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A Comparative Analysis of Rank based Feature Selection Methods for Epileptic Seizure Prediction using EEG Signals

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Abstract
Epilepsy prediction addresses the unpredictable nature of seizures, which disrupt brain function and pose risks like loss of consciousness or injury. Accurate forecasting enables timely interventions, such as medication or alerts, to prevent harm and enhance patient safety. Raw EEG-based epilepsy prediction generates many redundant and irrelevant features, which can degrade model performance. Feature selection methods enhance epilepsy prediction from EEG signals by identifying the most discriminative features, reducing dimensionality, and improving classifier sensitivity and accuracy. In order to overcome difficulties in managing high-dimensional, noisy EEG signals for epilepsy prediction, proposed work synthesizes time-domain, frequency-domain, and nonlinear feature extraction employing discrete wavelet transform (DWT) for band extraction and concentrating on ANOVA test, mRMR (Minimum-Redundancy–Maximum-Relevance), and Chi-square approaches for epilepsy prediction. Results show sensitivity of 97.34 % and accuracy of 93.60% with mRMR method which is higher than ANOVA and chi square. These methods effectively reduce feature dimensionality, enhancing computational efficiency and model interpretability, while multi-domain feature fusion further improves detection performance. However, variability in EEG data and limited generalizability across heterogeneous datasets remain challenges.

Keywords: Epilepsy, Feature selection, mRMR, ANOVA, Chi-square.

1. Introduction

Epilepsy is a chronic neurological disorder characterized by the recurrence of unprovoked seizures, a result of abnormal synchronous neuronal discharges in the brain. Electroencephalography remains a primary, non-invasive modality for monitoring cerebral activity and henceforth has a very significant role in the detection and prediction of epileptic events[1]. EEG recordings are normally high-dimensional, non-stationary, and subjected to considerable noise and artefacts. This complexity creates significant challenges for automated algorithms to accurately distinguish between ictal, preictal and non-ictal states [2].

In recent years, machine learning and signal processing techniques have been increasingly applied to EEG data for seizure detection and epilepsy diagnosis. An essential stage in creating dependable autonomous systems is feature selection, which involves reducing the initial big feature set to a subset that includes the most pertinent and discriminative features for the classification task. Feature selection further reduces computational complexity, avoids over-fitting problems, increases model interpretability, and opens paths toward real-time or wearable devices.

Research on feature selection methods for epilepsy detection using EEG data has emerged as a critical area of inquiry due to the increasing prevalence of epilepsy worldwide and the complexity of EEG signals in clinical diagnosis [3, 4]. Over the past decade, advancements in machine learning and signal processing have propelled the development of automated seizure detection systems, evolving from traditional statistical feature extraction to sophisticated multi-domain and deep learning approaches [5,6,7]. The practical significance of this research is underscored by the World Health Organization’s estimate of over 50 million people affected by epilepsy globally, with timely and accurate seizure detection being vital for effective treatment and improved patient outcomes [3,4]. Automated EEG analysis reduces the burden on clinicians and enhances diagnostic precision, addressing the challenges posed by the high dimensionality and non-stationary nature of EEG signals [8,9].

Despite extensive research, the problem of selecting the most relevant features from EEG data for epilepsy detection remains unresolved (Farawn et al., 2025 [10,11]. The high dimensionality of EEG features, coupled with redundancy and noise, complicates model training and reduces classification accuracy (Mera-Gaona et al., 2016) (Farawn et al., 2025) (Hussein et al., 2013)[8,11]. While various feature selection methods such as ANOVA, minimum redundancy maximum relevance (mRMR), and Chi-square tests have been applied, their comparative effectiveness and integration with classification algorithms lack consensus (Liu et al., 2024) (Hussain et al., 2023) (Wang & Zhou, 2020)[12, 13]. Some studies emphasize filter-based methods for computational efficiency, whereas others advocate wrapper or hybrid approaches for improved accuracy, leading to ongoing debate (Sánchez-Hernández et al., 2022) (Hakem et al., 2023) (Farawn et al., 2025)[10,11]. The consequences of this gap include suboptimal seizure detection performance and limited generalizability across patient populations and datasets (Aboyeji et al., 2024) (Farawn et al., 2025)[14]. Feature selection methods such as ANOVA test, mRMR, and Chi-square aim to identify features that maximize relevance to seizure events while minimizing redundancy (Liu et al., 2024) (Hussain et al., 2023) (Wang & Zhou, 2020)[13]. This review is important because effective feature selection is critical in handling the high-dimensional, noisy, and complex nature of EEG signals, which directly impacts the performance of automated epilepsy diagnosis systems. This paper works on identification and synthesis of multi-domain feature extraction techniques combined with statistical selection methods for seizure detection. The purpose of this research is to critically analyse and compare the performance of ANOVA test, mRMR, and Chi-square feature selection methods in the context of EEG-based epilepsy prediction. This paper includes pre-processing, feature extraction and feature selection methodology for detection of epilepsy using CHB MIT dataset.

