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RESEARCH ARTICLE

Automated Multi-Class Seizure-Type Classification System Using EEG Signals and Machine Learning Algorithms

S. ABIRAMI[1], TIKARAM[1], M. KATHIRAVAN[2], RAJAMANICKAM YUVARAJ[3], RAMSHEKHAR N. MENON[4], JOHN THOMAS[5], P. A. KARTHICK[6], (Member, IEEE), A. AMALIN PRINCE[7], (Senior Member, IEEE), AND JAC FREDO AGASTINOSE RONICKOM[1]

[1]Computational Neuroscience and Biology Laboratory, School of Biomedical Engineering, Indian Institute of Technology (BHU) Varanasi, Varanasi, Uttar Pradesh 221005, India
[2]Defence Bio-Engineering and Electro Medical Laboratory, DRDO, Ministry of Defence, Bengaluru 560093, India
[3]National Institute of Education (NIE), Nanyang Technological University (NTU), Singapore 639798
[4]Department of Neurology, R. Madhavan Nayar Center for Comprehensive Epilepsy Care, Cognition Behavioral Neurology Centre, Sree Chitra Tirunal Institute for Medical Sciences and Technology, Trivandrum, Thiruvananthapuram, Kerala 695011, India
[5]Montreal Neurological Institute, McGill University, Montreal, QC H3A 0G4, Canada
[6]Department of Sensor and Biomedical Technology, National Institute of Technology at Tiruchirappalli, Tiruchirappalli, Tamil Nadu 620015, India
[7]Department of Electrical and Electronics Engineering, BITS Pilani, K. K. Birla Goa Campus, Zuarinagar, Goa 403726, India

Corresponding author: A. Amalin Prince (amalinprince@goa.bits-pilani.ac.in)

ABSTRACT Epilepsy is a chronic brain disorder characterized by recurrent unprovoked seizures. The treatment for epilepsy is influenced by the types of seizures. Therefore, developing a reliable, explainable, and automated system to identify seizure types is necessary. This study aims to automate the process of classification of five seizure types: focal non-specific, generalized, complex partial, absence, and tonic-clonic using electroencephalogram (EEG) signals and machine learning algorithms. The EEG signals of 2933 seizures from 327 patients were obtained from the publicly available Temple University Hospital dataset. Initially, the signals were preprocessed using a standard pipeline, and 110 features from the time, frequency, and time-frequency domain were computed from each seizure. Further, the features were ranked using the statistical test and extreme Gradient Boosting (XGBoost) algorithm to identify the significant features. We built binary and multiclass seizure-type classification systems using the identified features and machine learning algorithms. Our study revealed that the EEG band power between 11-13 Hz, 27-29 Hz, intrinsic mode function (IMF) band power 19-21 Hz, and delta band (1-4 Hz) played a crucial role in discriminating the seizures. We achieved an average accuracy of 88.21% and 69.43% for the binary and multiclass seizure-type classification, respectively, using the XGBoost classifier. We also found that the combination of features performed well compared to any single domain. This automated system has the potential to aid neurologists in making diagnosis of epileptic seizure types. The proposed methodology can be applied alongside the established clinical approach of visual evaluation for the classification of seizure-types.

INDEX TERMS Epilepsy, seizure type classification, electroencephalography, feature extraction, machine learning.

I. INTRODUCTION

A seizure is a brief episode of signs and/or symptoms characterized by abnormally high levels of synchronous or excessive brain neuronal activity [1]. Seizures are the deterministic markers of epilepsy [2]. The main cause of epilepsy is

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unknown, while it is commonly seen in patients with brain tumors, trauma, neurodevelopmental disorders, and central nervous and cerebrovascular diseases [3]. Numerous studies have found that epilepsy is more common in newborns and older people, but it also affects people of all ages and geographical locations. A total of more than 80 million people are affected by epilepsy worldwide [4], [5]. Seizures are medically divided into two major groups based on the degree of impact in the regions of the brain focal and generalized seizures. Focal seizures affect a specific part of the brain and are classified as simple or complex, depending on the person's level of awareness. Generalized seizures affect most of the brain. Based on motor and non-motor symptoms, these types of seizures are categorized as absence, tonic, atonic, clonic, tonic-clonic, or myoclonic [6], [7]. As the drugs administered and the treatment for seizure patients are highly dependent on the type of seizure, it is important to precisely characterize and classify the seizures. Hence, it has attracted the attention of several researchers for building automated computer classification models to aid medical professionals.

Epilepsy is a highly individualized condition and varies over time, making diagnosis and treatment challenging. Identification of seizure type is challenging and can be achieved by clinical observation of medical history and reference of demographic information. However, manually matching a patient to a medicine introduces unnecessary errors and delays [8], [9]. Electroencephalogram (EEG) has become a common technique for seizure type classification in recent years [10]. It may convey the frequency and energy information regarding the nature of brain illnesses. In this study, we used the EEG signals of different seizure types to effectively classify focal non-specific (FNSZ), generalized (GNSZ), complex partial (CPSZ), absence (ABSZ), and tonic-clonic seizures (TCSZ).

EEG signals may suffer from the variability of symptoms across patients, poor inter-rater agreement, and signal artifacts [11]. Moreover, power frequency, respiration, scalp electrode vibrations, muscle movement, and other disturbances during EEG signal acquisition might introduce noises [12]. It is required to remove these noises before the analysis process for effective implementation of the model. However, it is crucial to select a suitable pre-processing technique specific to each dataset and an incorrect choice might lead to the removal of useful information in the EEG recording. Studies have used down sampling to 250Hz, application of lowpass/bandpass filter (LPF, BPF), notch filter of 60 Hz, and segmentation of EEG signals in the pre-processing steps [13], [14], [15], [16], [17]. In our study, we apply high pass filter and notch filters along with signal normalization techniques to effectively remove the artifacts.

Previous studies have examined the characteristics of seizure types through various feature extraction techniques [18], [19]. Time domain features such as standard deviation, kurtosis, Shannon entropy, and skewness, in addition to fractal features, energy, and non-linear energy features, have been utilized to identify seizure patterns [15]. Furthermore, features computed from different frequency bands of EEG signals have been employed for seizure-type characterization [20]. Time-frequency methods including independent component analysis, Mel frequency cepstral coefficients, and empirical mode decomposition (EMD) have also been applied in seizure analysis [21]. However, these studies have not compared the performance of combinations of different domain features in seizure characterization. In our study, we have employed time, frequency, and time-frequency domain features to assess their effectiveness in seizure characterization.

The seizure type classification is automated using computer-aided automated systems which helps in the effective treatment and management of patients. Machine learning algorithms were implemented for seizure type classification, as they can effectively handle and examine the patterns of long EEG recordings of epileptic patients. Linear classification models such as linear support vector machine (SVM) [21] have been used to study seizure-type classification. Non-parametric classifiers such as k-nearest neighbor were implemented in [8]. Deep learning algorithms such as variable weight convolutional neural networks [10], transfer learning [23], Alexnet, VGG16, and basic convolutional neural networks [22] were used for the multiclass seizure classification. Although deep learning algorithms can perform better than machine learning methods, there are additional requirements such as converting the EEG signal into an image by time-frequency spectrograms, large training datasets, and high computational costs. Recently, extreme gradient boosting (XGBoost) has been implemented to classify between 7- types of seizures and reported high classification accuracy [23]. In this study, we utilize the International League Against Epilepsy (ILAE) seizure type classification [1] for automatically distinguishing five types of seizure using machine learning methods. We utilized the XGBoost algorithm for feature ranking and classification and the results were compared with the logistic regression (LR) and SVM models.

The main contributions of this study are

- The study contributes by proposing a combination of time, frequency, and time-frequency features for multi-class seizure type classification.
- This research identifies the best features specific to each seizure type, highlighting the importance of using tailored features in seizure type classification.
- This study attempts to improve the performance of automated binary and multi-class seizure type classification systems using LR, SVM and XGBoost models.

The rest of the paper is organized as follows. Section II describes the pipeline, dataset used for multiclass seizure classification, preprocessing steps, different features extracted and multiclass classification approach. Section III and IV describes the results and discussion of the proposed system. Section V concludes the paper.

