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Epilepsy Classification Using Support Vector Machine with Frequency Domain Feature Extraction

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Abstract

Epilepsy is a brain-related condition characterized by abnormal electrical activity in the brain. This condition can be identified by observing EEG signals, which record the brain's electrical activity. Automatically detecting seizures using EEG signals helps doctors diagnose the condition more quickly and accurately. In this study, a method is proposed that uses a Support Vector Machine (SVM) to classify EEG signals. The features used for classification are extracted from the frequency domain using a technique called Fast Fourier Transform (FFT). The dataset used is called the UCI Epileptic Seizure Recognition Dataset, which includes 11,500 EEG samples divided into five classes. These samples are then categorized into two main types: seizures and non-seizures. The research process includes data preprocessing with MinMaxScaler normalization, feature extraction using FFT, and data classification using SVM with varying numbers of features. Model performance is measured using several metrics, including accuracy, precision, recall, F1 score, and ROC-AUC. The results showed that the use of 21 features with the SVM model provided the best performance, with an accuracy of 97.7%, a precision of 93.2%, a recall of 95.4%, an F1 score of 94.3%, and an AUC value of 0.9930. These results are better than previous studies using similar methods, indicating that the combination of FFT and SVM is effective for detecting epilepsy using EEG signals. These findings help build a more reliable system for medical diagnosis and highlight the importance of using balanced evaluation measures in healthcare.

Keywords: epilepsy, SVM, FFT, EEG, accuracy

I. INTRODUCTION

Epilepsy is a condition that affects the brain, which is part of the nervous system. It occurs when there is unusual electrical activity in the brain, causing repeated seizures or other episodes such as changes in behaviour, feelings, or consciousness [1]. The main characteristics of epilepsy include seizures that occur more than once, rather than just a single episode. These seizures can cause things like uncontrolled movements, blank stares, body stiffening, or loss of consciousness. These seizures often come on suddenly and stop on their own [2]. The causes of epilepsy can be different for each person. Some causes may include inherited genes, head or brain injuries, infections such as meningitis or encephalitis, stroke or brain tumours, and disorders that affect brain development [3]. There are different types of seizures in epilepsy. Partial seizures, also called focal seizures, occur in only one part of the brain and may cause symptoms in only one part of the body or cause partial loss of consciousness. Generalized seizures affect the entire brain and can cause complete loss of consciousness, body stiffening, falls, or shaking all over [4].

An EEG is a way to record the brain's electrical activity by placing electrodes on the scalp. EEG helps track brain performance in real-time and is often used to examine problems such as epilepsy, sleep disorders, coma, or to study brain function [5], [6]. This test observes changes in electrical voltage caused by brain neurons in different areas of the head [7]. Electrodes are usually placed following a standard system called the 10-20 system [8].

Epilepsy is measured using EEG signals, which involves placing electrodes on the scalp to record the brain's electrical activity. These electrodes help detect unusual brain wave patterns associated with epileptic seizures [9], [10]. This process helps identify both types of seizures—partial (focal) and generalized—and determine where in the brain the seizures begin. It also allows for real-time monitoring of brain activity, which is essential for diagnosing epilepsy, evaluating treatment, and conducting research. In summary, EEG is the primary method used to measure abnormal brain activity in people with epilepsy, supporting diagnosis, progress tracking, and research. It can also be used with machine learning techniques for automation [11], [12].

Several studies on epilepsy using EEG signals, such as [13], introduced a novel deep learning method combining a Convolutional Neural Network (CNN) and

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Long Short-Term Memory (LSTM) for multi-class classification of epileptic EEG signals. Another study [14] proposed an innovative model for classifying epileptic seizures using an Iterative Gated Graph Convolutional Network (IGGCN). Research [15] introduced an explainable EEG signal classification model using Friend Pattern (Friend Pat) feature engineering and the symbolic language DLob. A related study [9] focused on the STFFDA model for detecting epileptic seizures from EEG signals.

Several previous studies used data from the UCI Epileptic Seizure Recognition Dataset. For example, one study [10] used Discrete Wavelet Transform (DWT) to decompose EEG signals, then reduced the data using PCA and t-SNE. They clustered the data with K-means and used several classification methods such as XGBoost, KNN, Decision Tree, Random Forest, and MLP. Another study [16] compared various machine learning and deep learning methods, including LSTM, to detect epileptic seizures. Another study [17] examined five machine learning models—Random Forest, Decision Tree, Extra Trees, Logistic Regression, and Gradient Boosting—along with various pre-processing methods to predict seizures. A study [18] also used the UCI dataset and combined two techniques, SMOTE and hybrid feature selection, with SVM for classification. The results showed an accuracy of 97.30%, an AUC of 99.62%, and an F1-score of 93.08%.

