EPILEPTIC SEIZURE DETECTION FROM EEG SIGNALS USING SVM WITH TIME–FREQUENCY FEATURE EXTRACTION METHODS

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ABSTRACT

Epilepsy is a neurological disorder characterized by recurrent seizures, affecting approximately 50 million people worldwide. Early detection of seizures is crucial for accurate diagnosis and effective treatment. This study proposes several methods for EEG signal feature extraction in the time-frequency domain, including STFT, CWT, DWT, and HHT. The UCI dataset is the data used in this study, this data in 1 second contains 11,500 segments. This dataset is processed through several stages, first the pre-processing stage, then feature extraction using the time-frequency domain. The final stage of classification uses Support Vector Machines (SVM). The classification process is divided into 2 stages, namely the training and testing process, in this case 80% training and 20% testing. Evaluation of the classification results is carried out using evaluation metrics namely recall, F1 score, accuracy, precision, MCC, and Kappa. The results show that the performance reaches 96% more for all methods, except for feature extraction using DWT with 5 features. All methods achieve performance above 96%, except for the feature extraction method using DWT with 5 features. Feature extraction using the STFT method using 14 features and CWT using 49 features produces the highest accuracy of 98.39%, surpassing previous studies that used the SVM method for classification. The worst performance with a value of 86.7% using DWT feature extraction with 5 features. Compared with previous studies, the proposed method provides better accuracy. The study concluded that with a combination of appropriate pre-processing and a suitable feature extraction algorithm, accurate and reliable detection of epileptic seizures can be achieved.

Keywords: *Epilepsy, EEG, Seizure Detection, Time Frequency Domain, SVM.*

1. INTRODUCTION

Epilepsy is one of the most common chronic neurological disorders, characterized by recurrent seizures caused by abnormal electrical activity in the brain. Epileptic seizures can produce temporary disturbances in consciousness, movement, sensation, or behaviour, significantly impacting the quality of life of those affected [1]. According to the World Health Organization (WHO), epilepsy affects approximately 50 million people worldwide, with nearly 80% of cases occurring in low- and middle-income countries [2]. Early diagnosis and detection of epilepsy can provide patients with information necessary for appropriate treatment. This can reduce the risk of complications and improve their quality of life [3].

An EEG sensor is a device that can detect a person's brain activity. By placing an EEG sensor, changes in brain voltage can be detected. Recording the brain via EEG allows for analysis of epileptic seizure patterns and can support a diagnosis [4]. However, manual EEG signal processing by neurologists is time-consuming, dependent on clinical experience, and prone to human subjectivity. Therefore, automated approaches to analysing EEG signals using machine learning are a promising alternative.

In the last ten years, a number of methods using Machine Learning have been proposed to identify epileptic seizures from EEG data. Algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Gradient Boosting were chosen because of their ability to handle high-dimensional data and produce reliable classification decisions [5][6].

The UCI Epileptic Seizure Recognition dataset used in this study is a public version of the Bonn dataset, which is often used as a benchmark for seizure detection [7]. This dataset contains 11,500 one-second EEG samples, which are divided into 5 categories, including seizure and non-seizure signals.

Several studies using the above dataset, including research using the CNN method with 31 layers, provided an accuracy of 91% [8]. The 1D-CNN and Extra Tree methods with the bagging method were reported by [9]. The CNN method has a more efficient and accurate performance in detecting epilepsy compared to traditional approaches, reported by [10]. Feature extraction by combining PCA and DWT and classification using SVM achieved an accuracy of 97.30%, an AUC of 99.62%, and an F1-score of 93.08% [7]. EEG Signal Research using the PCA method, Research conducted by [11], namely Combining Robust Principal Component Analysis (RPCA) as a pre-processing stage with RNN as a classification model. Research using the DWT + PCA + SVM (RBF) based approach on EEG signals, especially in the beta band frequency, has proven effective and superior in recognizing emotions based on the valence–arousal model, with an accuracy above 91% [12]. Other research related to EEG signals using the DWT + PCA approach [7], [13].

Figure 1 shows various EEG waveforms under different conditions, such as eyes closed and open, a healthy brain area, a tumour-affected area, and during a seizure. A healthy brain exhibits a stable, regular pattern of EEG waves with consistent strength and frequency. Conversely, an irregular and unstable EEG pattern could indicate a disease, such as a brain tumour. In the figure, the X-axis represents time, while the Y-axis represents EEG signal strength.