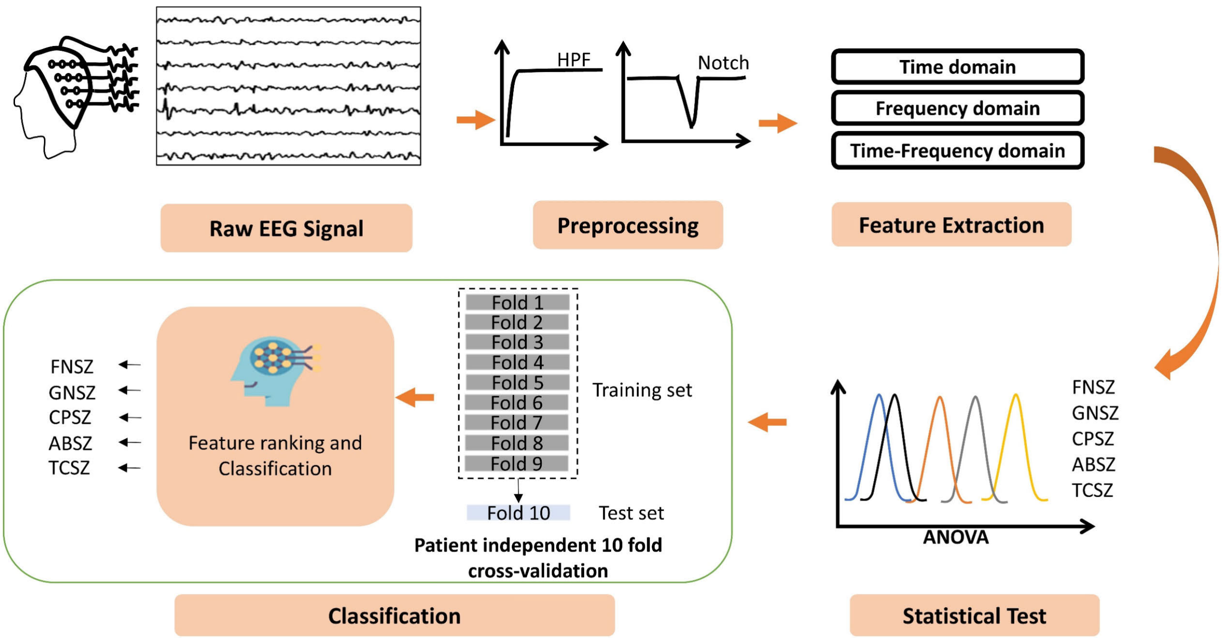


FIGURE 1. The process pipeline of the proposed study. The evaluation included preprocessing the raw EEG signal, feature extraction, statistical evaluation using one-way analysis of variance (ANOVA), and finally the 10-fold cross-validation based classification.

TABLE 1. Description of the EEG seizure data utilized in the study from TUSZ V1.5.2 dataset.

Type	Number of Seizures	Number of Patients	Age (mean±std)	Gender Female (Male)	Mean duration of EEG (s) (mean±std)	Mean duration of seizures (s) (mean±std)
FNSZ	1836	173	52 ± 18.2	83 (80)	766.5±537.8	54.3± 83.5
GNSZ	583	80	52 ± 19.8	47 (33)	874.3±614.3	66.7± 148.8
CPSZ	367	47	53 ± 16	24 (23)	692.6± 569.5	69.2± 50.6
ABSZ	99	13	13 ± 11.8	7 (6)	1310.2±590.6	7.6± 4.7
TCSZ	48	14	38 ± 17.4	5 (9)	974.3± 362.7	64.1± 34.3

II. MATERIAL AND METHODS

Fig. 1 provides an illustration of the pipeline utilized in this study. The evaluation pipeline included preprocessing the raw EEG signal, feature extraction, statistical evaluation using one-way analysis of variance (ANOVA), and finally the 10-fold cross-validation based feature ranking and classification of seizure types.

A. DATABASE

We utilized the largest publicly available epilepsy database, TUSZ version 1.5.2, for seizure type characterization [24], [25]. It consisted of 3,050 seizures across more than 300 patients. The recordings were divided into the train, dev, and eval groups. We combined the data from all these three groups and included the seizure types for which at least data from 10 patients was available. Subsequently, we utilized 2933 seizures of 327 patients from five seizure types in our analysis: FNSZ, GNSZ, CPSZ, ABSZ, and TCSZ. The EEG signals were recorded according to the 10-20 international system with multiple sampling frequencies (250-4000 Hz) and three different montages. Each EEG file was analyzed independently of sampling frequency. The dataset contains two types of unipolar montages: average reference and linked ear reference, with a maximum of 31 EEG channels. The patient and seizure information extracted in this study is given in Table 1.

B. PREPROCESSING

The EEG signals were initially filtered to remove electrical interference and reduce baseline fluctuations using a notch filter of 60 Hz and a high pass filter of 1 Hz. We applied a bipolar montage to the EEG signals. Later, the EEG was segmented to extract seizures based on the start and end time provided in the annotation file.

TABLE 2. The details of the features considered in the analysis.

Type	Feature	Equation/frequency range
Time-domain	Zero-crossing rate	$\frac{1}{T}\sum_{t=1}^{T}\lvert x(t)-x(t-1)\rvert$
	Entropy	$-\sum(p\ .*\ log_2\, p)$
	Mean (μ)	$\frac{\sum x(t)}{N}$
	Standard deviation (σ)	$\sqrt{\sum\frac{(x(t)-\mu)^2}{N}}$
	RMS	$\sqrt{\frac{1}{T}\int_0^T x(t)^2dx}$
	Mobility	$\sqrt{\frac{var\left(\frac{dx(t)}{dt}\right)}{var\ x(t)}}$
	Skewness	$\sum_i^N\frac{(x(i)-\mu)^3}{(N-1)*\sigma^3}$
	Form factor	$\frac{RMS}{Mean}$
	Maximum value	$Max(x(t))$
	Minimum value	$Min(x(t))$
	Mean line length	$\frac{1}{N}\sum_{i=1}^{N-1}\lvert x(i)-x(i-1)\rvert$
	Mean teager energy	$\frac{1}{N}\sum_{i=1}^{N-1}\lvert x(i)^2-x(i-1)x(i+1)\rvert$
	Shannon entropy	$-\,log\,p(x)$
	Sampling entropy	$-log\left(\frac{A}{B}\right)$
	Variance	$\sum\frac{(x(t)-\mu)^2}{N-1}$
	Mean power	$\frac{1}{N}\sum_i^{N-1}x(i)^2$
	Complexity	$\frac{Mobility\left(\frac{dx(t)}{dt}\right)}{Mobility(x(t))}$
	Kurtosis	$\frac{1}{N}\sum\left(\frac{x(t)-\mu}{\sigma}\right)^4$
	Total variance	$\sum_{i=1}^{n-1}\frac{\lvert x(i+1)-x(i)\rvert}{(x(max)-x(min)(n-1))}$
	Hurst exponent	$E\left(\frac{R(n)}{S(n)}\right)$
Fractal features	Katz fractal dimension	$\frac{log\left(\frac{L}{a}\right)}{log\left(\frac{d}{a}\right)}$
	Higuchi fractal dimension	*Dimension k is obtained by decomposition and similarity of the subseries*

TABLE 2. ***(Continued.)*** **The details of the features considered in the analysis.**

Frequency-domain	Total bandpower	*0-12 Hz*
	Bandpower 0-2Hz	*0-2 Hz*
	Bandpower 2-4Hz	*2-4 Hz*
	Bandpower 3-5Hz	*3-5 Hz*
	Bandpower 4-6Hz	*4-6 Hz*
	Bandpower 5-7Hz	*5-7 Hz*
	Bandpower 6-8Hz	*6-8 Hz*
	Bandpower 7-9Hz	*7-9 Hz*
	Bandpower 8-10Hz	*8-10 Hz*
	Bandpower 9-11Hz	*9-11 Hz*
	Bandpower 10-12Hz	*10-12 Hz*
	Bandpower 11-13Hz	*11-13 Hz*
	Bandpower 12-14Hz	*12-14 Hz*
	Bandpower 13-15Hz	*13-15 Hz*
	Bandpower 14-16Hz	*14-16 Hz*
	Bandpower 15-17Hz	*15-17 Hz*
	Bandpower 16-18Hz	*16-18 Hz*
	Bandpower 17-19Hz	*17-19 Hz*
	Bandpower 18-20Hz	*18-20 Hz*
	Bandpower 19-21Hz	*19-20 Hz*
	Bandpower 20-22Hz	*20-22 Hz*
	Bandpower 21-23Hz	*21-23 Hz*
	Bandpower 22-24Hz	*22-24 Hz*
	Bandpower 23-25Hz	*23-25 Hz*
	Bandpower 24-26Hz	*24-26 Hz*
	Bandpower 25-27Hz	*25-27 Hz*
	Bandpower 26-28Hz	*26-28 Hz*
	Bandpower 27-29Hz	*27-29 Hz*
	Bandpower 28-30Hz	*28-30 Hz*
	Bandpower Delta	*1-4 Hz*
	Bandpower Theta	*4-7 Hz*
	Bandpower Alpha	*8-13 Hz*
	Bandpower Gamma	*30-80 Hz*
	Bandpower high Gamma	*80-100 Hz*
	Bandpower Delta	*1-4 Hz*
	Bandpower Theta	*4-7 Hz*
	Bandpower Alpha	*8-13 Hz*
	Bandpower Gamma	*30-80 Hz*
	Bandpower high Gamma	*80-100 Hz*