In this study, the main objective is to solve the problem of automating epileptic seizure detection. This model uses the SVM algorithm to distinguish between individuals experiencing seizures and those without, based on data from the UCI Epileptic Seizure Detection Dataset. This system helps fill a gap in this field by offering a better way to extract features and classify signals. The model uses various feature extraction methods from the Fast Fourier Transform (FFT) to improve validation accuracy by observing the performance of other models. A detailed comparison between the feature extraction methods and the proposed model is conducted to address various challenges. The block diagram of the system plan being built shown in Fig. 1.

This study explicitly addresses a key limitation of previous FFT–SVM based epilepsy detection studies, which predominantly emphasize overall accuracy without adequately considering clinically critical errors such as false negatives. The main novelty of this work lies in the integration of FFT-based frequency features with a balanced evaluation framework using precision, recall, F1-score, and ROC-AUC, ensuring reliable medical decision support. Furthermore, the systematic comparison of feature dimensionality provides insight into optimal feature selection for EEG-based epilepsy classification.

II. RESEARCH METHOD

This study used data from the UCI Epileptic Seizure Recognition Dataset, which includes 11,500 samples. Each sample has 178 features collected from 23 different recording channels. There are five categories: one for epileptic seizures and four for non-seizure activity. Each entry in the dataset represents a 23.6-second segment of EEG data, divided into 178 points [10].

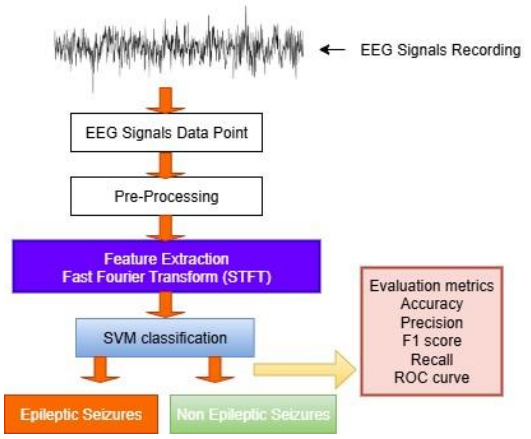

Figure 1. Block diagram of the system plan being built

A. Pre-processing of EEG signal data

After the data from the UCI Epilepsy seizure dataset was collected, the next step was to process the EEG signal data. The EEG signals were grouped into two categories: one for seizures labelled as class 1, and another for non-seizures labelled as class 0. To ensure all data features were on the same scale, MinMaxScaler was used for normalization [19]. After that, the data was divided into two parts—80% for training and 20% for testing.

B. Feature extraction

Feature extraction in EEG signal processing for epileptic seizure detection is used to represent important information from EEG signals, reduce data dimensions (dimensionality reduction), improve classification algorithm performance, reduce noise and artefacts and facilitate clinical interpretation [16], [20]. In this study, feature extraction was performed in the frequency domain using the Fast Fourier Transform (FFT), from which several spectral features were derived.

1) Fast Fourier Transform (FFT)

The FFT is a fast method for calculating the Fourier Transform of a signal [20]. The Fourier Transform helps convert a signal from the time domain to the frequency domain. Using the FFT, we can find out what frequencies are present in the EEG signal and how much power each frequency has [21], [22]. With the FFT, the EEG signal can be broken down into several frequency bands, making it easier to compare normal brain activity with seizure activity. The FFT is a tool that helps break down the EEG signal into its frequency parts, making it easier to study brain wave patterns to detect seizures. The FFT is derived from an algorithm that calculates the DFT more efficiently, so the basic formula is still based on the DFT. The regular DFT takes O (N^2) time, but the FFT takes O (N log N) time and is much faster, which works well for EEG signals that have thousands of data points. Here is the FFT formula, for a discrete EEG signal x[n] of length N:

$$\mathbf{X(k)} = \sum_{n=0}^{N-1} \boldsymbol{x(n)e^{-j\frac{2\pi}{N}kn}} \quad (1)$$

Where:
x[n] = EEG signal in the time domain (n = sample index); x[k] = frequency spectrum (transformed result); N = number of signal samples; $e^{-j2\pi kn/N}$ = complex basis that maps the signal to frequency; k = 0, 1, 2, 3, 4, ….., N-1.