The main objective of proposed work is on feature selection and prediction of preictal phases for performance improvement in terms of sensitivity.

2. Methodology

This paper focuses on feature selection approaches using freely available standard dataset of epileptic EEG signal. Process flow of work is shown in fig.1. Details of each block is explained as under.

2.1 Dataset

The CHB-MIT Scalp EEG Database contains EEG recordings from 22 paediatric subjects (5 males aged 3–22 years, 17 females aged 1.5–19 years) with intractable seizures, collected at Children's Hospital Boston. Signals use the International 10-20 electrode system, with most files having 23 channels, sampled at 256 Hz and 16-bit resolution.

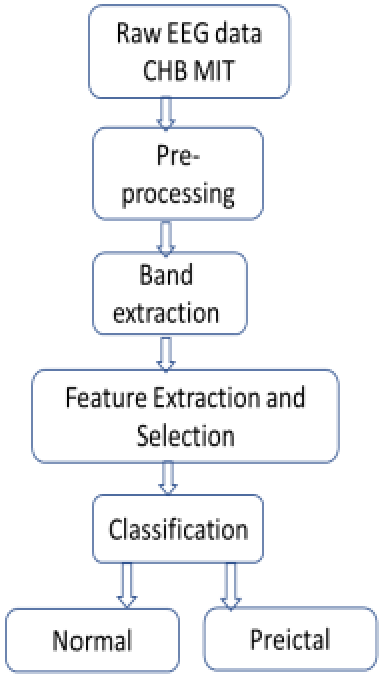


Figure.1 Process flow of proposed work

2.2 Preprocessing

Preprocessing of CHB-MIT scalp EEG data includes removing line frequency noise, applying bandpass filters, and segmenting the signals into 4-second windows[15]. These steps improve signal quality for epilepsy detection by eliminating artifacts such as 60 Hz powerline interference common in US recordings and filtering out irrelevant frequency components. These steps reduce noise, normalize spectra, and create fixed-length segments for feature extraction or model input, commonly yielding high sensitivity in seizure detection.

A bandpass filter (typically 0.5–30 Hz or 1–40 Hz Butterworth order 4–6) removes low-frequency drifts (e.g., eye blinks <0.5 Hz) and high-frequency muscle noise (20-300 Hz), retaining delta-theta-alpha-beta rhythms key to seizures[16, 17,18]. Signals taken from preictal and interictal phases are segmented into non-overlapping 4-second epochs (1024 samples at 256 Hz), balancing temporal resolution with computational efficiency for time-frequency features like STFT or wavelet transforms. To extract EEG rhythms the Daubechies db6 has been used as the mother wavelet, which has 6 vanishing moments. The segments of EEG signal were decomposed into a seven-level DWT decomposition equivalent to the δ, θ, α, β and γ rhythms. The approximation A7 and details coefficients D7 and D6 represent a frequency range from0 to 4 Hertz (δ). The details coefficients D5, D4 and D3 represent frequency ranges 4 to 8 Hz (θ), 8 to 16 Hz (α) and 16 to 32 Hz (β), respectively[15].

2.3 Feature Extraction

Feature selection in epilepsy research is applied to a broad set of candidate descriptors derived from four main domains: Time-domain features, Frequency-domain features, Time-frequency features and Nonlinear/dynamical features. Time-domain features include amplitude statistics, Hjorth parameters, zero crossing, and line length, which characterize the signal's behaviour over time[19]. Frequency-domain features involve measures such as band power, relative spectral power across delta to gamma bands, and spectral entropy, providing insights into the - frequency content of the signal. Time-frequency features are extracted using methods like wavelet or short-time Fourier decompositions, capturing details such as discrete wavelet transform coefficients and energy distribution within sub-bands[20]. Nonlinear or dynamical features encompass a range of complexity measures, including approximate, sample, permutation, and fuzzy entropies, fractal dimension, Lyapunov exponents, and recurrence quantification analysis, which assess the signal's underlying dynamic properties[21]. Reviews and experimental studies repeatedly show that nonlinear entropy measures and time-frequency (wavelet) coefficients are particularly discriminative for seizure vs interictal segments, motivating selection algorithms that can handle heterogeneous feature types [2,7,20,21]. The proposed work has combined a two approaches first wavelet decomposition to extract specific EEG band and then secondly time domain and frequency domain features as discussed below.