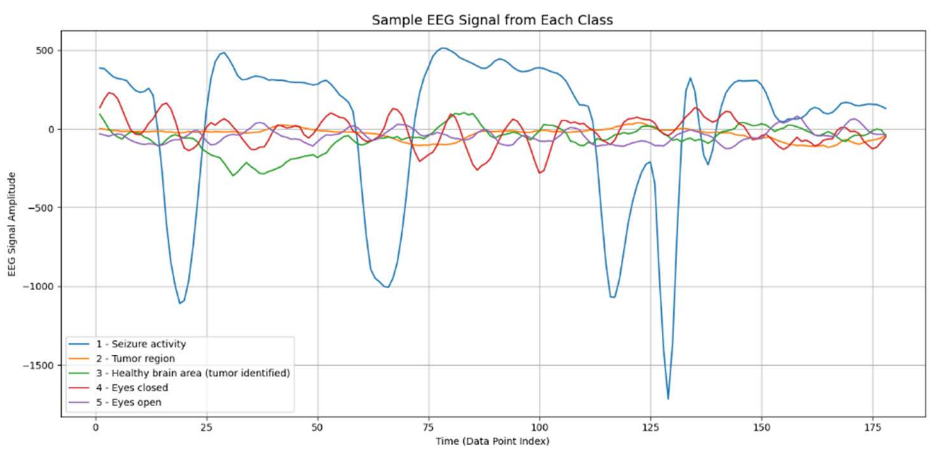

Figure 1: Variation of EEG signals under various conditions.

This research aims to compare various feature extraction methods using the time-frequency domain, using only one classification process, the SVM method. Furthermore, this study will compare with previous research [7] which took the same dataset and the classification process also used SVM. This study also evaluates the performance of the proposed model, focusing on accuracy, precision, recall, F1 score, Matthews Correlation Coefficient (MCC), and Cohen's Kappa. It also discusses pre-processing steps, such as normalization and dimensionality reduction using time-frequency domain methods, which can improve model performance. However, the main challenge addressed is how to identify the most effective feature extraction technique to improve classification results without requiring complex and computationally expensive models. Therefore, this study is expected to provide insights into selecting efficient methods for EEG-based epilepsy detection. The findings are significant not only for academic development in biomedical signal processing but also for supporting clinical practices, as more accurate and efficient detection systems can assist neurologists in early diagnosis and ultimately improve the quality of life for epilepsy patients.

Research on epilepsy detection using EEG signals has been widely conducted with various approaches. These can be categorized into three main groups:

1. Classical Machine Learning Approaches

Methods such as SVM, KNN, and Gradient Boosting are widely applied because they can handle high-dimensional EEG data [5][6]. Advantages, good interpretability, relatively fast to train. Limitations, heavily dependent on pre-processing and manual feature selection.

2. Deep Learning Approaches

CNN with 31 layers achieved 91% accuracy [8], while 1D-CNN combined with Extra Tree Bagging showed improved results [9]. Advantages, automatic feature extraction and better generalization. Limitations, require large

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datasets, high computational resources, and are less practical in resource-limited clinical settings.

3. Feature Extraction-Based Approaches

Combining PCA + DWT + SVM achieved 97.30% accuracy, 99.62% AUC, and 93.08% F1-score [7].

RPCA + RNN approaches have also been tested as preprocessing and classification pipelines [11].

4. Research Gaps

No agreement yet on the most effective time-frequency domain feature extraction method (STFT, WT, HHT). Most studies only test one approach instead of systematically comparing multiple methods on the same dataset. Model evaluation is often limited to accuracy, while comprehensive metrics (Precision, Recall, MCC, Kappa, AUC) are rarely applied.

5. Contribution of This Study

Systematically compares several time-frequency feature extraction methods using a single classifier (SVM) to focus on feature effectiveness. Provides comprehensive evaluation with multiple performance metrics. Aims to address gaps from prior studies that often focus narrowly on one method or limited metrics.

2. METHODOLOGY

2.1 Dataset

The UCI Epilepsy Seizure dataset, a generalized version of the Bonn dataset, is used as the EEG dataset in this study. Each segment has a duration of 1 second and a sampling rate of 178 Hz [7]. 178 Point data from each segment is divided into 5 classes, Epilepsy is class 1 which is seizures, and classes 2 to 5 are non-seizure classes.

