

Detection of seizures from EEG using KNN and Opti-KNN

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ABSTRACT

Epileptic seizures are caused by sudden and abnormal electrical disturbances in the brain, which can be identified through electroencephalogram (EEG) signals. Detecting seizures accurately at an early stage is important for providing timely treatment and improving patient care. In this study, two machine learning (ML) methods, namely k-nearest neighbour (KNN) and an optimized version of KNN (Opti-KNN), are proposed for automated seizure detection using EEG data. The research was carried using the BONN EEG dataset. The standard KNN model produced an accuracy of 94%, whereas the optimized KNN model improved the performance and achieved 97.33% accuracy. The findings indicate that proper hyperparameter tuning can greatly enhance the effectiveness of seizure classification. Overall, the proposed models provide a consistent and effective solution for automated seizure detection.

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1. INTRODUCTION

Epilepsy is a long-term illness categorized by repeated seizures caused by abnormal activities of brain. The world health organization (WHO) projects over 50 million people have seizures in entire world [1]. Most people who have seizures don't know that they have them. The early detection of seizures can be life-changing for people with epilepsy and can be an area of substantial research in medical informatics. The best way to monitor brain's electrical activity is to use electroencephalography (EEG) [1], [2]. EEG is an effective way for detecting seizures. However, EEG signals are complex and noisy. Traditional analysis of EEG requires a lot of time because it is done manually and it is prone to human error. The automated seizure detection is a good method that uses machine learning (ML) for continuous monitoring of patient's needs. The greatest challenge in automated seizure detection with EEG is to differentiate the seizure epochs from the non-seizure ones. Nowadays, wearable devices are used in combination with signal processing techniques to modify the signals and detect the autonomic nervous system and limb movements in order to help predict seizures [2]–[7]. Seizures are, in many cases, unprovoked, which makes it difficult to detect them. EEG analysis helps to identify seizures, but EEG's complex and noisy signals create challenges [8].

Analysis of EEG subjects poses an additional problem due to the lack of neurologists available night and day, which cannot be supported using current resources [9], [10]. To address these challenges, algorithms

have been created to identify seizures through the processing of both linear and non-linear EEG characteristics [11]–[18]. Multiple studies have been made regarding the discrimination of EEG data to predict seizures [17]–[26]. There are several different techniques that researchers have independently developed algorithms which can detect seizures early on based on their respective algorithms. Singh and Dehuri [19], conducted studies which included fuzzy logic along with traditional k-nearest neighbour (KNN) algorithms. The addition of fuzzy logic allowed for a decrease in the time consumed while performing a seizure detection analysis; however, there was minimal improvement provided the accuracy produced by the combination of fuzzy logic with traditional methods resulting in a reported accuracy rate of 93.33%. Serna *et al.* [20], used an SVM based approach to detect seizures and reported an accuracy level equal to 94.88%. Aayesha *et al.* [21], projected an innovative method for using a combination of fuzzy logic and recurrent neural networks (RNN) which resulted in an accuracy level equal to 92.79%. Additionally, Kunekar *et al.* [22], identified features that should not be used in determining seizure detection and drew upon algorithms such as SVM.

Seizure detection is crucial for improving the lifespan identifying patients with epilepsy and other neurological disorders. Real-time detection systems can reduce healthcare costs, prevent injuries, and enable timely intervention. Traditional methods face challenges such as noisy EEG data, seizure variability, and computational demands [23], [24]. This research offers a low-cost, real-time solution using KNN technique. Basic KNN algorithms offer a straightforward approach and may not always achieve the best performance due to their simplicity. Using the automated approach for optimizing the hyperparameters improved the efficacy of traditional KNN algorithms [25], [26]. This paper investigates the effectiveness of both KNN and Opti-KNN algorithm in improving seizure detection accuracy.

The main aim of this Study is to identify seizures from EEG subjects. The classes considered in this research are Normal, Pre-Seizure and Seizure. The EEG subjects are collected from BONN dataset. This Dataset is publicly available. This research's novelty lies in optimizing a simple, interpretable model KNN to handle the complex, noisy, and high-dimensional nature of EEG signals, which helps in efficient, personalized real-time seizure detection. The rest of this manuscript is organized as below. Section 2 discussed the proposed methodology in detail. Section 3 discusses the experimental results and analysis, along with a comparison with existing state-of-the-art techniques. Finally, Section 4 summarizes the major findings of the study and concludes the paper.