This study uses FFT-based features. For an EEG signal x[n] of length N, the FFT is calculated as shown in formula (1), and then the Power Spectral Density (PSD) is determined from the FFT magnitude using another formula.

$$\mathbf{X(k)} = \frac{\mathbf{1}}{\boldsymbol{N}} |\boldsymbol{X(k)}|^2 \quad (2)$$

With fk = k/N, fs (frequency to-k, fs = sampling rate).

2) Band Power Absolut

For each EEG frequency band, such as Delta (0.5–4 Hz), the k index corresponding to the frequency is used [21], then calculated:

$$BP_{band} = \sum_{f \in band} P[f].\Delta f \quad (3)$$

With Δf=fs/N (resolution frequency).

3) Spectral Entropy (SE)

SE is a way to measure how randomly or uncertainly the energy is distributed across the frequency regions of an EEG signal [23]. When most of the energy is in one main frequency, the signal is regular and repetitive, so its entropy is low. However, if the energy is spread across many different frequencies, the signal is more random or chaotic, like noise, and its entropy is high. To find the spectral entropy, first use the FFT to obtain the power spectral density of the EEG signal. Then convert it to a probability by normalizing it. After that, use the formula to calculate the entropy:

$$\mathrm{SE} = -\sum_{f=f_{min}}^{f_{max}} \mathrm{p(f)log(p(f))} \quad (4)$$

4) Spectral Centroid (SC)

SC is a measure used in spectral analysis that indicates the "centre of mass" of a signal's frequency spectrum [24]. Simply put, SC indicates the frequency at which the signal's energy is most concentrated. This helps understand how energy is distributed across frequencies, for example, whether an EEG signal has more energy at lower or higher frequencies. The general formula for spectral centre of mass is: if f(k) represents the kth frequency and P(k) is the spectrum or power value at that frequency, then the formula is:

$$\mathrm{SC} = \frac{\sum_{k=1}^{N} \mathrm{f(k)} \cdot \mathrm{P(k)}}{\sum_{k=1}^{N} p(k)} \quad (5)$$

5) Peak Frequency (PF)

The PF is the frequency that has the strongest signal power in a frequency spectrum, obtained through methods such as the Fourier transform (FFT or other spectral analysis techniques) [25]. The PF can be thought of as the main peak in the frequency domain. In EEG, the PF is usually determined in a specific frequency range, such as the alpha or beta band. If P(f) represents the spectral power at a particular frequency f, then:

$$PF = \underset{f}{\operatorname{argmax}}\, pf \quad (6)$$

So, the frequency f at which P(f) reaches its maximum value.

6) Total Power (TP)

TP is the total amount of energy or power contained in all EEG signals in a certain frequency range [24]. Mathematically, TP is calculated as the area under the power spectrum curve, also known as the power spectral density or PSD. In simple terms, TP shows the amount of energy that all EEG signals have when observed in the frequency domain. If P(f) represents the spectral power at a certain frequency f, and fmin to fmax are the limits of the EEG frequency range, for example 0.5 to 40 Hz, then TP is the sum of all P(f) values in that range, then:

$$TP = \sum_{k=1}^{N} p(f_k) \quad (7)$$

7) Median Frequency (MF)

The median frequency is the frequency that divides the power spectrum (Power Spectral Density/PSD) into two parts, each with the same area or power [26]. Mathematically:

$$\int_0^{f_{med}} \mathrm{P(f)df} = \frac{1}{2} \int_0^{f_{max}} \mathrm{P(f)df} \quad (8)$$

8) Variance (Varian)

Variance indicates how much the numbers in a data set spread out from the average value, called the mean [27]. Mathematically, variance is calculated to measure this spread:

$$var\,(x) = \frac{1}{N} \sum_{i=1}^{N} (\mathrm{xi} \quad - \mu)^2 \quad (9)$$

With: xi = i-th data; μ = average data; N = number of data

9) Skewness

Skewness is a statistical tool used to check whether data is evenly distributed around the mean or tends to be skewed in one direction [28]. Mathematically:

$$\mathrm{Skewness} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_i - \mu}{\sigma}\right)^3 \quad (10)$$

With: xi = i-th data; μ = mean; σ = standard deviation; N = number of data.