2.3.1 Energy of the signal: Ei is the energy of approximation and detail components Ci given by:

$$E_i = \sum_{n=1}^{N} C_i^2[n] \tag{1}$$

Where, N is the length of C_i

2.3.2 Standard deviation

$$S = \sqrt{\frac{\sum_{i=1}^{N}(Ci-\mu)^2}{N-1}} \quad \text{Where, mean of } C_i \text{ is } \mu. \tag{2}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} C_i \quad \text{where, } N \text{ is the length of } Ci. \tag{3}$$

2.3.3 Signal peaks: The peaks of the pre-ictal and inter-ictal state were calculated by calculating the peaks of each segment.

2.3.4 Derivative of spectrum of the signal: The FFT of each rhythm is taken during each 4 sec segment and then derivative of its magnitude is taken for whole segment.

$$D_{\widehat{f}_i} = \sum_{m=1}^{M-1} \widehat{f}_i'[m]^2 \tag{4}$$

Where $\widehat{f}_i'[n] = \widehat{f}_i[m+1] - \widehat{f}_i[m]$ for m=1,….,M-1, M is length of $\widehat{f}_i$

Data is segmented into 4 sec with sampling rate of 256 Hz. No. of samples per channel with 30 minutes of preictal data and 30 minutes of interictal data gives samples of 9,21,600 for one channel. Each 4 sec segment is used to extract four band alpha, theta, beta and delta using DWT and from each band four features are extracted. Final feature matrix size is 16x900.

2.4 Feature Selection

In recent years, machine learning (ML) and signal-processing techniques have been increasingly applied to EEG data for the purpose of seizure detection and epilepsy diagnosis. A crucial step in developing reliable automatic systems is **feature selection**, which involves identifying the subset of features from the original large feature set that is most relevant and discriminative for the classification task. Employing feature selection not only helps in reducing computational complexity and mitigating the risk of over-fitting, but also enhances model interpretability and paves the way for real-time or wearable implementations.

Feature selection methodologies are broadly classified into three categories: (i) **filter methods**, which rank or select features independent of any learning algorithm (such as mutual information, ANOVA, chi-square)[12,22]; (ii) **wrapper methods**, which evaluate subsets of features by iteratively training a classifier (for example, recursive feature elimination, genetic algorithm-based search)[18]; and (iii)

embedded methods, where feature selection is integrated within the classifier training process like genetic algorithm or tree-based feature importance [23,24]. In the context of EEG-based epilepsy detection, each of these approaches has been applied with varying degrees of success. A n evaluation of multiple feature-selection schemes found that although no single method consistently outperforms all others across classifiers and datasets, combinations such as K-nearest neighbour with support vector machine and embedded random-forest selection achieved strong results (F1 ≈ 0.90) [12]. Bandarabadi M et al used adaptive stepwise feature-selection method combined with minimum-redundancy–maximum-relevance (mRMR) ranking to improved classifier sensitivity and specificity [25].

Selecting the optimal feature-subset is particularly critical for EEG seizure detection systems, as practical deployment often requires low latency, minimal computational burden, and high robustness to artefacts and inter-subject variability. Effective feature selection thus contributes to improved classification performance, lower power and memory requirements for portable devices, and enhanced clinical interpretability of the selected biomarkers.

In this paper, we present a comprehensive overview of feature-selection methods applied in EEG-based epilepsy detection, discuss key challenges in selecting optimal subsets for this domain, and propose a hybrid framework that combines filter and embedded strategies to improve real-time applicability.