2. METHODS

The primary objective of this study is to detect epileptic seizures accurately and efficiently. The details of our proposed approach is represented in Figure 1.

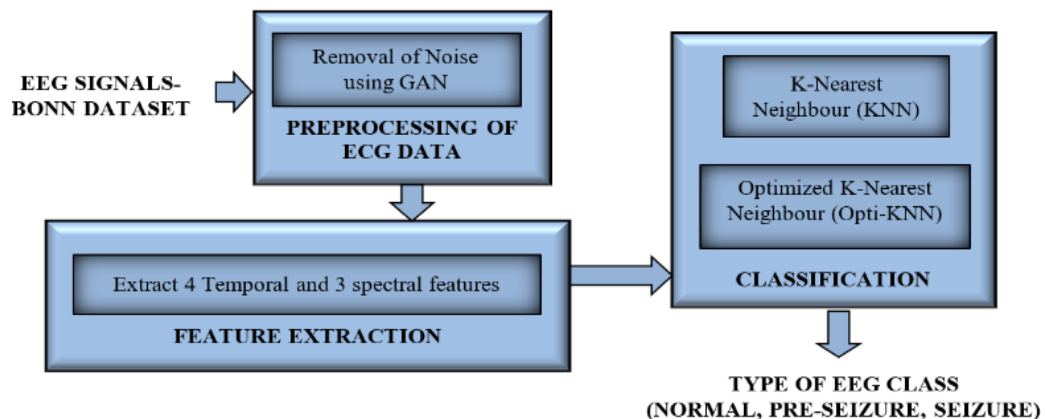


Figure 1. Block diagram of method

2.1. Database

In this investigation on seizure detection, we utilized a labelled BONN EEG dataset. The data consists of five categories that make it ideal for classification tasks. There are five classes or categories within the dataset: Z, O, N, F, and S. Class Z refers to EEG recordings of subjects with their eyes open (healthy), while Class O refer to EEG recordings of subjects with their eyes closed (healthy). Class N

consists of seizure-free EEG recordings (epilepsy-free subjects), and Class F consists of seizure-free EEG recordings (subjects with epilepsy). Class S consists of EEG recordings during the seizure episodes for subjects with epilepsy. Each of the five classes contains a total of 100 EEG recordings; therefore, there are a total of 500 EEG recordings in the dataset.

Based on our research, we combined the five classes into three main classes: Normal (composed of the Z and O classes); Interictal (composed of the N and F classes); and Ictal (composed of the S class). During our research, we utilized samples from the Normal and Interictal classes to create a training and test dataset. A summary of the training and testing samples used for this study can be found in Table 1.

Table 1. Summary of dataset

	Total samples	Training samples	Testing samples
Normal subjects (class 1)	200	140	60
Pre-seizure subjects (class 2)	200	140	60
Seizure subjects (class 3)	100	70	30
Total subjects	500	400	100

2.2. Pre-processing EEG subjects

EEG signals were pre-processed to enhance the quality of data for feature extraction. The preprocessing steps included filtering and normalization. Generative adversarial network (GAN) [23] is used to remove noise, and then normalized to ensure consistent scaling across different recordings.

2.3. Feature extraction

Seven features are derived from the EEG signals, including four temporal-domain features and three spectral-domain features. The temporal features considered in this study are presented below.

$$A_{min} = \text{minimum}(A_{in}) \quad (1)$$

$$A_{max} = \text{maximum}(A_{in}) \quad (2)$$

$$A_{mean} = \sum_{k=1}^m \frac{A_{in}(k)}{m} \quad (3)$$

$$\sigma = \sqrt{\sum_{k=1}^m \frac{(A_{in}(k) - A_{mean})^2}{m}} \quad (4)$$

where $A_{in}(k)$ is the given EEG subject, A_{min} , A_{max} , A_{mean} and σ are minimum, maximum, mean and standard deviation of given EEG subject.