10) Kurtosis

Kurtosis is a statistical measure that indicates how "peaked" or "flat" the data is compared to a normal distribution [29]. Skewness examines the left-right balance, while kurtosis examines how sharp or flat the shape of the data is. The mathematical formula for this is called excess kurtosis:

$$\text{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4 - 3 \quad (11)$$

C. Support Vector Machine (SVM) Classification

Support Vector Machine Classification (SVM) EEG classification using SVM involves extracting features from the EEG signal and placing them in a feature space. Then, the best hyper plane, which can be linear or non-linear (using a kernel), is found to separate the various brain conditions [30], [31]. SVM identifies the hyper plane that has the largest margin between classes, such as normal and epilepsy, regardless of whether a kernel is used or not. This is the general formula for SVM in EEG classification:

Hyper plane

$$\omega . x + b = 0 \quad (12)$$

Decision Function

$$f(x) = sign(\omega . x + b) \quad (13)$$

Optimization (Soft Margin)

$$\min_{\omega,b,\xi} \frac{1}{2}\|\omega\|^2 + C\sum \xi i \quad (14)$$

Kernel Trick (for non-linear EEG)

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i \quad y_i \quad K(x_i \quad , x) + b\right) \quad (15)$$

Kernel Trick (for Non-linear EEG) in this study, SVM was used as a classification method, following the feature extraction and feature retrieval processes. Several classification and feature extraction models were used to find the best performance for the tested system. The features used in this study are in the frequency domain, namely FFT. Table 1 shows the system models tested, indicating that in this study, multiple models will be tested to achieve the best performance in detecting epileptic seizures.

TABLE 1. VARIATIONS OF THE PROPOSED MODELS

Classification Type	Features used	Number of features
SVM + FFT Using Train-Test Split (80/20)	Absolute band power for 5 EEG bands (delta, theta, alpha, beta, gamma), Spectral entropy, Spectral centroid, and Peak frequency	8
	Absolute band power for 5 EEG bands (delta, theta, alpha, beta, gamma), Spectral entropy, Spectral centroid, Peak frequency, Skewness, and Kurtosis	10
	Absolute band power for 5 EEG bands (delta, theta, alpha, beta, gamma), Relative band power for each of the 5 bands, Spectral entropy, Spectral centroid, Peak frequency, and Total power	14
SVM + FFT Using Stratified K-Fold Cross Validation + SMOTE	Absolute band power for 5 EEG bands (delta, theta, alpha, beta, gamma), Relative band power for each of the 5 bands, Spectral entropy, Spectral centroid, Peak frequency, Total power, median_freq, spectral variance, spectral_skewness. spectral kurtosis, theta_alpha_ratio, beta_alpha_ratio, and theta_beta_ratio	21

D. Evaluation metrics

Evaluation metrics are numbers that help us examine how good or bad a classification model is at separating different groups, such as seizures and non-seizures [32]. These metrics indicate how well the model can distinguish one group from another.

1) Accuracy

Accuracy is a measure that shows how often a model makes correct predictions from all test data [33]. The formula for accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (16)$$

Where: TP (True Positive) = positive cases (e.g., seizures) that were correctly predicted as positive; TN (True Negative) = negative cases (e.g., non-seizures) that were correctly predicted as negative; FP (False Positive) = negative cases that were incorrectly predicted as positive; FN (False Negative) = positive cases that were incorrectly predicted as negative.

2) Precision

Precision is a measure that tells you how many of the model's predictions about positive outcomes actually correct [34] are. The formula for precision is:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (17)$$

3) Recall

Recall is a measure that shows how well a model can find all positive cases [35]. The formula for recall is:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (18)$$

Where: TP (True Positive) = positive cases (e.g., seizure EEG signals) that were predicted as true positive; FN

(False Negative) = positive cases that were not detected (incorrectly predicted as negative).

