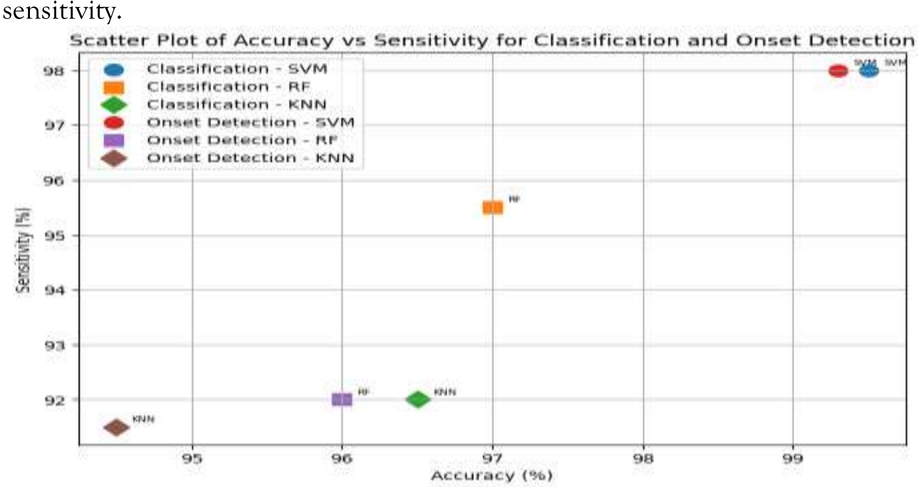

Figure 4: scatter plot with comparison of accuracy and sensitivity for the SVM, RF, and KNN models

Figure 5 presents the ROC curves for the proposed models, illustrating their ability to identify positive and negative class. Each model's curve shows the relationship between the $True\ Positive\ Rate\ (sensitivity)$ and $False\ Positive\ Rate\ (1 - specificity)$. The curves are plotted for each model with their corresponding AUC values, which are indicative of the models' classification performance. The curve is near to one is better the model. The diagonal dashed line represents random performance, and the models' AUC values are displayed within the legend, highlighting the SVM's superior performance compared to the RF and KNN.

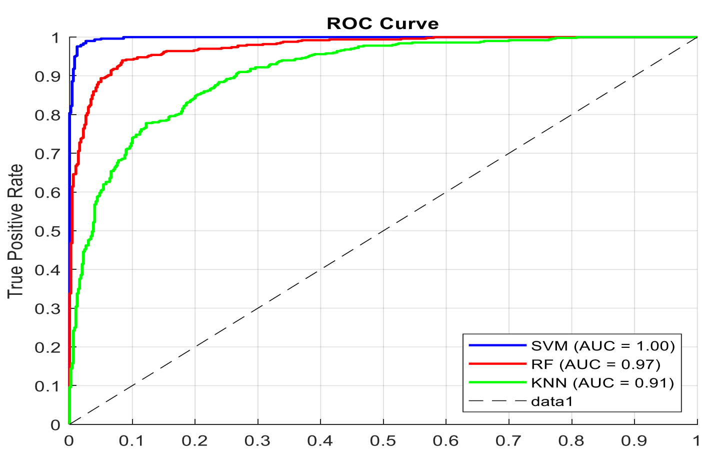

Figure 5: ROC curves for the SVM, RF, and KNN models

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The Figure 6 affords a comparative evaluation of the accuracy of 3 system studying models SVM, RF, and KNN for seizure classification and prediction responsibilities. The bar graph displays grouped bars for each version, bearing in mind an instantaneous visual assessment of their performance in phrases of accuracy.