The features derived from the frequencies of the EEG help to determine the non-linear and non-stationary nature of the EEG signals. Power spectral density (PSD) [27], a measure of the signal's frequency content, is calculated to determine the frequency or spectral features. The frequency features based on the PSD are represented as the: Maximum PSD, Mean PSD and Standard deviation of PSD. Statistically,

$$P_{max} = \text{maximum}(P(\omega)) \quad (5)$$

$$P_{mean} = \frac{\sum_{\omega} (\omega P(\omega))}{\sum_{\omega} (P(\omega))} \quad (6)$$

$$\sigma_s = \sqrt{\frac{\sum_{\omega} (\omega P(\omega)) - \sum_{\omega} (P_{mean}^2 P(\omega))}{\sum_{\omega} (P(\omega))}} \quad (7)$$

where $P(\omega)$, P_{max} , P_{mean} and σ_s are calculated powers at frequency ω .

2.4. Classification

For Classification of EEG Subjects KNN and Opti-KNN algorithms are used. KNN classifier is an unsupervised ML algorithm. It finds the distance from train data points to test data points and assigns label based on the distance measure.

The KNN algorithm is used to predict the target class/value based on the similarity between a test sample and the training samples. For each test instance, the algorithm calculates the distance between the test

instance and all training instances, identifies the K nearest neighbors, and determines the prediction based on the neighbors. The value of K is selected to obtain reliable prediction performance. The overall procedure of the conventional KNN algorithm is presented in Algorithm 1 KNN Algorithm.

Algorithm 1. KNN algorithm

- Step 1 Consider training data points $\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$ where $x_i \in S_i = \{s_1, s_2, s_3, s_4, \dots, s_M\}$ a set of instances, and M features for each set and labels $y_i \in Y = \{0, 1, 2, \dots, p\}$, p denotes the total number of classes.
- Step 2 Here, distance measure to be selected. The Euclidean measure between $S = \{s_1, s_2, s_3, s_4, \dots, s_N\}$ and $T = \{t_1, t_2, t_3, t_4, \dots, t_N\}$ is given as

$$D(S, T) = \sqrt{\sum_{i=1}^N (s_i - t_i)^2}$$

- Step 3 Initialize the value for K i.e. Number of neighbours to be considered.
- Step 4 Train the model until the label or attributes for each subset is achieved.
- Step 5 Test the model with test data.

Feature set attributes can sometimes use different measurement scales, which means that the resulting classifications depend solely on one attribute. Standardization of the data addresses this issue. Then, we can choose hyper parameters for the KNN classifier such as the distance measure and the number of neighbors. The KNN classifier will be optimized with the best hyper parameter values for classification. In this study, we will investigate the four hyper parameter values that have been applied previously.

To improve the prediction performance of the conventional KNN model, an optimized KNN approach is employed by selecting suitable model parameters and identifying the most appropriate neighborhood size. The optimization process aims to reduce prediction error and improve the overall accuracy of the model. The optimized KNN procedure, including parameter selection and prediction using the optimized neighborhood, is presented in Algorithm 2 Opti-KNN algorithm.

Algorithm 2. Opti-KNN algorithm

- Step 1 Consider training data points $\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$ where $x_i \in S_i = \{s_1, s_2, s_3, s_4, \dots, s_M\}$ a set of data points each with M features and labels $y_i \in Y = \{0, 1, 2, \dots, p\}$, p gives us the total number of classes.
- Step 2 Training data points $\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$ are separated into subsets, where each subset contains data with common label or attribute based on predefined criteria.
1. Number of Neighbours: For N observations the neighbours selected are at a range $[1, N/2]$.
 2. Distance Measure: The best distance measure to be selected among different distance measure.

Distance = [cityblock, hamming, chebychev, correlation, cosine, euclidean, jaccard, mahalanobis, Minikowski, seuclidean, spearman].

After optimization if Euclidean distance measure selected. The measure between $S = \{s_1, s_2, s_3, s_4, \dots, s_N\}$ and $T = \{t_1, t_2, t_3, t_4, \dots, t_N\}$ is given as

$$D(S, T) = \sqrt{\sum_{i=1}^N (s_i - t_i)^2}$$

3. Distance weight: This could be 'equal', 'inverse', and 'squaredinverse'. If d is the considered distance then equal uses the distance d inverse uses $1/d$ and squared inverse used $1/d^2$ as weight.

4. Standardize: When there is a collection of values having different scales, we use standardization. Standardization involves converting the values to zero mean and standard deviation of one. Where standardization is applied, then true; otherwise false

3. RESULTS AND FINDINGS

In this Study, initially a KNN algorithm was used for evaluation of seizure detection and classification. The features extracted from the EEG (i.e., temporal and spectral) served an important role in improving classification performance of the KNN Classifier. The confusion chart result obtained is shown in Figure 2.