RMS-Root Mean Square, bp-bandpower, x(t)-Signal, N-Number of samples, p-probability, T-Time interval, var- variance, Max-Maximum, A-Number of matches of length m+1, B-number of matches of length m with ith, R(n)-range of the first n cumulative deviations from the mean, S(n)-sum of the first n standard deviation, E[x] is the expected value, d-Euclidean distance of each point, L-sum of the Euclidean distances from d, a-average of the Euclidean distances from d.

C. FEATURE EXTRACTION

A total of 110 features (20 time, 35 frequency, and 55 time-frequency) were computed from each seizure signal as tabulated in Table 2 [15], [17], [19], [21], [22], [26], [27], [28], [29]. The same time and frequency domain features (20+35) were extracted from the first IMF of the EMD signal for time-frequency features. We defined the signal 20 seconds preceding or succeeding to the corresponding seizure as the background. The features extracted from the background segment were used to normalize the amplitude-dependent features such as the energy, mean amplitude, etc. The time-frequency features were extracted from the intrinsic mode functions (IMFs) obtained from the empirical mode decomposition (EMD). We used the sifting method for decomposing the signals which extracts the oscillatory components of the signal.

The number of IMFs computed from the seizure segments varies from 9 to 16 between the samples and channels. Hence, optimizing the number of IMFs for each seizure is required. We computed the entropy for each of the IMFs across all the channels. The IMF number after which the entropy dropped dramatically was found, and their counts are plotted in Fig. 2. The entropy and the information content of the signal were inversely proportional, implying that the signal information would be highest when the entropy was low [30]. It can be observed from the Fig. 2 that the entropy value drops after the first IMF in more than 70,000 IMFs. We found that the first IMF was optimal for 70.3% of data and hence, we computed the time and frequency features from the first IMF [31]. Each of these features was computed for a single channel, and later, for each feature, the values from multiple channels were combined by considering the mean (across multiple channels) to provide a global value, per seizure.

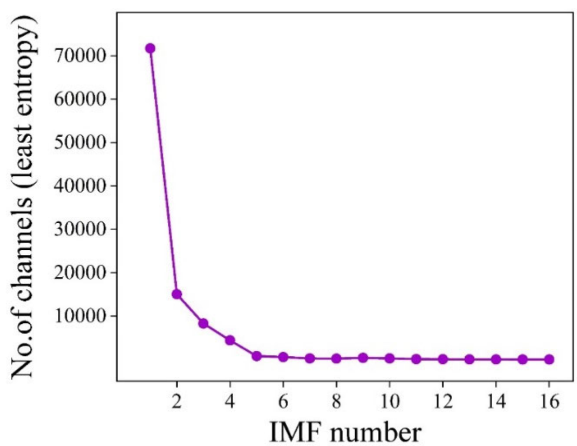


FIGURE 2. Optimal IMF identification using minimum entropy count.

D. STATISTICAL EVALUATION OF FEATURES

We used ANOVA to analyze the significance of the 110 time, frequency and time-frequency domain features extracted from the five seizure types. A p-value, significance level of less than 0.05 was used to assess the presence of differences between the groups.

E. FEATURE IMPORTANCE AND CLASSIFICATION

We utilized XGBoost feature ranking algorithm [32] to derive the feature importance of 104 significant features identified through statistical test. Further, we build the classification models using XGBoost classifier and compared our results with two other traditional models, the LR and the SVM to classify the seizure types [22]. The classification was performed in two ways: binary and multiclass classification, as shown in Fig. 3 (a) and (b). In the binary classification, the model was trained with one type of seizure as a positive class and the remaining seizure types as a negative class. The same procedure was repeated for each type of seizure. In contrast, the multiclass model is trained using all five types of seizures simultaneously. Both these classification tasks were evaluated using an extensive patient-level 10-fold cross-validation shown in Fig. 3 (c). The ten folds were created by dividing the patients into folds by keeping the number of seizure types almost similar across the different folds. This resulted in a train and test dataset which contained seizure samples from different patients without any overlap of the same patients. The results from binary classification will help identify features unique to specific seizure types, while analyzing multiclass features will pinpoint the most discriminative feature across all types. Further, as a secondary outcome, we also present the results for seizure type classification in terms of accuracy, specificity, sensitivity, precision and F1 score. Accuracy is the proportion of correct predictions made by the model across the entire dataset. It is calculated as the ratio of true positives (TP) and true negatives (TN) to the total number of samples. Sensitivity measures the proportion of TP predictions among all actual positive instances. It is calculated as the ratio of TP to the sum of TP and false negatives (FN). Specificity is computed as the ratio of TN to the sum of TN and FP. Precision measures the proportion of true positive predictions among all positive predictions made by the model. It is calculated as the ratio of TP to the sum of TP and false positives (FP). F1-Score is a metric that balances precision and recall. It is calculated as the harmonic mean of precision and recall [23].

III. RESULTS

Fig. 4 (a) and (b) shows the typical raw EEG signal and its corresponding pre-processed signal. It can be observed that the raw EEG signals consist of artifacts due to eye blinks and interference. These noises were removed in the pre-processed signals and well observed in the figure. Fig. 5 (a-e) shows the preprocessed EEG segments for each seizure type: FNSZ, GNSZ, CPSZ, ABSZ and TCSZ. We observed a few differences between seizure types; however, it can be observed that the seizure segments share common characteristics of high frequency and spike-like patterns in most seizure types, particularly FNSZ, GNSZ, and CPSZ. We preprocessed the EEG