4) F1-Score

The F1 score is a measure that indicates the balance between precision and recall. It is calculated as the harmonic mean of these two metrics [33]. This score helps evaluate how accurate and complete a model is. The formula for the F1 score is:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (19)$$

5) ROC curve & AUC

The ROC curve is a graph that helps assess how well a classification model works [36]. The X-axis shows the False Positive Rate (FPR).

$$FPR = \frac{FP}{FP + TN} \quad (20)$$

Y-axis = True Positive Rate (TPR) or Recall.

$$TPR = \frac{TP}{TP + FN} \quad (21)$$

An ROC curve is created by adjusting the threshold used to determine whether data is classified as positive or negative, for example by changing it from 0 to 1. The ROC curve shows how well a model can balance sensitivity (which is the same as recall) and specificity at various decision points. AUC stands for the area under the ROC curve. AUC values range from 0 to 1. If the AUC is 1.0, the model is perfect and makes no errors. If the AUC is 0.5, the model is no better than random guessing. And if the AUC is less than 0.5, the model actually performs worse than random guessing.

III. Result and Discussion

The metrics used for evaluation in this study include F1 score, AUC, accuracy, precision, and Recall which are calculated to assess the performance of the proposed method in accurately distinguishing between seizure and non-seizure conditions.

A. Confusion Matrix

Key evaluation metrics such as precision, accuracy, sensitivity (recall), and specificity are derived from the confusion matrix. Figure 2 displays a visual representation of the confusion matrix for a classifier using SVM. This confusion matrix provides in-depth insight into model performance by displaying True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

Figure 2(a): SVM + FFT with 8 features incorrectly classifies 128 non-seizure data as seizures, and 426 seizure data as non-seizures. Figure 2(b): SVM + FFT with 10 features incorrectly classifies 171 non-seizure data as seizures, and 301 seizure data as non-seizures. Figure 2(c): SVM + FFT with 14 features misclassified 38 non-seizure data as seizures, and 20 seizure data as non-seizures. Figure 2(d): SVM + FFT with 21 features misclassified 32 non-seizure data as seizures, and 21 seizure data as non-seizures.

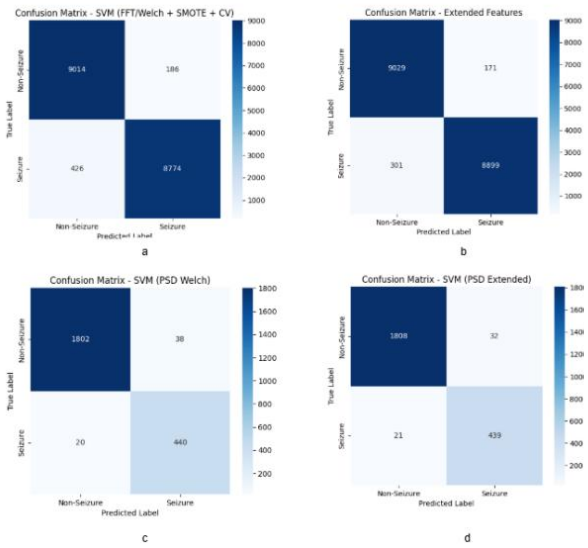

Figure 2. Confusion Matrix of SVM Classification with FFT

Figure 2 shows that with more features using FFT, performance improves, especially with 21 features, consisting of Absolute band power for 5 EEG bands (delta, theta, alpha, beta, gamma), Relative band power for each of the 5 bands, Spectral entropy, Spectral centroid, Peak frequency, Total power, median_freq, spectral variance, spectral_skewness, spectral kurtosis, theta_alpha_ratio, beta_alpha_ratio, and theta_beta_ratio. Table 2 shows the comparison of FP and FN confusion matrices.

B. AUC-ROC curve

ROC-AUC is used to describe how effective the model is in classifying epilepsy and non-epileptic classes. ROC describes the relationship between True Positive Rate (TPR) and False Positive Rate (FPR) at various classification threshold levels. The AUC value assesses the model's ability to distinguish two classes in the classification, in this case epilepsy and non-epileptic. Figure 3 shows the AUC values of each model. Figure 3 shows the AUC values of the SVM classification model and FFT feature extraction with AUC values of (a) AUC value of 8 features = 0.9925, (b) AUC value of 10 features = 0.9947, AUC value of feature 14 = 0.9931, and feature 21 = 0.9930.

Figure 3 shows that the SVM classification and feature extraction using FFT had an average AUC of 0.99. This indicates the model's near-perfect ability to distinguish seizure and non-seizure data. Table 3 shows

TABLE 2. COMPARISON OF FP AND FN CONFUSION MATRICES.