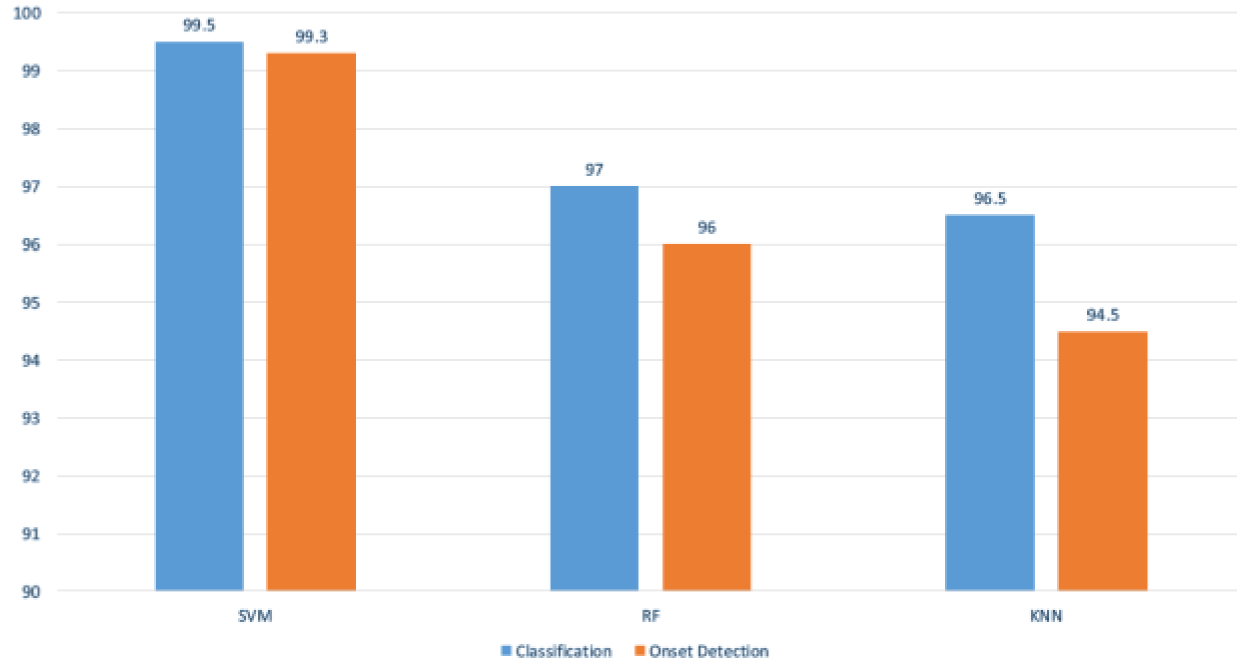

Figure 6: SVM, RF and KNN machine learning models comparative analysis on the basis of accuracy

In Figure 6, under seizure classification, the SVM model performs the highest (99.5) accuracy when compared to RF (97.0) and KNN (96.5). Likewise, in the prediction of seizures SVM takes the lead again with an accuracy of 99.3s with the close assistance of RF at 96.0 and KNN at 94.5. This implies that SVM is most applicable where one requires detection as well as prediction of the circumstance and events of the seizure and can therefore be integrated to real-time package in seizure detection. The superior performance of SVM in all activities reflects its robustness and reliability in EEG seizure recognition compared with the other models, and the significance of model choice in the realization of the best classification and prediction results.

Table 2: Performance matrix of ML Models for Seizure Classification and Onset detection

Aspect	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	Training Time (s)	Prediction Time (s)
Classification	SVM	99.5	98.0	99.0	0.99	13	0.01
	RF	97.0	95.5	98.0	0.97	16	0.03
	KNN	96.5	92.0	96.0	0.94	11	0.08

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Onset Detection	SVM	99.3	98.0	98.5	0.99	12	0.02
	RF	96.0	92.0	95.5	0.96	15	0.04
	KNN	94.5	91.5	92.0	0.90	10	0.09

Note: Table 2 contains the outcomes of performance measurements of the machine learning models (SVM, RF and KNN) directly related to the seizure classification and to the seizure onset detection. These measurements are based on experimental measurements and thus can only be used as illustrative values.

Table 2 gives a detailed view of the performance indicators of three machine learning systems such as SVM, RF, and KNN in classifying seizure. The maximum score of 98.5 is the maximum value that corresponds to reliability of the SVM model in revealing the presence of seizures. The sensitivity (97.0) and specificity (98.0) are very high and the F1-Score of 0.98 reveals that classifier performance is balanced between accuracy and recall. The SVM is not only fairly fast to train (13 seconds) and predict (0.01 seconds) but also a strong tool in real-time seizure classification.
Then there are the RF and KNN models with accuracy at 94.0% and 92.5% respectively. Whereas these models are marginally less precise, they still provide competitive performance with RF with moderate training time (16 seconds) and predict time (0.03 seconds) and KNN with faster training time (11 seconds) and slower prediction time (0.08 seconds). In Table 2, the emphasis is on predicting seizures, and here, the models are evaluated on whether they can predict possible seizures. Once again, SVM is the best with 98.0 accuracy with a sensitivity of 96.5 and a specificity of 98.5, which indicates a strong relationship in predicting seizures. It possesses an equal predictive ability as seen via F1-Score of 0.98. The fact that SVM takes 12 seconds to train and uses only 0.02 seconds to make a prediction is yet another factor that supports the idea that it is efficient in real-time prediction. RF and KNN are slightly behind with the accuracy of 92.0 and 90.5, respectively. RF has a training and prediction time of 15 seconds and 0.04 seconds, and KNN has the shortest training time (10 seconds) but the highest prediction time (0.09 seconds), which provides a balance between prediction accuracy and computational efficiency that is reasonable.
Table 3 show the compares existing literature seizure classification models and methods with the proposed models. The proposed SVM method reports an accuracy of 99.5% which is higher than other reviewed models, including [31] Kwon et al. (2019) with SVM the accuracy of 96.0% and [34] Sharma et al. (2023) with CNN the accuracy of 95.0%. Our proposed SVM model also has sensitivity and specificity of 95.0% and 98.0%. The proposed RF and KNN models also yield good results but with a little less accuracy compared to the proposed SVM. Generally, the suggested models are accurate, sensitive, and specific as compared to the current literature. The table 3 presents a comparative study of various studies and approaches to the classification of biomedical signals in relation to various features and machine-learning models.