2.4.1 Minimum redundancy and Maximum Relevance (mRMR)[12,13,25,26,27, 28]

In terms of mutual information, the purpose of feature selection is to find a feature set S with m features $\{x_i\}$, which jointly have the largest dependency on the target class c. This scheme, called Max-Dependency, has the following form:

$$max D(S,c), D = I(\{x_i, i = 1, \dots m\}; c) \quad (5)$$

Max-Relevance is to search features satisfying (6), which approximates $D(S,c)$ in (5) with the mean value of all mutual information values between individual feature xi and class c:

$$D = \frac{1}{|S|}\sum I(x_i; c) \quad (6)$$

It is likely that features selected according to Max Relevance could have rich redundancy, i.e., the dependency among these features could be large. When two features highly depend on each other, the respective class-discriminative power would not change much if one of them were removed. Therefore, the following minimal redundancy (Min Redundancy) condition can be added to select mutually exclusive features.

$$min R(S), R = \frac{1}{|S|^2}\sum I(x_i, x_j) \quad (7)$$

The criterion combining the above two constraints is called "minimal-redundancy-maximal-relevance" (mRMR)

2.4.2 Chi square Test [29,30,31]

Chi-square statistic is calculated as:

$$\chi c2=\sum(Oi-Ei)2Ei\chi c2=\sum Ei(Oi-Ei)2 \quad (8)$$

where,

- c is degree of freedom
- *Oi* is the observed frequency in cell *i*
- *Ei* is the expected frequency in cell *i*

Feature selection plays a crucial role in improving classification performance by reducing dimensionality, enhancing model generalizability, and decreasing computational complexity. In this study, a top-k ranking strategy with value of k=10,20 is used to select the most informative features from the dataset before classification with Support Vector Machines (SVM). Initially, all features were ranked according to a specified criterion, such as p<0.5, ANOVA F-values, $Chi^2$and mRMR. After ranking, the top *k* features were selected to evaluate the impact of *k* on classifier performance. The value of *k* was systematically varied across a predefined range (e.g., k=5,10,15,20)[27–30] to identify the optimal subset size.

2.5 Classificationss

The SVM classifier with a linear kernel was trained and validated using 5-fold cross-validation, which helps ensure reliable performance estimation by partitioning data into five subsets and iteratively training on four while testing on the remaining one. This method maximizes the use of data for both training and validation, reducing bias and variance in performance estimates.

Accuracy, sensitivity, specificity, and false positive rate (FPR) are standard metrics for binary classification models, derived from the confusion matrix elements: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN)

Accuracy represents the proportion of correct predictions overall.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Sensitivity measures the model's ability to detect positive cases correctly.

$$Sensitivity = \frac{TP}{FN+TP} \tag{10}$$

Specificity indicates the proportion of actual negatives correctly identified

$$Specificity = \frac{TN}{TN+FP} \tag{11}$$

FPR quantifies the rate of incorrectly labelling negatives as positives.

$$FPR = \frac{FP}{TN+FP} \tag{12}$$

These equations enable precise evaluation of SVM classifiers under 5-fold cross-validation by averaging metrics across folds.

3. Implementation and Results

CHB MIT dataset of 10 patients taken with 30 minutes of ictal and 30 minutes of preictal phase. After preprocessing features are extracted from each band (alpha, theta, beta and delta). Feature selection is done using three methos: ANOVA test, Chi square method and mRMR approach [12,22,27]. Top 10 and 20 features are used to train SVM classifier with linear kernal and 5 fold cross validation. Table 1 and table 2 demonstrates patient specific performance of proposed method like accuracy, sensitivity, specificity and false positive rate with k=20 and k=10 respectively. Table 3 shows average value of performance parameters without feature selection algorithm and with various approach of feature selection. Model performs better with k=20 and with mRMR approach.