2.2 Data Pre-processing

The pre-processing stage includes, Normalization, namely all features are normalized to the range [0, 1] to ensure all features have balanced weights in the training process. Dimensionality Reduction with the time-frequency domain method is a reduction technique using effective dimensions to simplify high-dimensional data such as EEG signals while maintaining important information. Therefore, a time and frequency analysis method is needed that is able to provide information [14]. This study uses the time-frequency domain method on the EEG signal covariance matrix to detect early seizures.

2.3 Proposed Approach

The research will involve the Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Hilbert-Huang Transform (HHT), as well as a classification algorithm using the SVM algorithm. The steps in this research include: first, pre-processing, which is carried out to normalize and standardize each EEG signal data. Next, feature extraction is carried out using time and frequency domain methods. Before classification, the obtained feature data is divided into two data sets: 80% trial data and 20% testing data. To evaluate the performance of the tested model, metric evaluation is used by looking at system performance, including accuracy, precision, and others. Thus, with this evaluation, it is hoped that the best system performance model will be obtained for detecting seizures and non-seizures.

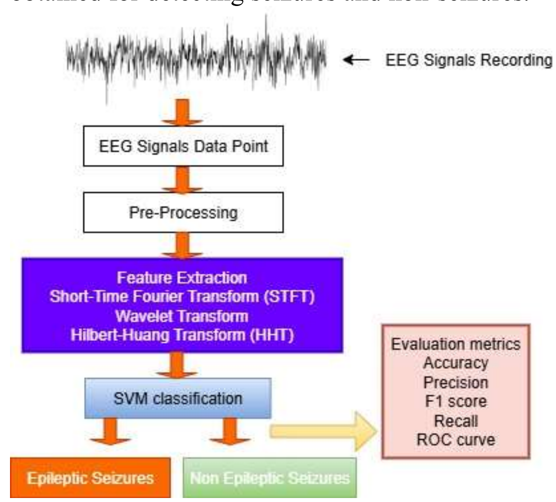

Figure 2: Block diagram of the system plan being built

2.4 Feature Extraction Using the Short-Time Fourier Transform (STFT)

The STFT is used to view the frequency spectrum of a signal locally in time [15]. Unlike the conventional (global) Fourier Transform, the STFT breaks the signal into short segments (windows) and then calculates the spectrum in each window.

The STFT formula for a discrete signal x[n] is:

$$\mathbf{X(m,\omega)} = \sum_{n=-\infty}^{\infty} \mathbf{x[n]\omega[n-m]}e^{-j\omega n} \quad (1)$$

Where:

X[n] = discrete EEG signal

ω[n] = window (e.g., Hamming)

m = window position (time shift)

ω = angular frequency

X (m, ω) = STFT, time-frequency function

The result is a complex matrix of size (number of frequencies × number of windows). The spectrum magnitude is calculated:

$$|\mathbf{X}(\mathbf{m}, \boldsymbol{\omega})| = \sqrt{\mathbf{Re}\ (\mathbf{X})^2 + \mathbf{Im}(\mathbf{X})^2} \quad (2)$$

Statistical Features of the STFT Magnitude

From the STFT magnitude matrix per frequency, we can extract numerical features that represent the characteristics of the EEG signal. For example, for each frequency row fi in the magnitude matrix M:

(a) Energy

$$\mathbf{Energy} = \sum_{k=1}^{n} |\mathbf{M}(f_i, t_k)|^2 \quad (3)$$

Measures the total “power” of the signal at frequency f_i.

(b) Mean

$$\mathbf{Mean} = \frac{1}{N} \sum_{k=1}^{n} |\mathbf{M}(f_i, t_k)| \quad (4)$$

Average amplitude of the spectrum.

(c) Standard Deviation (Std)

$$\mathbf{Std} = \sqrt{\frac{1}{N} \sum_{k=1}^{n} (|\mathbf{M}(f_i, t_k)| - \boldsymbol{Mean})^2} \quad (5)$$

The measure of amplitude variation at that frequency.

(d) Max

$$\mathbf{Max} = \max_k |\mathbf{M}(f_i, t_k)| \quad (6)$$

Maximum amplitude at frequency f_i.