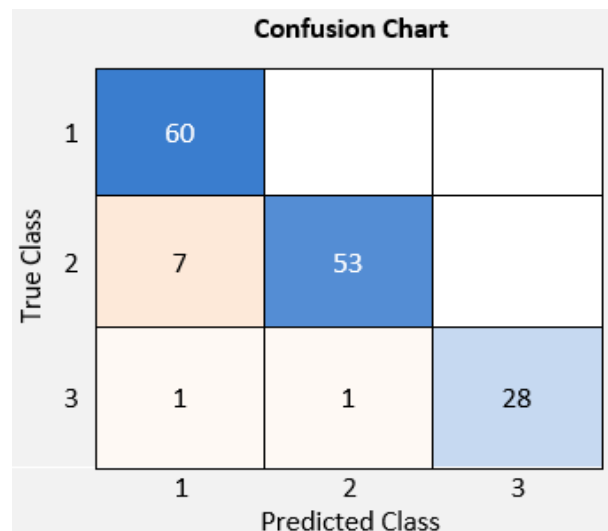


Figure 2. Confusion chart obtained using KNN algorithm

The classification result showed that the KNN algorithm classifies seizures and non-seizures with a high degree of specificity and a low number of misclassifications as determined by performance metrics shown in Table 2. By optimizing the classification process, not only does this increase performance; but it produces an optimized set to identify probable objective function through the use of a model created from gaussian process. Evaluation of a function is required for the training of any model and occurs during the overall optimization procedure. The objective function model will reveal the hyperparameters that will provide the best performance from the model. Step-by-step guideline for performing hyperparameter optimization is provided in Figure 3.

Table 2. Performance metrics using knn algorithm

	Precision	Recall	Specificity	F-Score
Normal	100	88.25	100	93.75
Pre-seizure	88.33	98.14	92.70	92.98
Seizure	93.33	100	98.36	96.55
Accuracy of DT algorithm = 94 %				

The model's prediction of the feasible point is shown in Figure 4. The minimum leaf size is used in generating an objective model function. The minimized objective function value observed is related to the total number of function evaluations in Figure 5. Total function evaluations estimate the optimized output frequency. The Confusion Chart obtained using Opti-KNN is shown in Figure 6. Performance metrics using Opti-KNN algorithm is presented in Table 3. Comparison of performances between KNN and Opti-KNN is shown in Figure 7.

In order to evaluate the performance of Decision Trees, we looked at how they performed relative to other ML models described in the literature. Table 4 provides a comparison of the various algorithms used in our study to the existing best-performing model and shows that our model outperformed all best-performing models with an accuracy of 97.33%.

Table 3. Performance metrics using opti-knn algorithm

	Precision	Recall	Specificity	F-score
Normal	100	96.77	100	98.36
Pre-seizure	95	98.27	96.73	96.61
Seizure	96.67	96.67	99.16	96.67
Accuracy of Opti-KNN algorithm = 97.33 %				