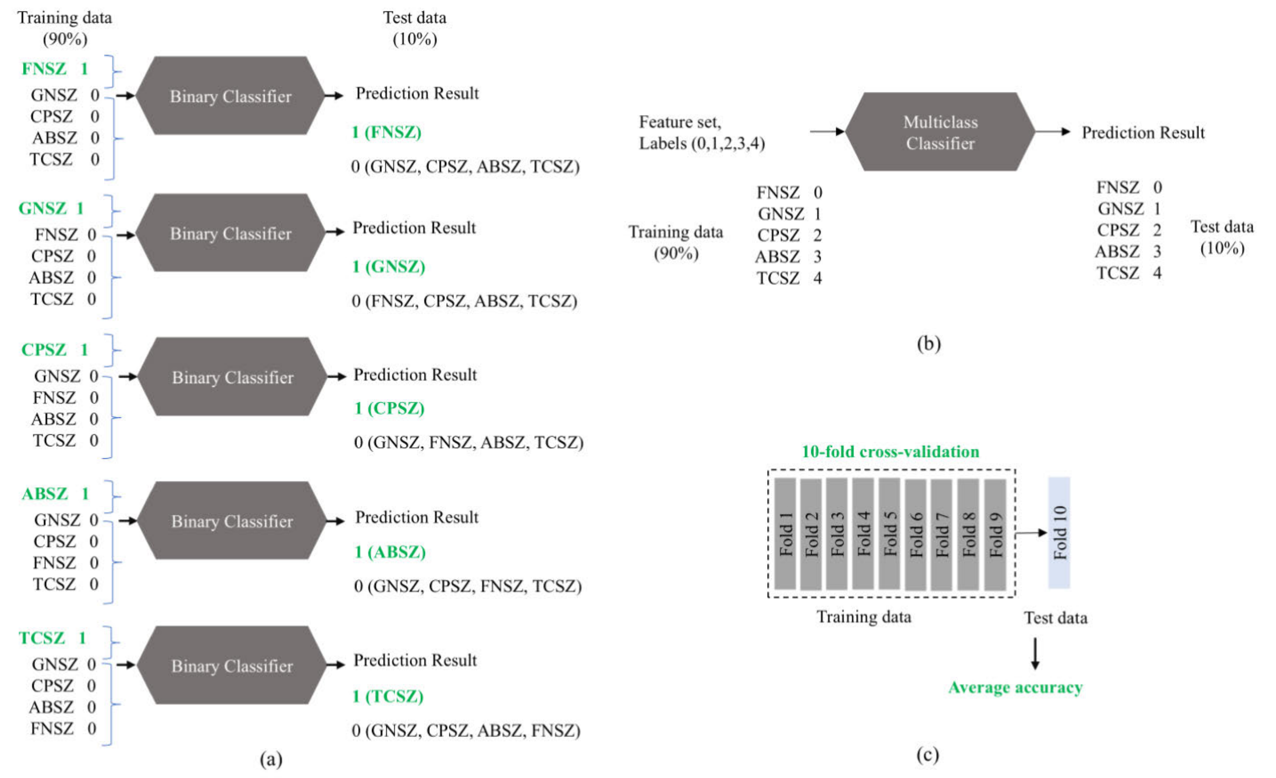


FIGURE 3. Evaluation scheme implemented in this study (a) Binary classification (b) Multiclass classification (c) 10-fold cross-validation.

signals and extracted time, frequency, and time-frequency domain features from each seizure type.

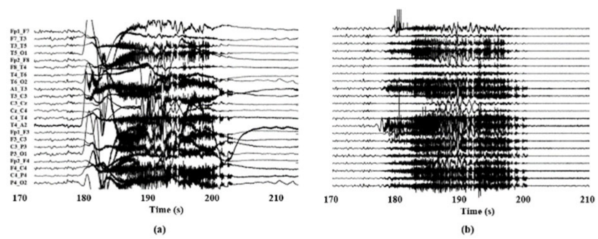


FIGURE 4. Representation of (a) Raw EEG, and corresponding (b) Filtered EEG.

The one-way ANOVA statistical test showed that out of the 110 features extracted, 104 features were found to be significant (p <0.05) in distinguishing at least two or more types of seizures. Further, these 104 features were ranked based on the feature importance and used for classification.

Fig. 6 (a-f) depicts the features with feature importance scores >0.01 computed by the XGBoost feature ranking algorithm on the binary classification model of FNSZ, GNSZ, CPSZ, ABSZ, TCSZ, and multiclass classification. We found that features such as BP 11-13Hz, peak frequency, BP 14-16 Hz, Higuchi fractal, and IMF Hjorth mobility ranked top in the discrimination of FNSZ from the other seizure types. It can be seen that features such as BP 27-29Hz, IMF BP 6-8Hz, IMF mean line length, IMF BP 18-20HZ, and IMF BP 16-18Hz significantly help in differentiating GNSZ. Features such as IMF BP 19-21Hz, IMF BP 21-23 Hz, zero-crossing rate, IMF zero-crossing rate, and sample entropy were found to be significant in the case of CPSZ. Our results revealed that BP delta, IMF entropy, Higuchi fractal, IMF zero-crossing rate, and BP 11-13 Hz play a major role in discriminating ABSZ from other seizures. TCSZ was differentiated by features such as mean line length, IMF standard deviation, IMF variance, RMS, and Higuchi fractal. The best features of multiclass classification were the BP 11-13 Hz, BP 27-29 Hz, IMF entropy, delta BP, and IMF BP 6-8 Hz. We can see that BP features significantly help in discriminating between seizures compared to other features considered in the analysis. It can be noted that the features corresponding to the binary classification models highly vary between the seizure types. This shows the importance of identifying the significant features specific to seizure types. Further, the features between the binary and multiclass classification models also seem to be different. Moreover, we can see that the feature importance score > 0.01 was highly varying between the binary and multiclass models with 28, 32, 41, 16, 25, and 29 for FNSZ, GNSZ, CPSZ, ABSZ, TCSZ, and multiclass classification, respectively.

We have listed the best features for binary and multiclass seizure type classification from each domain in Table 3. We can observe that the features vary across seizure types;

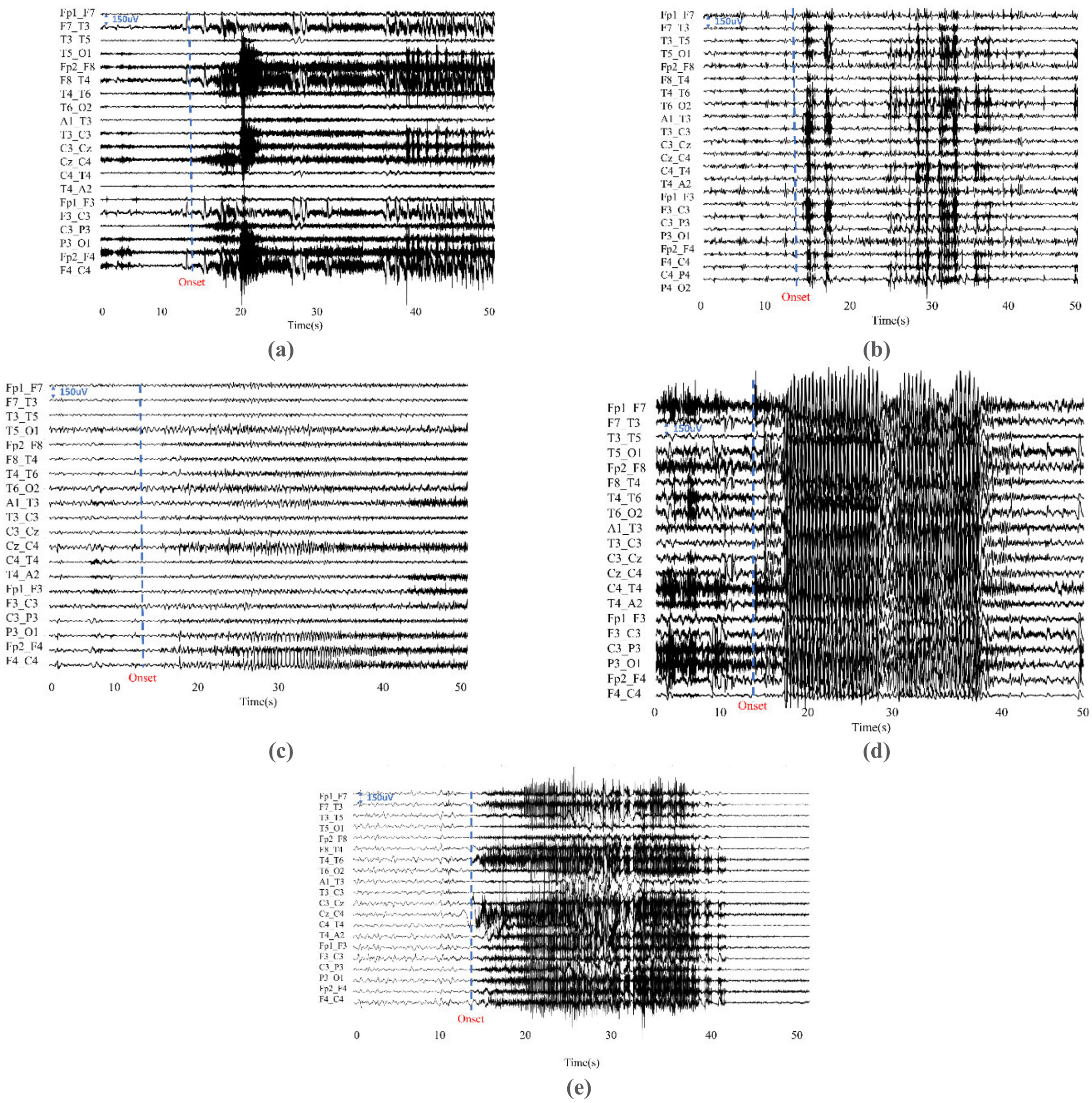


FIGURE 5. **Typical preprocessed seizure signal segments with annotations. Examples of (a) FNSZ, (b) GNSZ, (c) CPSZ, (d) ABSZ, and (e) TCSZ.**

however, the BP 11-13 Hz plays a significant role in FNSZ and multiclass classification. Additionally, features from different domains such as BP 11-13 Hz, RMS, and IMF BP 25-27 Hz, which helped discriminate FNSZ, have also significantly contributed to multiclass classification. This shows that features significant in the classification of FNSZ can also be used for multiclass classification.