Method	Number of Features	False Positive	False Negative	Total Error
FFT (Figure 2a)	*8*	*128*	*426*	*554*
FFT (Figure 2b)	*10*	*171*	*301*	*472*
FFT (Figure 2c)	*14*	*38*	*20*	*58*
FFT (Figure 2d)	*21*	*32*	*21*	*53*

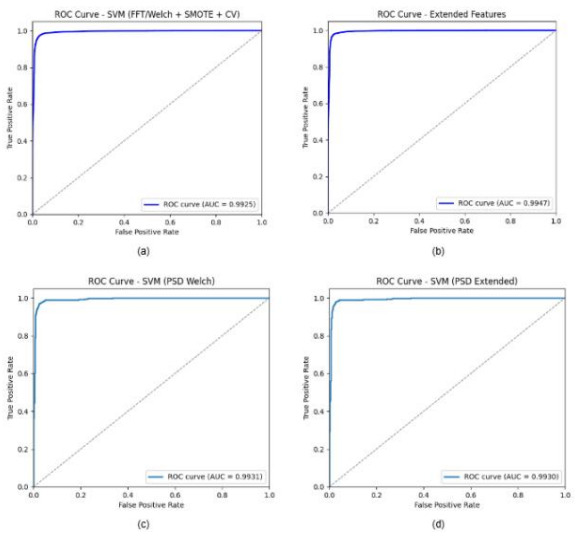

Figure 3. ROC-AUC curve values for the SVM classification type

TABLE 3. COMPARISON OF AUC VALUES OF THE SVM MODEL WITH THE FFT FEATURE EXTRACTION METHOD.

Method	Number of Features	AUC value	Description
SVM + FFT	8	0.9925	Very high
	10	0.9947	Very high
	14	0.9931	Very high
	21	0.9930	Very high

TABLE 4. COMPARISON OF PERFORMANCE EVALUATION OF VARIOUS FEATURE MODELS.

Method	Number of Features	Accu-racy	Preci-sion	Recall	F1-Score
FFT	8	0,967	0,979	0,954	0,966
	10	0,974	0,980	0,967	0,973
	14	0,975	0,921	0,957	0,938
	21	0,977	0,932	0,954	0,943

the difference values for each model's performance. By comparing them, we can determine the best performance for detecting epileptic and non-epileptic symptoms. Table 3 shows that SVM classification and feature extraction using FFT are on average able to achieve an AUC close to 1.00, which is perfect.

C. Classification Report

This study presents a classification evaluation report based on Accuracy, Recall, Precision, and F1 score for each category (seizure and non-seizure). Table 4 presents this report and shows that the proposed method produces effective results in EEG classification.

Table 4 shows that all methods above 96% can be categorized as very good. Feature extraction using the FFT method (21 features) produces the highest accuracy, namely 0.977, this result exceeds previous research [19] which used the SVM method as a classifier. Feature extraction using the FFT method with the number of features 8 has the worst performance, namely 0.967.

IV. CONCLUSION

This study aims to detect epileptic and non-epileptic seizures using EEG signals as data. Every step has been carried out, from pre-processing to classification. The feature extraction used in this study uses a frequency domain approach. One of the classifiers used in this study is the SVM method. Our main achievement focuses on creating a robust model that can not only predict epileptic and non-epileptic seizures with high accuracy but also prioritizes important metrics such as accuracy, recall, precision, and F1 score. These metrics are crucial in the medical field, although they may have been overlooked in previous studies. By using these metrics, this study highlights the importance of accurately recognizing negative cases (non-seizure events) and positive cases (seizure events) in the context of healthcare diagnostic services. By adding additional metrics, we present a comprehensive evaluation framework, covering various dimensions of model effectiveness. This study produces better accuracy than previous studies that also used SVM classification, with an accuracy of 0.977.

Clinically, the proposed model demonstrates strong potential as a decision-support tool to assist neurologists by reducing false-negative seizure detection, which is critical in epilepsy management. However, this study is limited to a single public dataset and binary classification. Future research will focus on multi-class seizure classification, cross-dataset validation, and real-time implementation using embedded systems.

DECLARATIONS

Conflict of Interest

The authors have declared that no competing interests exist.

CRediT Authorship Contribution

Hindarto Hindarto: Conceptualization, Methodology, Supervision, Writing - Original Draft, Writing - Review & Editing; Ade Eviyanti: Data Curation, Investigation, Validation, Writing - Review & Editing; Ahmad Ahfas: Methodology, Formal Analysis, Validation, Visualization; Egha Arya Affandi: Software, Data Curation, Investigation, Visualization.

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