Iter	Eval	Objective	Objective	BestSoFar	BestSoFar	Num	Distance	Distance	Exponent	Standardize
	result		runtime	(observed)	(estim.)	Neighbors		Weight		
1	Best	0.52857	1.1036	0.52857	0.52857	1	hamming	inverse	-	true
2	Accept	0.6	0.23817	0.52857	0.53392	69	jaccard	inverse	-	true
3	Best	0.14286	0.096315	0.14286	0.14316	6	cosine	inverse	-	false
4	Best	0.071429	0.06643	0.071429	0.07169	21	euclidean	squaredinverse	-	true
5	Best	0.048571	0.17846	0.048571	0.048685	21	cosine	squaredinverse	-	true
6	Accept	0.14286	0.040918	0.048571	0.048639	7	cosine	squaredinverse	-	false
7	Accept	0.24286	0.053407	0.048571	0.048633	13	euclidean	squaredinverse	-	false
8	Accept	0.057143	0.067696	0.048571	0.048617	1	cosine	inverse	-	true
9	Accept	0.054286	0.068123	0.048571	0.0486	1	correlation	inverse	-	true
10	Accept	0.054286	0.062256	0.048571	0.048631	1	correlation	squaredinverse	-	true
11	Accept	0.16286	0.042231	0.048571	0.048636	3	correlation	squaredinverse	-	false
12	Accept	0.19143	0.044667	0.048571	0.048613	2	correlation	inverse	-	false
13	Accept	0.062857	0.044766	0.048571	0.048613	1	chebychev	squaredinverse	-	true
14	Accept	0.062857	0.045229	0.048571	0.048639	1	chebychev	inverse	-	true
15	Accept	0.29143	0.041662	0.048571	0.048656	2	chebychev	squaredinverse	-	false
16	Accept	0.051429	0.051748	0.048571	0.048655	1	cityblock	squaredinverse	-	true
17	Accept	0.051429	0.039443	0.048571	0.048647	1	cityblock	inverse	-	true
18	Accept	0.16	0.055174	0.048571	0.048648	1	cityblock	inverse	-	false
19	Accept	0.051429	0.044041	0.048571	0.048659	1	cityblock	equal	-	true
20	Accept	0.062857	0.052597	0.048571	0.048653	1	chebychev	equal	-	true
21	Accept	0.054286	0.044228	0.048571	0.048648	1	correlation	equal	-	true
22	Accept	0.057143	0.049427	0.048571	0.048642	1	cosine	equal	-	true
23	Accept	0.16	0.043811	0.048571	0.048611	1	cityblock	equal	-	false
24	Accept	0.29143	0.03931	0.048571	0.048623	1	chebychev	equal	-	false
25	Accept	0.06	0.048758	0.048571	0.048633	1	euclidean	equal	-	true
26	Accept	0.22	0.045642	0.048571	0.048626	1	euclidean	equal	-	false
27	Accept	0.16	0.04295	0.048571	0.048616	1	cosine	equal	-	false
28	Accept	0.19143	0.039335	0.048571	0.04863	1	correlation	equal	-	false
29	Accept	0.16	0.044369	0.048571	0.048589	1	cityblock	squaredinverse	-	false
30	Accept	0.071429	0.10921	0.048571	0.048666	59	spearman	inverse	-	true

Optimization completed.
MaxObjectiveEvaluations of 30 reached.
Total function evaluations: 30
Total elapsed time: 16.0788 seconds
Total objective function evaluation time: 2.9439

Best observed feasible point:

NumNeighbors	Distance	DistanceWeight	Exponent	Standardize
21	cosine	squaredinverse	NaN	true

Observed objective function value = 0.048571
Estimated objective function value = 0.048666
Function evaluation time = 0.17846

Best estimated feasible point (according to models):

NumNeighbors	Distance	DistanceWeight	Exponent	Standardize
21	cosine	squaredinverse	NaN	true

Estimated objective function value = 0.048666
Estimated function evaluation time = 0.17839