We compared the performance of the XGBoost classification model with that of the LR and SVM classifiers, and the results were tabulated in Table 4. The classification results for FNSZ, GNSZ, CPSZ, ABSZ, TCSZ, and multiclass using the XGBoost model were 75.56%, 82.86%, 85.1%, 98.07%, 98.65%, and 69.43%, respectively. We achieved superior 10-fold cross-validation performance for binary and multiclass classification using the XGBoost classifier compared to LR and SVM. We observe a similar pattern in both binary and multiclass models. Therefore, we performed further analysis using the XGBoost classifier.

Fig. 7 (a) and (b) show the binary and multiclass classification performance using time, frequency, time-frequency, and all features on an XGBoost classifier. For binary classification, the combination of all features yielded the highest performance, followed by time, time-frequency, and frequency domain features. We achieved a 10-fold average cross-validation accuracy, sensitivity, specificity, precision, and F1-score of 88.21%, 54.29%, 86.59%, 70.9%, and 53.57%, respectively, using all 104 features. Similar results were achieved for multiclass seizure-type classification. The model with 104 features achieved a superior average classification accuracy of 69.4%.

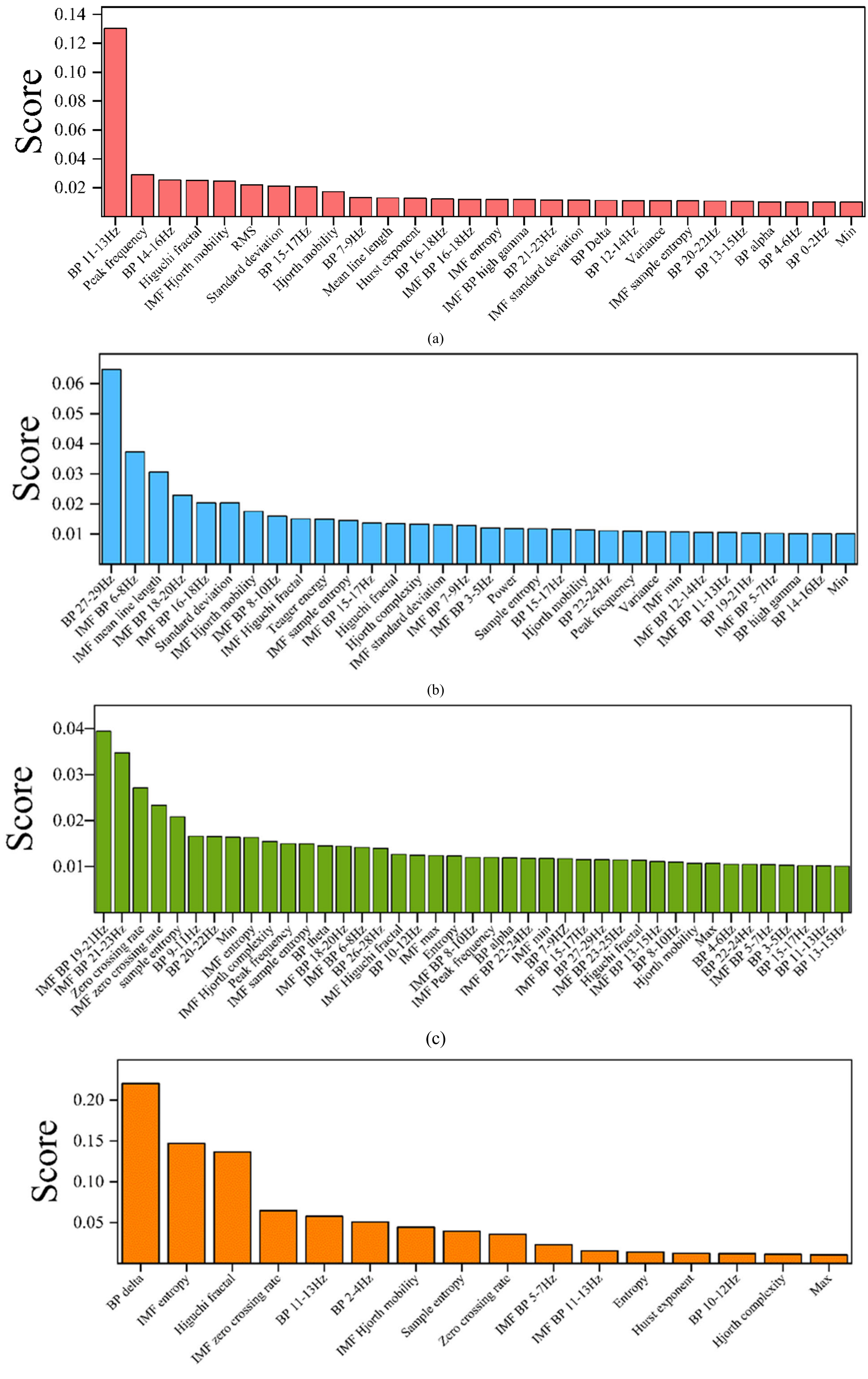
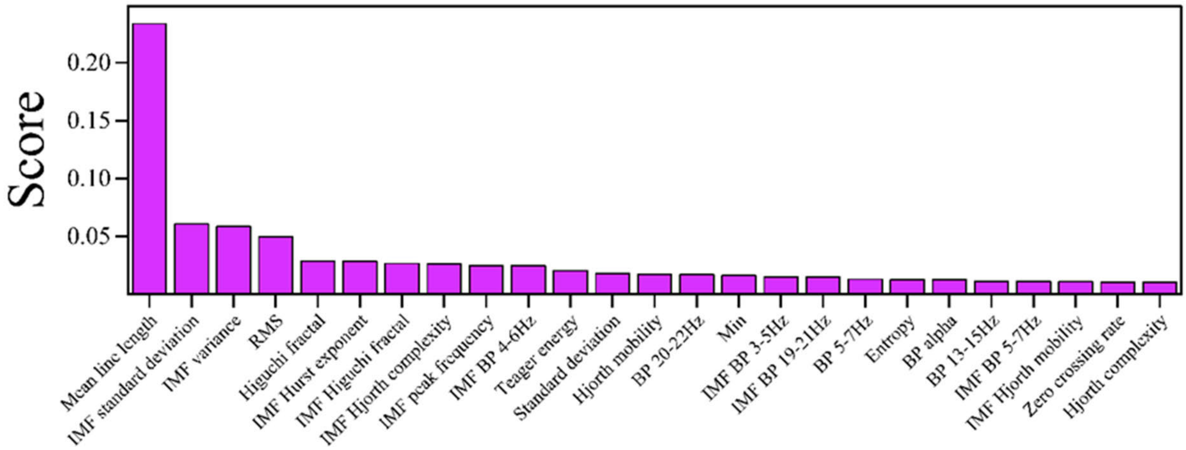
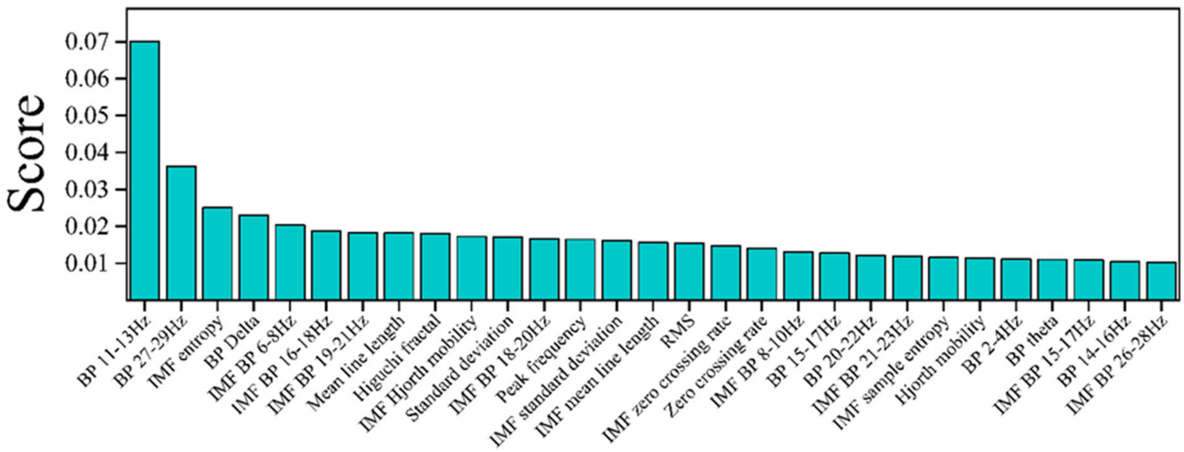


FIGURE 6. Feature ranking of all the features with average features importance score>0.01 obtained using binary classification (a) FNSZ, (b) GNSZ, (c) CPSZ, (d) ABSZ, (e) TCSZ and (f) Multiclass class. IMF: intrinsic mode function, BP: band power, RMS: root mean square, ZCR: zero crossing rate.