Table 1: Classification results with top 20 features

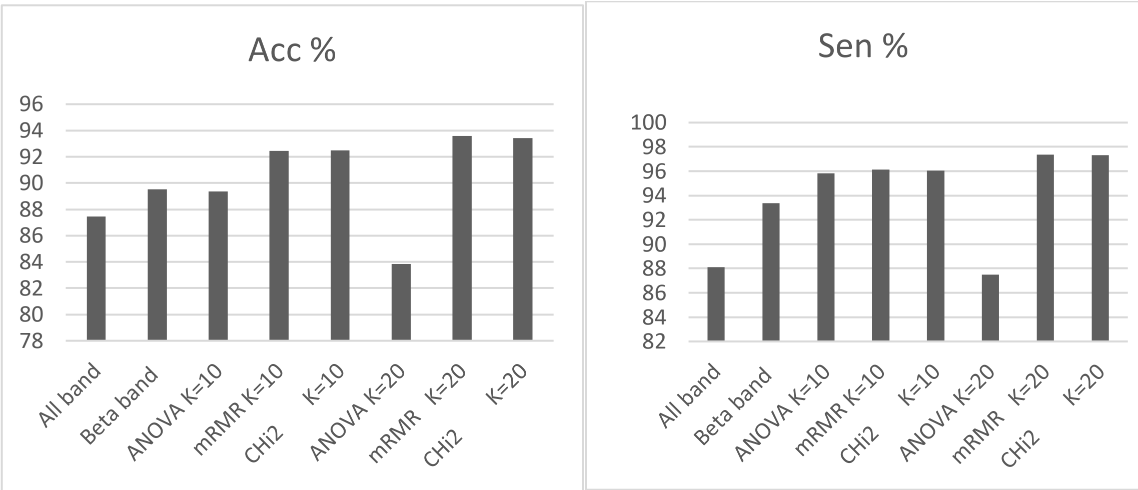
Data	Using mRMR k=20				Using Chi^2 k=20				ANOVA k=20			
	ACC	Sen	Spec	FPR	ACC	Sen	Spec	FPR	ACC	Sen	Spec	FPR
chb03	92.35	96.23	89.07	0.11	93.21	97.82	89.41	0.11	93.09	97.81	89.21	10.79
chb08	93.95	98.90	89.91	0.10	94.07	98.64	90.29	0.10	70.74	76.42	67.07	32.93
chb11	95.80	99.47	92.64	0.07	95.31	99.20	91.99	0.08	50.494	51.30	50.30	49.70
chb12	92.56	96.23	89.43	0.11	93.67	99.16	89.29	0.11	92.68	98.32	88.22	11.78
chb13	93.46	96.07	91.12	0.09	93.58	96.33	91.14	0.09	93.09	98.8	90.68	9.32
chb15	93.21	97.81	89.41	0.11	91.98	94.97	89.35	0.11	89.63	94.96	85.43	14.57
chb16	92.96	92.86	93.07	0.07	91.36	91.56	91.15	0.09	65.80	64.75	67.02	32.98
chb19	93.83	98.90	89.71	0.10	93.46	98.62	89.29	0.11	93.21	98.08	89.24	10.76
chb21	95.52	99.20	92.46	0.08	94.79	98.92	91.43	0.09	93.94	97.33	91.11	08.89
chb22	92.35	97.77	88.03	0.12	92.96	97.80	89.01	0.11	95.59	97.00	88.94	11.06
AVG	**93.60**	**97.34**	**90.49**	**0.10**	**93.44**	**97.30**	**90.24**	**0.10**	**83.83**	**87.48**	**80.72**	**19.28**

Table 2: Classification results with top 10 features

Data	Using mRMR k=10				Using Chi2 k=10				ANOVA k=10			
	ACC	Sen	Spec	FPR	ACC	Sen	Spec	FPR	ACC	Sen	Spec	FPR
chb03	92.10	95.23	89.38	10.62	92.35	96.23	89.07	10.93	92.84	96.77	89.52	10.48
chb08	94.20	99.18	90.13	09.87	93.70	98.36	89.86	10.14	84.20	98.26	76.48	23.52
chb11	95.80	99.73	92.45	07.55	95.06	98.15	92.34	07.66	93.70	98.90	89.51	10.49
chb12	92.43	97.77	88.17	11.83	92.43	97.77	88.17	11.83	95.06	99.46	91.38	08.62
chb13	91.48	92.42	90.58	09.42	93.83	97.84	90.43	09.57	92.56	98.86	87.69	12.31
chb15	91.36	93.51	89.41	10.59	91.73	94.71	89.12	10.88	93.33	96.06	90.91	09.09
chb16	88.52	91.71	85.78	14.22	87.41	86.86	87.97	12.03	83.69	91.19	78.48	21.52
chb19	91.11	95.87	87.25	12.75	92.96	97.54	89.19	10.81	82.72	83.89	81.62	18.38
chb21	94.79	98.40	91.80	08.20	92.85	95.77	90.38	09.62	92.84	96.77	89.52	10.48
chb22	92.72	97.53	88.71	11.21	92.59	97.26	88.76	11.24	82.59	97.93	74.68	25.32
AVG	92.45	96.14	89.37	10.63	92.49	96.05	89.53	10.47	89.35	95.81	84.98	15.02

Table 3: Comparative Performance of Machine Learning Models with and without Feature Selection