Figure 3. Step-by-step evaluation

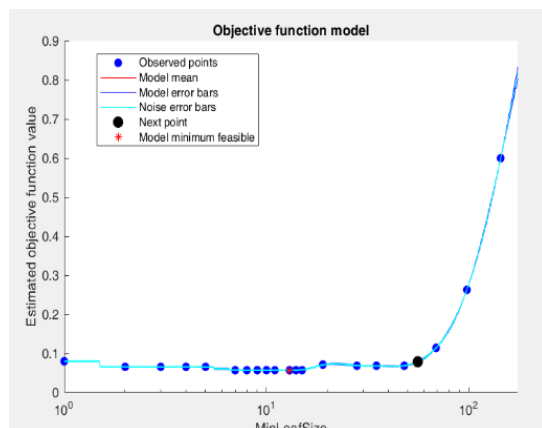


Figure 4. Objective function model

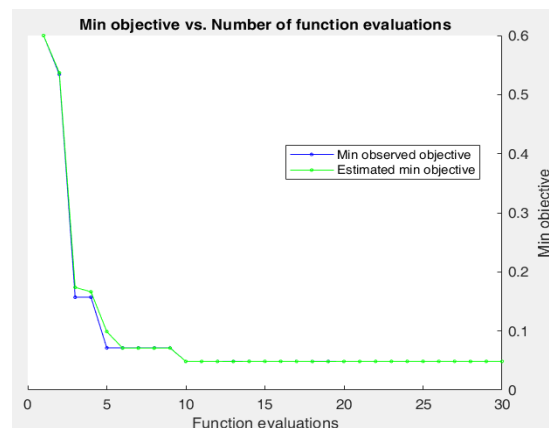


Figure 5. Minimum objective vs. function evaluations

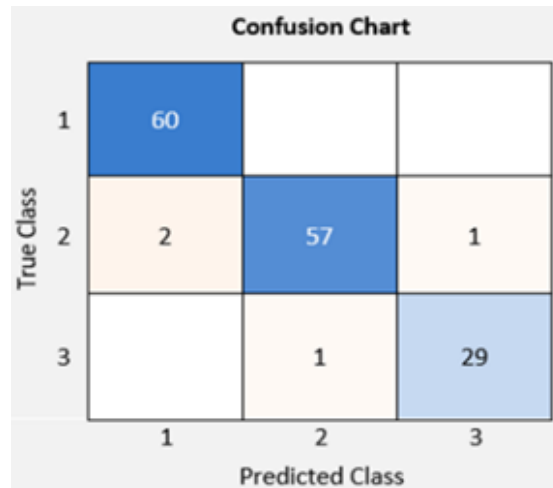


Figure 6. Confusion chart obtained using the opti-KNN algorithm

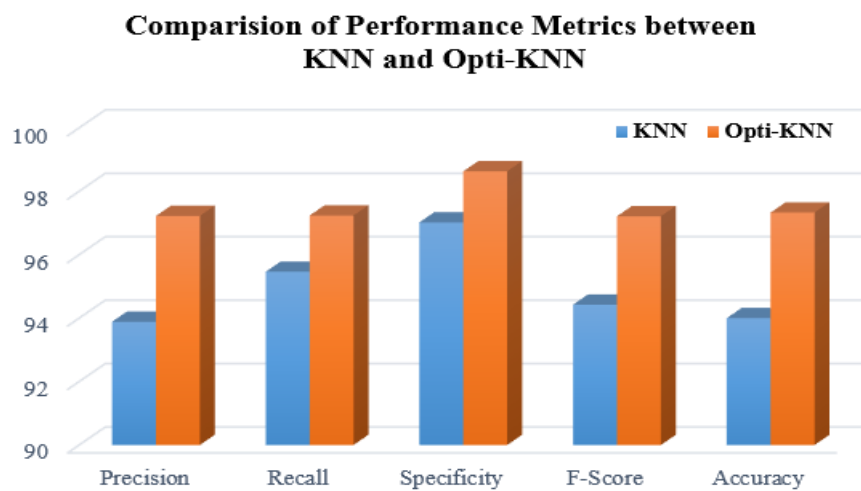


Figure 7. Performance metrics comparison

In order to evaluate the performance of Decision Trees, we looked at how they performed relative to other ML models described in the literature. The Table 4 provides a comparison of the various algorithms used in our study to existing best-performing model and shows that our model outperformed all best-performing models with an accuracy of 97.33%.

Table 4. Comparisons with existing state-of-art models

Study	Technique used	Classification accuracy
Serna <i>et al.</i> (2020) [20]	SVM	94.88%
Aaysha <i>et al.</i> (2021) [21]	FRNN	92.79%
	KNN	94.00%
Mohebbanaaz <i>et al.</i> (2025) [23]	SVM	96.77%
	Decision tree	96.66%
Proposed method – algorithm 1	KNN	94.00%
Proposed method – algorithm 2	Optimized KNN	97.33%

4. CONCLUSION

The study attempts to develop and test two ML models: KNN and Optimized KNN for detecting epileptic seizures. The results of the experiments indicate proposed algorithm performed very well for classifying seizure types, where Opti-KNN provided a better classification accuracy at 97.33% versus 94%

for KNN. The enhancements produced by Opti-KNN elaborate on the need for parameter optimization to be used for optimizing classification performance. The results have shown that both models can be used reliably and efficiently for automating the detection of seizure types to assist with the early diagnosis and assist health care professionals in making timely decisions clinically. Future research can explore combining EEG with other physiological signals (e.g., heart rate, respiration) or contextual data (e.g., movement, sleep patterns) to improve detection accuracy and reduce false positives. While KNN and Opti-KNN provide a simpler, interpretable model, integrating deep learning methods (such as CNNs or LSTMs) could further improve performance, especially in complex, noisy, or large datasets.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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