(e)



(f)

FIGURE 6. ***(Continued.)*** **Feature ranking of all the features with average features importance score>0.01 obtained using binary classification (a) FNSZ, (b) GNSZ, (c) CPSZ, (d) ABSZ, (e) TCSZ and (f) Multiclass class. IMF: intrinsic mode function, BP: band power, RMS: root mean square, ZCR: zero crossing rate.**

IV. DISCUSSION

We utilized the TUSZ corpus of the TUH database in this study for the classification of five types of seizures. The seizure segments were extracted after preprocessing the raw EEG recordings. Time, frequency, and time-frequency domain features were computed, and various combinations of these features were analyzed for seizure-type classification. The BP 11-13 Hz feature was identified as the most effective feature in differentiating between the five epileptic seizure types. Additionally, we achieved accuracies of 88.21% and 69.43% in binary and multiclass classification, respectively, using the XGBoost classifier. The findings of this study have the potential to improve the usefulness of seizure type classification models in real-world scenarios.

A. FEATURES ACROSS TIME, FREQUENCY, AND TIME-FREQUENCY DOMAINS

We analyzed 110 features that can be easily included in the current clinical setup for seizure type classification. This study aimed to determine the most useful features for differentiating between types of seizures. The model produced better classification results using all the features, followed by time, time-frequency, and frequency domain features (see Fig. 6) for both binary class and multiclass classification results. During a seizure event, there is a significant effect on the amplitude, frequency, and energy-related components of the signal. Hence, multi-domain feature extraction helps in providing a diverse set of features for classification. Previous studies have used time [16], [17], [28], [39], [41], [46], frequency [8], [43], time-frequency domain features [21], [29], [33], [40], [42], [47], [48], and combination of features [34], [35] for seizure type classification, however never compared between time, frequency and time-frequency. Our results match with the previous finding which revealed that time domain features performs better than frequency domain features [34], [35]. Few studies have used deep learning algorithms for feature extraction but never revealed the patterns learned by the algorithms [11], [13], , [14], [30], [36], [37],

TABLE 3. Significant features identified in the binary and multiclass cross-validation.

Features	Binary classification					Multiclass classification
	FNSZ	GNSZ	CPSZ	ABSZ	TCSZ	
All features	BP 11-13 Hz	BP 27-29 Hz	IMF BP 19-21 Hz	Delta BP	Mean line length	BP 11-13 Hz
Time domain features	RMS	Total power	ZCR	ZCR	Mean line length	RMS
Frequency domain features	BP 11-13 Hz	BP 27-29 Hz	BP 15-17 Hz	Delta BP	BP 27-29 Hz	BP 11-13 Hz
Time-frequency domain features	IMF BP 25-27 Hz	IMF mean line length	IMF ZCR	IMF BP 10-12 Hz	IMF standard deviation	IMF BP 25-27 Hz

TABLE 4. Comparison of performance of machine learning algorithms in the seizure type classification with all the features.

Classifier	FNSZ	GNSZ	CPSZ	ABSZ	TCSZ	Multiclass
LR	67.05%	80.22%	86.54%	96.88%	97.19%	63.06%
SVM	63.09%	80.71%	86.48%	95.48%	98.37%	60.84%
XGBoost	75.56%	82.86%	85.1%	98.07%	98.65%	69.43%

[38], [44], [45]. Moreover, seizure types and features vary between these studies, making it difficult to compare the results.

B. FEATURES FOR DISCRIMINATING SEIZURE TYPES

We found that the best features specific to each seizure type vary, highlighting the importance of using tailored features in seizure type classification. BP 11-13 Hz, BP 27-29 Hz, IMF BP 19-21 Hz, delta BP, and mean line length were the significant features in classifying FNSZ, GNSZ, CPSZ, ABSZ, and TCSZ, respectively. The frequency of seizures varies widely with varying levels of intensity and characteristics. In our study, the BP within the range of 11-13 Hz was found to be the best feature in distinguishing all types of seizures (multiclass classification). The average BP values obtained between 11-13 Hz for FNSZ, GNSZ, CPSZ, ABSZ, and TCSZ are 3.6, 8.7, 13.2, 23.3, and 364.5 μV^2, respectively. There is a distinct margin in the average BP values within the 11-13 Hz band for each type of seizure. FNSZ and GNSZ exhibited lower power in the 11-13 Hz band, while TCSZ demonstrated the highest power. Although the frequency of the seizure BP primarily lies between 12.5-25 Hz [30], it can be inferred that the range of the BP for each feature lies in distinct regions. Hence, BP in the 11-13 Hz range was able to effectively distinguish between types of seizures. Various studies have yielded inconsistent findings regarding the identification of significant frequency bands in classifying seizure types. A recent study has highlighted the importance of BP features from high-frequency bands like alpha and gamma for seizure type classification [43]. Conversely, another study has indicated that theta predominates in GNSZ, FNSZ, and CPSZ, while beta activity is commonly associated with TNSZ and TCSZ [20]. Nonetheless, our previous results are consistent with our current findings, emphasizing the significance of BP in the 11-13 Hz range [35].

C. BINARY VS MULTICLASS CLASSIFICATION PERFORMANCE

We compared our study with the existing approaches which is listed below in Table 5. Our study produced binary classification accuracies of 75.56%, 82.86%, 85.1%, 98.07%, and 98.65% for FNSZ, GNSZ, CPSZ, ABSZ, and TCSZ, respectively, using the XGBoost model. These binary classification models helped us understand the characteristics of each seizure type. We were able to better discriminate TCSZ and ABSZ, followed by CPSZ, GNSZ, and FNSZ (Table 3). However, it's important to note that the number of patient data available for all seizure types was not equal. ABSZ and TCSZ had a comparatively smaller number of patients for analysis. Despite the potential bias from the uneven distribution of patient data, the XGBoost model produced an average patient-specific multiclass accuracy of 69.43%. It can be noted that the multiclass classification provides an estimate of our system's performance in real-world