			Top 10 features			Top 20 features		
	All band	Beta band	ANOVA K=10	mRMR K=10	Chi^2 K=10	ANOVA K=20	mRMR K=20	Chi^2 K=20
Acc %	87.44	89.53	89.35	92.45	92.49	83.83	**93.60**	93.44
Sen %	88.12	93.35	95.81	96.14	96.05	87.48	**97.34**	97.32
Spec %	86.90	86.71	84.98	89.37	89.53	80.72	**90.49**	90.24
FPR %	15.88	13.29	15.02	10.63	10.47	19.28	**09.60**	10.00



(a) (b)

Figure.2 (a) Plot of accuracy for various approaches (b) Plot of sensitivity for various approaches

Comparative analysis of proposed work is given in Table. 3. Performance is tested on features extracted from each band first. Based on analysis of each band beta band selected and then further reduction on feature matrix is done using rank-based methods. Results of mRMR is better with Accuracy of 92.45% of accuracy and 96.14% of sensitivity with top 10 features only. Performance of model in terms of accuracy and sensitivity is also shown in Fig. 2.

Table 4: Model Metrics: Baselines and Our Method

Author	**Feature selection method**	**No. of features**	**Accuracy**	**Sensitivity**	**FPR/F score**
Lisha Zhong et al.	Pearson correlation	-	95.93%	-	4.7%/94.97%
Ali Imren et al.	Chi^2	34	-	75.34%	5.32%
Varsha Harpale	ANOVA	-	96.02%	94.44%	3.52%
Prathap et al.	sparse feature selection	-	-	86.11 %	13.8%
Sergio E.	LIME Shap Value	50	95% 95%	63% 57%	-
Peng et al.	F statistics	61	99.5%	92.63%	/91.21%
Aboyeji et al.	mRMR	30 15	86.05% 80.33%	81.38% 94.94%	-
Proposed work	mRMR	20	93.6%	97.3%	-

4. Discussion and Conclusion

Overall, these feature selection techniques offer significant benefits for real-time and wearable epilepsy monitoring, yet further research is needed to standardize methodologies and validate performance in clinical settings. The collective body of research on feature selection methods for epilepsy detection using EEG data demonstrates that statistical and information-theoretic techniques such as the ANOVA test, minimum redundancy maximum relevance (mRMR), and Chi-square methods play a pivotal role in enhancing the performance of automated seizure detection systems. These methods effectively reduce the high dimensionality of extracted EEG features, which often encompass complex, noisy, and nonlinear signal characteristics. Varsha Harpale used ANOVA test for feature reduction and proposed model with sensitivity of 94.44%.

Ali Imren et al. used Chi^2 method to get sensitivity of 75.34% with 34 features. Aboyeji et al. proposed model with mRMR method which gives sensitivity of 94.94% using 15 features. Our model uses only four features from beta band using 23 channels and compares prediction performance using ANOVA, Chi^2 and mRMR approaches. Results shown in table 3 using mRMR method outperforms (Sensitivity of 96.14% with rank 10 and 97.34% with rank 20) against the work of Aboyeji et.al. (Sensitivity of 94.94%).

Moreover, literature highlights the advantage of combining multi-domain feature extraction with robust feature selection, leveraging temporal, spectral, nonlinear, and entropy-based attributes derived from EEG signals. This fusion captures complementary information critical for distinguishing seizure states, although challenges remain in managing feature redundancy and maintaining computational efficiency. While ANOVA offers straightforward statistical discrimination, mRMR emphasizes relevance and redundancy balance, and Chi-square provides an effective ranking mechanism; their combined or hybrid use often yields superior feature subsets. Adaptive and patient-specific strategies, though promising for personalized seizure detection, introduce additional complexity and computational demands, which may limit real-time or wearable applications unless carefully optimized. There is a discernible need for more extensive validation across diverse populations and real-world conditions to ensure clinical applicability. Furthermore, the balance between aggressive dimensionality reduction and preservation of critical information is delicate; excessive feature elimination may impair classifier performance. Future research should focus on standardized benchmarking, exploration of nonlinear dependency capture within feature selection, and the development of lightweight, adaptive algorithms that maintain robustness and efficiency in practical deployment scenarios. By synthesizing current methodologies and their comparative effectiveness, this work aims to identify strengths, limitations, and gaps in the literature, thereby guiding future research and practical implementations in clinical and wearable seizure detection technologies.

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