(e) Shannon Entropy

$$\mathbf{Entropy} = -\sum_{k=1}^{n} \mathbf{pk}\, log_2(\mathbf{pk}) \quad (7)$$

With probability:

$$\mathbf{pk} = \frac{|\mathbf{M}(f_i, t_k)|^2}{\sum_{j=1}^{N} |\mathbf{M}(f_i, t_j)|^2} \quad (8)$$

Entropy measures the uncertainty of the power distribution:

High values → more complex/random signal

Low values → more ordered signal

In this study using STFT, there were 4 trials conducted by taking from STFT. First, the features used were 5 features by taking the Delta-Theta-Alpha-Beta-Gamma band energy ratio values for each signal. The classification used was the RBF kernel model from SVM. The results of the classification process were evaluated against Accuracy, Precision, Recall, F1, MCC, Kappa, and AUC. Second, by using 4 features namely STFT Mean, STFT vary, STFT Max, STFT Energy on each signal. The third uses 9 features extracted from each EEG signal, namely STFT Mean (average magnitude spectrum), STFT Vary (variance magnitude spectrum), STFT Max (peak value of magnitude spectrum), STFT Energy (total energy spectrum), Spectral Centroid (Centre of spectral mass (average dominant frequency)), Spectral Bandwidth (spectral bandwidth), Spectral Entropy (randomness of spectrum distribution), Spectral Flatness (comparison of geometric and arithmetic means (spectral texture)), and F50 (Median Frequency). The fourth uses 14 features, consisting of a combination of frequency domain (STFT) and time domain. The features are frequency domain features (6 pieces), consisting of Mean Frequency, Vary frequency, Max frequency, Min frequency, Median frequency, and Standard frequency and time domain features (3 pieces) namely Mean Time, Vary Time, and RMS Time as well as delta, theta, beta, alpha, gamma. So in this study, by taking features from STFT there are 4 trials that will be carried out.

2.5 Feature Extraction Using the Wavelet Transform (WT)

The Wavelet Transform is a time-frequency analysis method that is particularly well-suited for non-stationary signals such as EEG [16]. WT allows us to view the frequency components of a signal locally at specific times, making it very effective for detecting transient patterns, such as epileptic seizures.

2.5.1 Continuous Wavelet Transform (CWT)

The CWT projects the signal x(t) onto a scaled and shifted basis wavelet ψ(t) [17]:

$$\mathbf{C}(\mathbf{a}, \mathbf{b}) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \mathbf{x}(\mathbf{t}) \boldsymbol{\psi}^* \left(\frac{t-b}{a}\right) dt \quad (9)$$

Where:

a = scale (inverse frequency)

b = translation (time)

C (a, b) = wavelet coefficient (time-frequency representation)

In this study using CWT, two trials were conducted using CWT features. First, each signal generated 7 features (mean, vary, std, energy, entropy, skew, kurtosis). Therefore, if there are 64 scales and groupings of 10 scales, there will be approximately 6–7 groups × 7 features, ≈ 42–49 features in total. Second, features were taken from the Continuous Wavelet Transform (CWT) with the condition that the number of CWT scales used is 1–64, resulting in a total of 64 scales. The scales were divided into 10 groups (group size =10), so the number of groups is ≈ 64 / 10 = 6.4, rounded to 7 groups. From each group, 7 statistics were calculated using Mean, Variance, Standard Deviation, Energy, Entropy, Skegness, and Kurtosis. Therefore, from 1 EEG signal, the CWT extraction results = 49 features.

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2.5.2 Discrete Wavelet Transform (DWT)

DWT breaks down the signal into Approximation (A) and Detail (D) at several levels [18]:

$$\mathbf{x(t)} = \mathbf{An} + \sum_{k=1}^{n} \boldsymbol{D_k} \quad (10)$$

Where:
A_n = low frequency (trend)
D_k = high frequency (detail)
Each DWT level provides a different frequency resolution.
In this research using DWT, there are 3 trials conducted by taking features from the DWT process. First, the feature from the DWT process by taking the db4 wavelet with level 4, the decomposition results are 5 sets of coefficients (cA4, cD4, cD3, cD2, cD1), then each coefficient is taken to produce 5 energy values of the wavelet energy feature per EEG signal. Second, using the db4 wavelet DWT with decomposition produces 5 components, namely cA4, cD4, cD3, cD2, and cD1. For each component (cA4, cD4, cD3, cD2, cD1), 5 types of statistical features are calculated, namely Mean, Variance, Standard Deviation, Energy, and Shannon Entropy, so that the number of features becomes 5 x 5 = 25 features. The three features used come from the results of Wavelet decomposition (DWT, db4, level 4). For each wavelet coefficient (cA4, cD4, cD3, cD2, cD1) the following 7 statistical features are calculated, namely Mean, Variance, Standard Deviation, Energy, Entropy, Skegness, and Kurtosis. So there are 5 levels of DWT result coefficients (cA4, cD4, cD3, cD2, cD1) for each level of 7 statistical features, So the total features = 5 × 7 = 35 features per EEG signal.

2.6 Feature Extraction with the Hilbert-Huang Transform (HHT) method

HHT is an effective adaptive method for analysing non-linear and non-stationary signals, such as EEG. HHT extracts signal features through Empirical Mode Decomposition (EMD) and Hilbert Transform [19].

2.6.1 Empirical Mode Decomposition (EMD)

EMD breaks down the original signal x(t) into several Intrinsic Mode Functions (IMF) and residuals r(t) [20]:

$$\mathrm{x(t)} = \sum_{i=1}^{n} IMF_i\,(t) + r(t) \quad (11)$$

The IMF meets two conditions:
1. The number of extreme and the number of zero-crossings are nearly equal or differ by at most 1.
2. The average of the upper and lower envelopes is close to zero.

The IMF represents local oscillations of the signal at various frequencies.
EMD Process
1. Identify all extreme points (maximum and minimum).
2. Create upper and lower envelopes using interpolation.
3. Calculate the average of the envelopes and subtract it from the signal → the residual.
4. Repeat until the residual satisfies the IMF requirement → save the IMF.
5. Subtract the IMF from the original signal → the residual → repeat for the next IMF.

2.6.2 Hilbert Transform at the IMF

After obtaining the IMF, perform the Hilbert Transform to obtain the analytical signal [21]:

$$\boldsymbol{z_i}(\mathbf{t}) = \mathrm{IMF}_i\,(t) + j.H \quad (12)$$

- H[·] = Hilbert Transform
- Amplitude envelope: $A_i(t)=|z_i(t)|$
- Instantaneous phase: ϕi(t)=arg(zi(t))
- Instantaneous frequency: $\boldsymbol{f_i}(\mathbf{t}) = \frac{\mathbf{1}}{\mathbf{2\pi}} \frac{\boldsymbol{d\phi_i(t)}}{\boldsymbol{dt}}$

2.6.3 Statistical Features of HHT

For each IMF, commonly used features are energy, mean, amplitude, standard deviation, median amplitude, Skegness, kurtosis, max/min, Shannon, entropy, and mean frequency. These features are calculated per IMF and then combined into a single final feature vector. In this research using HHT, there are 3 trials conducted by taking features from the HHT process. First, the feature through Empirical Mode Decomposition (EMD), the EEG signal is decomposed into several IMFs (Intrinsic Mode Functions). For each IMF (maximum of the first 5 IMFs), 2 features are calculated, namely Energy IMF (sum of squares of the analytic signal amplitude) and Mean Instantaneous Frequency (average instantaneous frequency of the Hilbert phase), so that there are 5 IMFs × 2 features = 10 features per EEG signal. Second, EMD is taken a maximum of 5 IMFs (Intrinsic Mode Functions), from each IMF 4 features are extracted, namely Energy, Mean amplitude, Std amplitude, and Mean frequency. So the total features per signal = 5 IMFs × 4 features = 20 features. Third, feature extraction with HHT (Hilbert-Huang Transform) produces statistical features from each IMF. Only the first 5 IMFs from the EMD results were taken, for each IMF, 10 features were extracted, namely Energy, Mean amplitude, Std amplitude, Mean frequency, Median amplitude, Skegness

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amplitude, Kurtosis amplitude, Max amplitude, Min amplitude, and Entropy amplitude. So the total features in the third trial with HHT, namely features = 5 IMF × 10 features = 50 features.