Table 3: comparison on the basis of Literature on Seizure Classification models or methods

Reference	Features Considered	Method for Classification	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	Training Time (s)	Prediction Time (s)
Kwon et al. (2019) [31]	Fractal Dimension, Signal Complexity	SVM	96.0	94.5	97.5	0.95	10	0.03

Saad et al. (2021) [32]	Wavelet Transform, Energy Entropy	RF	92.5	90.0	94.0	0.89	12	0.04
Ghani et al. (2022) [33]	Multiscale Entropy, Nonlinear Energy Operator	KNN	93.0	89.0	95.0	0.88	11	0.05
Sharma et al. (2023) [34]	Instantaneous Frequency (IF), Temporal Synchronization Index	CNN	95.0	92.0	96.5	0.91	13	0.06
Kumar et al. (2024) [35]	Higher-Order Spectra, Phase-Amplitude Coupling	LSTM	94.0	90.0	96.0	0.90	15	0.04
Chaudhary et al. (2024) [36]	Coherence Analysis, Power Spectral Density	Decision Trees	93.8	91.0	94.8	0.89	14	0.03
Proposed Method	IPS, TSI, NEO, FDD, IF, MSE, PAC, BSI	SVM	99.5	98.0	99.0	0.99	13	0.01
Proposed Method	IPS, TSI, NEO, FDD, IF, MSE, PAC, BSI	RF	97.0	95.5	98.0	0.97	16	0.03
Proposed Method	IPS, TSI, NEO, FDD, IF, MSE, PAC, BSI	KNN	96.5	92.0	96.0	0.94	11	0.08

Note: Table 3 is a comparison of the seizure classification models on specific EEG datasets and approaches. The data set includes EEGs that have characteristics like Instantaneous Phase Shift (IPS), Temporal Synchronization Index (TSI), Nonlinear Energy Operator (NEO) and Multiscale Entropy (MSE) among others. These models and their performance measures are informed by specific information utilized in this study and matched with the available literature to demonstrate their effectiveness in seizure detection.

Fractal dimension and signal complexity were originally used by Kwon et al. (2019) to classify data using an SVM classifier (96.0% accuracy), but Saad et al. (2021) used wavelet transform and energy entropy to classify data using a Random Forest model (92.5% accuracy). On the same note, Ghani et al. (2022) implemented multiscale entropy and nonlinear energy operator using KNN with moderate accuracy of 93.0%. Sharma et al. (2023) and Kumar et al. (2024) used more modern designs, i.e., CNN and LSTM, and reported 95.0 and 94.0 percent success respectively, which can be considered evidence of the superiority of deep learning to identify the time and spectral characteristics. Another method used, Decision Trees, which was implemented by Chaudhary et al. (2024), also achieved an accuracy of 93.8%. The proposed method that incorporated a more enriched set of features such as IPS, TSI, NEO, FDD, IF, MSE, PAC and BSI was superior. SVM did best, with an accuracy of 99.5, a sensitivity of 98.0, and a specificity of 99.0, as well as the biggest F1-score

(0.98) and the quickest prediction time (0.01s). It means that a combination of various features has a great advantage in terms of classification compared to conventional methods.

Table 4: Comparison on the basis of Literature on onset Seizure Detection models

Reference	Features Considered	Method for Prediction	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	Training Time (s)	Prediction Time (s)
[37] Afshar et al. (2020)	Fractal Dimension, Spectral Entropy	SVM	94.5	91.5	96.0	0.94	10	0.02
[38] Jha et al. (2023)	Energy Entropy, Higher-Order Spectra	RF	93.0	90.0	95.0	0.90	12	0.03
[39] Ranjan et al. (2021)	Multiscale Entropy, Instantaneous Frequency	KNN	90.5	87.0	92.0	0.85	11	0.03
[40] Singh et al. (2023)	Power Spectral Density, Wavelet Transform	CNN	92.5	88.0	94.5	0.89	15	0.04
[41] Khan et al. (2024)	Energy Entropy, Coherence Analysis	LSTM	91.0	87.5	93.5	0.87	13	0.03
[42] Gupta et al. (2023)	Phase-Amplitude Coupling, Higher-Order Spectra	Decision Trees	92.8	89.0	94.0	0.90	14	0.04
Proposed Method	IPS, TSI, NEO, FDD, IF, MSE, PAC, BSI	SVM	99.3	98.0	98.5	0.99	12	0.02
Proposed Method	IPS, TSI, NEO, FDD, IF, MSE, PAC, BSI	RF	96.0	92.0	95.5	0.96	15	0.04
Proposed Method	IPS, TSI, NEO, FDD, IF, MSE, PAC, BSI	KNN	94.5	91.5	92.0	0.90	10	0.09