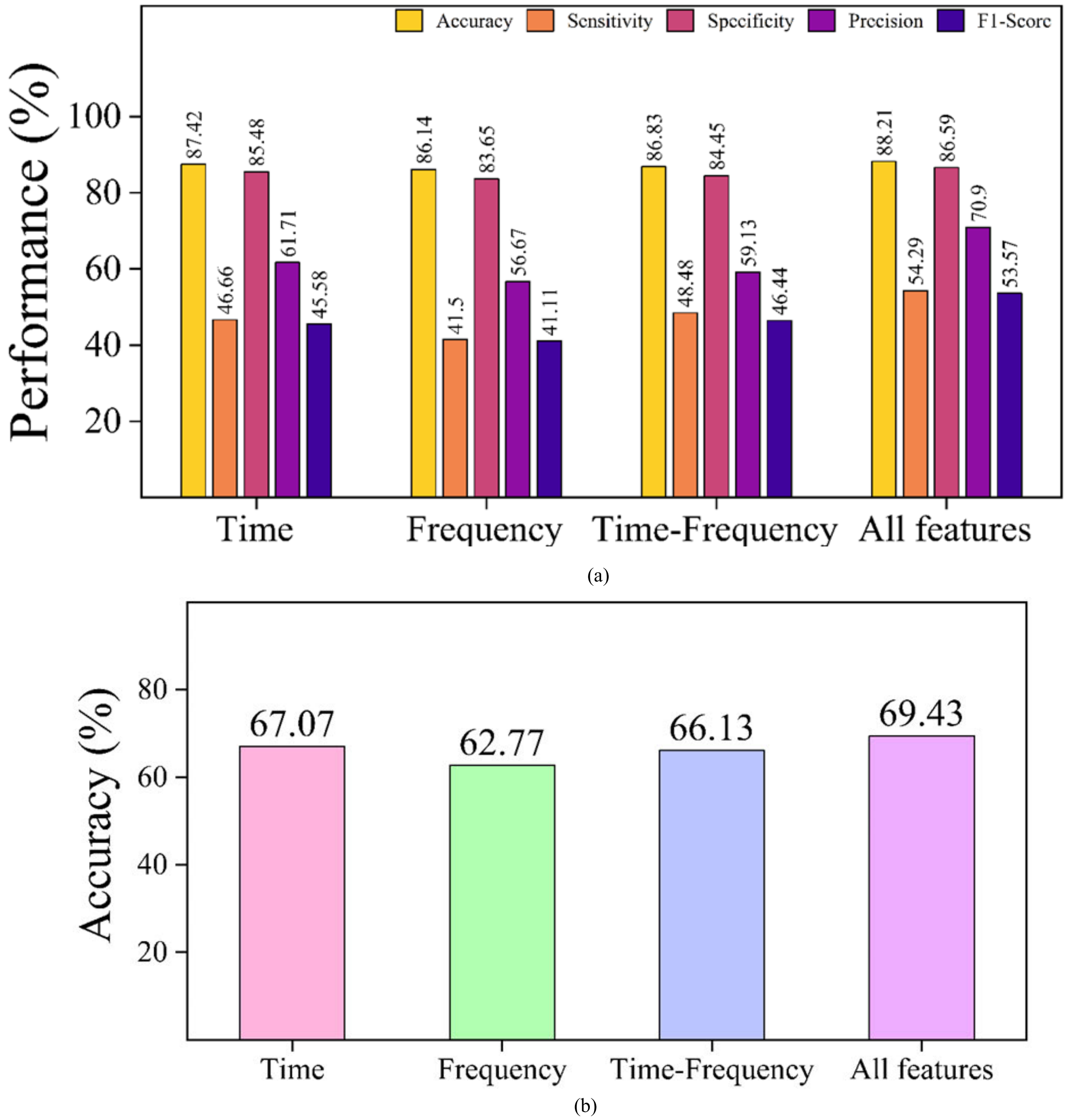


FIGURE 7. 10-fold classification results with time, frequency, time-frequency, and all features: (a) Binary and (b) Multiclass classification.

scenarios, where prior information about newly incoming patients may not be available. We attained high accuracy in binary classification, surpassing several prior studies [35], [45], [47]. However, many previous studies achieved higher accuracy in binary classification by sacrificing computational simplicity, employing complex algorithms like LSTM, CNN, and various intricate deep learning models for feature extraction or classification, as seen in studies [8], [11], [13], [16], [17], [19], [20], [28], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [44], [45], [46], [48]. Conversely, only a handful of studies have pursued multiclass classification and achieved higher accuracy utilizing similar computationally complex algorithms [29], [40], [44]. Furthermore, many studies have achieved high classification accuracy while considering fewer seizure types [19], [28], [42], [43], [48]. In conclusion, our study achieved comparable performance by utilizing a computationally efficient novel pipeline, making it suitable for real-time applications.

D. LIMITATIONS AND FUTURE SCOPE

In our research, we examined the distinct features of various seizure types using the TUSZ dataset accessible in the TUH database. This dataset encompasses EEG data from eight seizure types, with some types having limited patient recordings. We focused on analyzing five seizure types, as we employed a 10-fold cross-validation method requiring a min-

TABLE 5. Comparison of performance of our study with the existing approaches in the seizure type classification.

Authors	Seizure types	Number of seizures and patients	Feature extraction	Feature reduction	Classification	Performance
Our study	FNSZ, GNSZ, SPSZ, ABSZ, TCSZ	2933 seizures and 327 subjects	Time, frequency and time-frequency based features	ANOVA, XGBoost	LR, SVM, XGBoost	Binary Acc: 88.21%, Multiclass Acc: 69.43%
[30]	CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, MYSZ, GNSZ	202 subjects	Deep learning	-	LSTM-attention	Acc: 98.41%
[33]	CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, MYSZ, GNSZ	3050 seizures and 304 subjects	DWT, DTCWT, WPD	-	CNN sub-model, Bi-LSTM sub-model, MP-SeizNet	Acc: 98.1% F1-scores: 87.6%
[34]	FNSZ, GNSZ, SPSZ, CPSZ, TNSZ, TCSZ	1227 seizures and 115 subjects	CEEMDAN, MSBCSP	RF, LDA	LightGBM, LR	Acc: 96.14%, F1-score: 96.79%
[35]	FNSZ, GNSZ, SPSZ, ABSZ, TCSZ	3050 seizures and 300 subjects	Time, frequency domain features	XGBoost	XGBoost	Acc: 79.72%
[36]	CPSZ, ABSZ, TNSZ, TCSZ, FNSZ, GNSZ, SPSZ, MYSZ	242 seizures and 642 patients	Deep learning	-	1D-MSCNet LSTMNet	F1-score: 98.4%
[37]	CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, MYSZ, GNSZ, TNSZ	3050 seizures and 642 subjects	Deep learning	-	LSTM	F1-score: 97.4%
[20]	GNSZ, ABSZ, MYSZ, TNSZ, TCSZ, FNSZ, SPSZ, CPSZ	3050 seizures	Sub-zones and sub-bands features	-	RF, SVM, MLP	Acc: 98.7%
[38]	FNSZ, GNSZ, CPSZ, ABSZ, TNSZ, TCSZ, SPSZ	3050 seizures and 300 subjects	Deep learning	-	VWCNNs	Acc: 91.67%
[29]	FNSZ, GNSZ, CPSZ, ABSZ, TNSZ, TCSZ, SPSZ	3050 seizures and 300 subjects	Wavelet transform	-	LightGBM	5 class Acc: 74.7% 7 class Acc: 56.22%
[28]	CPSZ, ABSZ	23 subjects	Variance, asymmetry, kurtosis, Shannon entropy, safe entropy, log energy entropy, energy, min–max value, standard deviation	-	KNN, SVM, RF, LSTM	Acc: 98.08%
[39]	ABSZ, FNSZ, GNSZ, CPSZ, TNSZ, MYSZ	510 seizures	RQA and texture-based approach	-	SVM	Acc: 94.26%, F1-score-79.13%

TABLE 5. *(Continued.)* **Comparison of performance of our study with the existing approaches in the seizure type classification.**

[40]	FNSZ, GNSZ, CPSZ, ABSZ, TNSZ, TCSZ, SPSZ,	3050 seizures and 300 subjects	Wavelet based	-	LightGBM, SVM	F1 score 7 class: 64%, 5 class: 66.6%, 2 class: 87.6%
[41]	ABSZ, SPSZ, CPSZ, TCSZ, TNSZ, MYSZ	256 seizures	Time domain, fractal analysis	Genetic algorithm	Naive Bayes classifier	F1-score: 96%
[42]	ABSZ, FNSZ, GNSZ, CPSZ	31 subjects	Wavelet based	-	DWT, KNN	Acc: 97.7% Sen: 92.9% Spe: 98.7%
[13]	CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, MYSZ, GNSZ, FNSZ	215 subjects	Deepnet features	-	Attentive fusion network	Acc: 95-98%
[43]	ABSZ, TCSZ	-	frequency domain features	Permutation test	RF, SVM	Acc: 94.3% ∓ 5.3%
[44]	CPSZ, GNSZ, SPSZ, TCSZ, seizure-free	18 subjects	Deep learning	-	CNN	2 class Acc: 96.01%, 3 class Acc: 89.91%, 4 class Acc: 84.19%, 5 class Acc: 84.20%
[17]	CPSZ, FNSZ, GNSZ, seizure-free	18 subjects	Statistical features	PCA	ANN, DT, KNN, RF, and XGBoost	Acc: 100%
[16]	ABSZ, CPSZ, FNSZ, GNSZ, and TCSZ for TUH, Focal and non-focal for BB EEG, Ictal, interictal, and normal for BU EEG, Normal and abnormal for simulated datasets	100 subjects	Statistical, autoregressive, entropy features	ReliefF algorithm	LSTM	Acc: 98.78%
[11]	FNSZ, CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, GNSZ	2009 seizures and 213 subjects	RCNN	-	Neural Memory networks with softmax classification	F1-score: 94.5%
[45]	FNSZ, CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, GNSZ, BCKG	1703 seizures and 352 subjects	Deep learning	-	Alexnet, VGG16, VGG19, Squeezenet, Googlenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101	Acc: 82.85%
[46]	SPSZ, CPSZ, FNSZ, GNSZ, ABSZ, TNSZ, TCSZ	637 subjects	Fractal spectrum features	-	SVM, WPD, LDFA	Acc: 97.8%
[14]	CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, GNSZ	3050 seizures	Deep learning: multi-spectral features	-	SeizureNet	Weighted F1-score: 95%