2.7 SVM Classification

The SVM algorithm is applied in machine learning for classification and regression [22][23]. SVM is well-known for its ability to process high-dimensional and complex data, especially in the context of classification problems.
Find the optimal separating hyper plane between two classes.

$$\mathbf{f(x) = W^T.x + b} \quad (13)$$

In this study, SVM was used as the classification method, after the feature extraction process and taking features from the feature ecstasy process. Several classification and feature extraction models were used, these models were used to find the best performance of the tested system. The features used in this study were in the time-frequency domain, including the Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Hilbert-Huang Transform (HHT). Table 1 shows the system models tested, showing that in this study, many models will be tested to produce the best performance in detecting epilepsy seizures.

Table 1: Variations of the proposed model

Classification Type	Features used	Number of features
SVM + STFT	Delta-Theta-Alpha-Beta-Gamma band energy ratio	5
	STFT Mean, STFT Vary, STFT Max, STFT Energy	4
	STFT Mean, STFT Vary, STFT Max, STFT Energy, Spectral Centroid, Spectral Bandwidth, Spectral Entropy, Spectral Flatness, F50	9
	The frequency domain is Mean frequency, Vary frequency, Max frequency, Min frequency, Median frequency, and Std frequency. The time domain is Mean Time, Vary Time, and RMS Time, along with the values of delta, alpha, beta, theta, and gamma.	14
SVM + CWT	mean, vary, std, energy, entropy, skew, kurtosis	6
	Mean, Variance, Standard Deviation, Energy, Entropy, Skegness	49
SVM + DWT (db4)	Energy wavelet	5
	Mean, Variance, Standard Deviation, Energy, and Shannon Entropy	25
	Mean, Variance, Standard Deviation, Energy, Entropy, Skegness, and Kurtosis	35
SVM + HHT	Energy IMF and Mean Instantaneous Frequency	10
	Energy, Mean amplitude, Std amplitude, and Mean frequency	20
	Energy, Mean amplitude, Std amplitude, Mean frequency, Median amplitude, Skegness amplitude, Kurtosis amplitude, Max amplitude, Min amplitude, and Entropy amplitude.	50

2.8 Detailed Methodology: Pseudocode & Experiments

To improve the reproducibility of the research, this section includes the algorithmic flow in pseudocode form and the experimental setup.
Pseudocode of EEG Seizure Detection.

```
SET random_seed = 42
LOAD dataset (UCI Epileptic Seizure Recognition)
# Preprocessing
FOR each EEG signal:
   segment = normalize(signal, range=[0,1])
   OPTIONAL: bandpass_filter(0.5–45 Hz)
# Split dataset
train_set, test_set = stratified_split(dataset, 80/20)
# Feature extraction
FOR method in [STFT, WT (CWT/DWT), HHT]:
   features_train = extract_features(train_set, method)
   features_test = extract_features(test_set, method)
   # Classification
   model = SVM_RBF(C, γ tuned via grid search CV=5)
   model.fit(features_train, labels_train)
   predictions = model.predict(features_test)
   metrics = evaluate(predictions, labels_test,
                 [Accuracy, Precision, Recall, F1, MCC, Kappa, AUC])
   SAVE results
END FOR
```

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Experiment
Dataset: UCI Epileptic Seizure Recognition (11,500 EEG segments, 1 second, 178 Hz).
Preprocessing: Normalization [0,1]; optional bandpass filter (0.5–45 Hz).
Data Split: 80% training, 20% testing, stratified.
Feature Extraction:
STFT (4–14 features per trial).
WT (CWT & DWT with 25–49 features).
HHT (10–50 features per trial).
Classifier: SVM (RBF kernel), C & γ parameter optimization with grid search, 5-fold cross-validation.
Evaluation: Accuracy, Precision, Recall, F1-score, Matthews Correlation Coefficient (MCC), Cohen's Kappa, and Area Under the Curve (AUC).

Software/Tools: Python 3.x, NumPy, SciPy, Scikit-learn, PyWavelets, PyEMD.