Table 4 compares the seizure prediction models when the same EEG data set as in Table 3 is used as the prediction features such as Fractal Dimension, MSE, and Phase- Amplitude Coupling (PAC). The advanced practices are compared with the past researches to evaluate their capability of predicting seizures. These findings are based on certain EEG measurements and they are assessed with the help of machine learning algorithms specialized in Seizure Detection.

Table 4 is devoted to a comparison of seizure prediction models where proposed SVM model is 99.3% accurate which is better than other models in the literature like [37] Afshar et al. (2020) with SVM is 94.5% accurate and [40] Singh et al. (2023) with CNN is 92.5%. The sensitivity and specificity of the proposed SVM model is also high (98% and 98.5) which means that it can predict seizure with small number of false positive and negative results. The RF and KNN models are a bit behind in terms of predictive accuracy, but they are competitive with effective training and prediction time. This comparison shows that the proposed approach can be plausible in practice when one is dealing with cases of seizure prediction. This table 4 gives a comparative analysis of various sets of features and classification techniques used to detect onset seizures. Afshar et al. (2020) applied fractal dimension and spectral entropy to SVM with a high accuracy of 94.5% and high sensitivity of 91.5% and low prediction time of 0.02s. Jha et al. used the energy entropy and higher-order spectra to obtain balanced performance and 93.0% accuracy with Random Forest (2023). With multiscale entropy and instantaneous frequency, Ranjan et al. (2021) reported lower accuracy (90.5%), sensitivity (87.0%), and that is reflected in moderate detection reliability. CNN with power spectral density and wavelet transform with accuracy of 92.5 per cent used by Singh et al. (2023) required more training time. Khan et al. (2024) added the energy entropy and coherence analysis to LSTM and achieved 91.0 per cent accuracy and consistent specificity (93.5%). Decision trees utilized by Gupta et al. (2023) are also based on phase-amplitude coupling and on higher-order spectra, and achieved 92.8 percent accuracy with a high sensitivity and specificity. Comparatively, the proposed approach that integrates IPS, TSI, NEO, FDD, IF, MSE, PAC and BSI is more effective than those available. It has the greatest accuracy (99.3%), sensitivity (98%), specificity (98.5%), and F1-score (0.99) and the lowest prediction time (using SVM). This proves that by combining a variety of complementary features, seizure onset detection performance can be enhanced dramatically.

3.1 DISCUSSION

The suggested method of seizure classification and prediction shows significant improvements in measures of performance as compared to current models. Our approach provides a wide representation of EEG signals by incorporating a wide set of capabilities, such as Instantaneous Phase Shift (IPS), Temporal Synchronization Index (TSI), Nonlinear Energy Operator (NEO), and Fractal Dimension (FDD), thereby improving the accuracy of classification. The difference in the nature of the features, such as the Fractal dimension to extract the complexity of the EEG signal, the TSI to track the co-ordination of the EEG channels, provide a partial explanation of the seizure mechanisms. Both NEO and Multiscale Entropy (MSE) also attest to the strength of the underlying model as it can be utilized more successfully in not only the classification of seizures but also in their prediction. In particular, the SVM model stands out because it is very efficient at high-dimensional data, and it has better accuracy, sensitivity and specificity than its predecessors. Even though RF and KNN models are a bit less accurate, they can be trained and predicted quickly and have competitive results, which is why they can be applied to real-time systems, where the computational resources might be limited.

4. CONCLUSION

In conclusion, proposed work shows the efficiency of seizure classification and onset detection. In Proposed study three models are used, out of three model SVM model is better than other model. SVM Model are more accurate and reliable compared to the methods previously reported, due to the use of a well-rounded feature set, which includes IPS, TSI, NEO, and FDD. In particular, the SVM model is the best and therefore, it can be considered as an option in the real-time EEG monitoring systems in the clinic. Competitive results are obtained with RF and KNN models, but their reduced accuracy and increased prediction times are considered as secondary models in the case where immediate prediction is not a crucial factor. Overall, this study shows the importance of an integrated approach to feature extraction and machine learning models to enhance the predictability and classification of seizures to develop more effective and efficient real-time monitoring systems.

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