TABLE 5. ***(Continued.)*** **Comparison of performance of our study with the existing approaches in the seizure type classification.**

						Patient specific: 62%
[8]	CPSZ, ABSZ, TNSZ, TCSZ, SPSZ, GNSZ	3050 seizures	FFT, correlation coefficients	-	KNN, XGBoost, SGD, Adaboost and CNN	Weighted F1-score: 90.7%, Patient-wise F1-score: 56.1%
[51]	FNSZ, GNSZ, CPSZ, ABSZ, TCSZ	5 different datasets from TUH site with number of subjects 4689, 4829, 4520, 6363, 4815	DWT, WPD and KPCA	-	Transfer learning methods	Acc: 81.21%
[48]	FNSZ, GNSZ, SPSZ, TNSZ	400 seizures	EMD	-	SVM	Acc: 95%
[21]	GNSZ, FNSZ, TCSZ, Normal	210 seizures	ICA, MFCC and Hjorth descriptor	-	SVM	Acc: 91.4%

Acc-Accuracy, Sen-Sensitivity, Spe-Specificity, RQA-Recurrence quantification analysis, VWCNNs-Variable weight convolutional neural networks, CNN-Convolutional neural networks, LSTM-Long short-term memory, Light GBM-Light gradient-boosting machine, LR-Logistic regression, SGD-Stochastic Gradient Descent, KNN-K-nearest neighbor, RF-Random forest, SVM-Support vector machine, ANN-Artificial neural network, DT-Decision tree, DWT-Discrete wavelet transform, WPD-Wavelet packet decomposition, DTCWD-Dual-tree complex wavelet decomposition, PCA-Principal component analysis, KPCA-Kernel principal component analysis, MFCC-Mel Frequency Cepstral Coefficients, ICA-Independent Component Analysis, EMD-Empirical mode decomposition, FFT-Fast Fourier transform, WPD-Wavelet packet decomposition, GAFT-Gramian Angular Field Transformation, CEEMDAN-Complete ensemble empirical mode decomposition with adaptive noise, MSBCSP-Multi-class specific bands common spatial pattern, TNSZ-Tonic Seizure, MYSZ-Myoclonic Seizure, CPSZ-Complex Partial Seizure, WPD-Wavelet packet decomposition, LDFA-Local detrended fluctuation analysis, RCNN-Recurrent convolutional neural networks, BB-Bern-Barcelona dataset, BU-Bonn University dataset

imum of 10 unique patient recordings. Further, the imbalance in patient recordings across seizure types hindered achieving a balanced classification. Additionally, we refrained from utilizing deep learning algorithms due to the dataset's size limitations and their intricate 'black box' nature, which poses challenges for integration into current clinical settings.

In future, more EEG recordings from multiple datasets can be included which will increase the number of patient recordings in seizure types. Furthermore, it will be beneficial to build a global multiclass model which can discriminate against all eight types of seizure. Moreover, the characteristics of seizure type can be more precisely studied by considering patients with specific age ranges, demographic information and high-quality recording. The study can also be extended by combining time and frequency, time and time-frequency, and frequency and time-frequency domain features. Exploring alternative classifiers based on ensemble methods or tree-based approaches could provide valuable insights and enhance the analysis process. Additionally, delving into the characteristics of seizure types using time-frequency spectrograms would be avenues for future research.

V. CONCLUSION

In this study, an attempt has been made to characterize the patterns of five seizure types such as FNSZ, GNSZ, CPSZ, ABSZ, and TCSZ using EEG signals. Initially, signals were preprocessed using a standard pipeline, and time, frequency, and time-frequency features were extracted. The significant features were identified with a statistical test followed by the XGBoost feature ranking technique. Further, seizure type classification was automated using machine learning algorithms such as LR, SVM, and XGBoost. The performance of the model was evaluated based on accuracy, specificity, sensitivity, precision, and F1 score. We found that combining features from different domains along with the XGBoost classifier achieved the best performance in classifying the five types of seizures. We achieved high average 10-fold binary and multiclass accuracies of 88.21% and 69.43%, respectively. Our results revealed that the BP 11-13Hz was able to discriminate the seizure types. The identification of the best features corresponding to each seizure type in our study enhances the general understanding of each type. The proposed framework for automated multiclass seizure classification using scalp EEG has the potential to assist clinicians in making reliable diagnoses and providing better treatment for epilepsy.

DECLARATION OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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S. ABIRAMI is currently pursuing the M.Tech. degree with the School of Biomedical Engineering, Indian Institute of Technology (BHU) Varanasi. Her master's thesis focuses on EEG signal analysis and AI methods for seizure identification. The roles are data curation, formal analysis, software validation, visualization, and writing-original drafts. Her main research interest includes electronics and signal processing.

TIKARAM is currently pursuing the M.Tech. degree with the School of Biomedical Engineering, Indian Institute of Technology (BHU) Varanasi. The roles are data curation, formal analysis, software, validation, visualization, and writing-original draft. His main research interest includes signal and image processing.

M. KATHIRAVAN received the Bachelor of Engineering degree in electronics and communication engineering, in 2011, and the Master of Engineering degree in medical electronics, in 2014. He is currently a Research Associate with the Defence Bio-Engineering and Electro Medical Laboratory (DEBEL), Bengaluru, India. He is an Expert in biomedical signal processing, artificial intelligence, and machine learning. The roles are data curation, formal analysis, software, validation, visualization, and writing-original draft.

RAJAMANICKAM YUVARAJ received the Ph.D. degree in biomedical electronics from University Malaysia Perlis (UniMAP), Malaysia. He is currently a Lecturer (a Research Scientist) with the Science of Learning in Education Centre (SoLEC), National Institute of Education (NIE), Singapore. His research interests include machine learning algorithms, with application to biomedical signal processing, such as electroencephalogram (EEG) that includes affective computing, brain–computer interface (BCI), and cognitive neuroscience. The roles are: Conceptualization, supervision, and writing-review and editing.

RAMSHEKHAR N. MENON received the M.B.B.S. and M.D. degrees. He is currently a Professor with the R. Madhavan Nayar Center for Comprehensive Epilepsy Care and the Cognition-Behavioural Neurology Centre, Department of Neurology, Sree Chitra Tirunal Institute for Medical Sciences and Technology, Trivandrum. The roles are: Conceptualization, validation, and writing-review and editing. His research interests include epilepsy, EEG, cognitive neurology, neuroimmunology, and clinical neurology.

JOHN THOMAS received the Ph.D. degree from the School of Electrical and Electronic Engineering, NTU Singapore. He is currently a Postdoctoral Fellow with Montreal Neurological Institute, McGill University, Canada. His research work focuses on identifying biomarkers in the intracranial EEG that will improve the management and treatment of epilepsy. The roles are conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing-original draft, and writing-review and editing.

P. A. KARTHICK (Member, IEEE) is currently an Assistant Professor with the Department of Instrumentation Engineering, National Institute of Technology, Tiruchirappalli, India. His research interests include exploiting the engineering principles, methods, and algorithms for the effective diagnosis and treatment of neurological disorders like epilepsy. The roles are supervision, validation, visualization, writing-original draft, and writing-review and editing.

A. AMALIN PRINCE (Senior Member, IEEE) received the Ph.D. degree from BITS Pilani, Pilani, India, in 2011. He is currently a Professor with the Department of Electrical and Electronics Engineering, BITS Pilani, Goa, India. His research interests include FPGA-based System design, hardware-accelerated data processing, affective computing, and applications of artificial intelligence.

JAC FREDO AGASTINOSE RONICKOM received the Ph.D. degree from the Department of Electronics Engineering, Anna University. He is currently an Assistant Professor with the School of Bio-Medical Engineering, Indian Institute of Technology (BHU) Varanasi. The roles are conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing-original draft, and writing-review and editing. His research interests include bio-medical signal and image processing, bio-medical instrumentation, artificial intelligence, computational neuroscience, and computational biology.