2.9 Research Methods and Execution Protocol
To ensure the replicability of this study, the following details the execution protocol implemented:
Dataset
The dataset used is the UCI Epileptic Seizure Recognition dataset (a generalized version of the Bonn dataset).
Total: 11,500 1-second EEG segments with a sampling rate of 178 Hz.
Classes: Class 1 = Seizure, Classes 2–5 = Non-Seizure.
Data Preprocessing Steps
Normalize all EEG signals to the range [0,1] to balance feature weights.
Segment the EEG signals into 1-second windows (178 data points).
Optional filtering with a bandpass filter (0.5–45 Hz) to reduce high-frequency noise.
Dimensionality reduction in the exploratory phase (e.g., PCA for comparison validation).
Algorithm Settings
STFT: Window Hamming, window size = 64 samples, 50% overlap.
Wavelet Transform (WT):
CWT uses Morlet wavelets, scales 1–64, divided into 7 groups.
DWT uses Daubechies wavelets (db4), decomposition level = 4.
Hilbert-Huang Transform (HHT): A maximum of the first 5 IMFs are used for feature extraction.
SVM: RBF kernel, C and γ parameters are determined using grid search and 5-fold cross-validation.

Hardware & Software Environment
Hardware:
Processor: Intel Core i7-11700 @ 2.5GHz
RAM: 16GB DDR4
GPU: NVIDIA GTX 1660 Ti (6GB)
Software:
Python 3.9
Libraries: NumPy, SciPy, Scikit-learn, PyWavelets, PyEMD, Matplotlib
Operating System: Windows 10 Pro 64-bit
Experiment Execution Protocol
Load the dataset → perform preprocessing (normalization, segmentation, filtering).
Split the dataset into 80% training data and 20% test data using stratified sampling.
Extract features using STFT, WT, and HHT according to the configuration above.
Train an SVM model (RBF kernel) with grid search for parameter tuning.
Test the model with test data and calculate evaluation metrics (Accuracy, Precision, Recall, F1, MCC, Kappa, AUC).
Save the experimental results, compare the performance of each method, and analyze their strengths and limitations.

3 PERFORMANCE EVALUATION AND RESULTS

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

3.1 Confusion Matrices

Key evaluation metrics such as precision, accuracy, sensitivity (recall), and specificity are derived from the confusion matrix [24]. Figures 3, 4, 5, and 6 display a visual representation of the confusion matrix for a classifier using SVM. This confusion matrix provides in-depth insight into model performance by showing the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) settings. Referring to the results shown in Figures 3, Figures 4, Figures 5, and Figures 6.
Figure 3(a): SVM + STFT with 5 features incorrectly classifies 37 non-seizure data as seizures, and 127 seizure data as non-seizures.
Figure 3(b): SVM + STFT with 4 features incorrectly classifies 39 non-seizure data as seizures, and 39 seizure data as non-seizures.

Figure 3(c): SVM + STFT with 9 features, incorrectly classifies 20 non-seizure data as seizures, and 22 seizure data as non-seizures.
Figure 3(d): SVM + STFT with 14 features, incorrectly classifies 16 non-seizure data as seizures, and 21 seizure data as non-seizures.

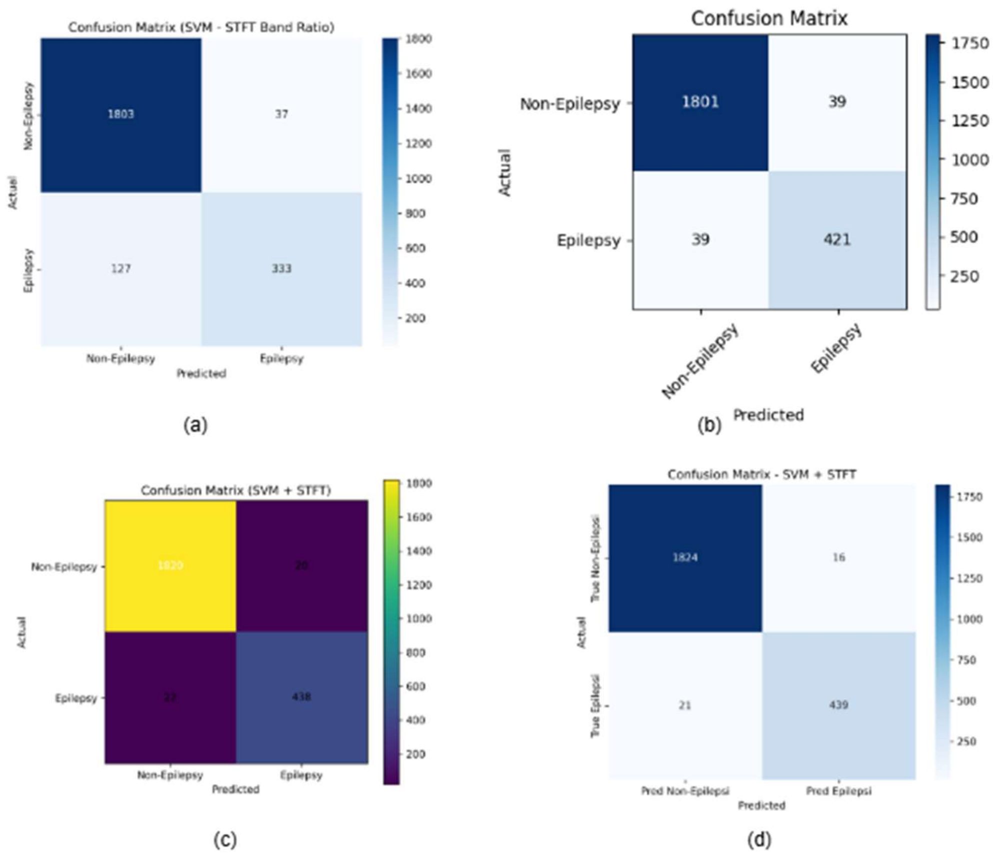

Figure 3: Confusion Matrix of SVM Classification with STFT

Figure 3 shows that with more features using STFT, performance improves, particularly with 14 features, consisting of the Frequency Domain (Mean Frequency, Vary Frequency, Max Frequency, Min Frequency, Median Frequency, Std Frequency), the Time Domain (Mean Time, Vary Time, RMS Time), and delta values: alpha, beta, theta, and gamma.

Figure 4(a): SVM + CWT with 6 features incorrectly classifies 66 non-seizure data as seizures and 17 seizure data as non-seizures.
Figure 4(b): SVM + CWT with 49 features incorrectly classifies 16 non-seizure data as seizures and 21 seizure data as non-seizures.

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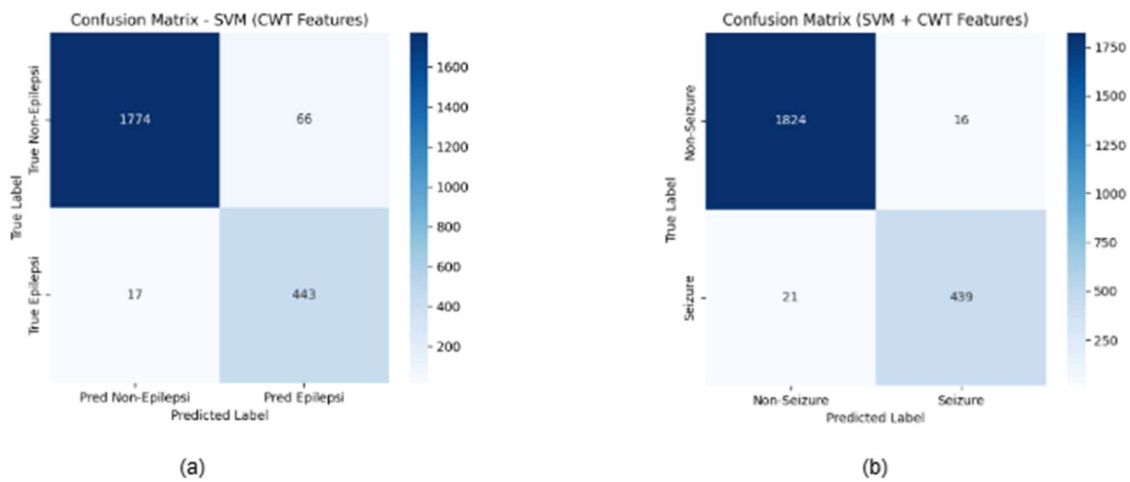

Figure 4: Confusion Matrix of SVM Classification with CWT

Figure 4 shows that with the addition of features, model performance improves. In this case, with 49 features, performance is even better.

Figure 5(a): SVM + DWT with 5 features incorrectly classifies 85 non-seizure data as seizures, and 220 seizure data as non-seizures.

Figure 5(b): SVM + DWT with 25 features incorrectly classifies 28 non-seizure data as seizures, and 24 seizure data as non-seizures.

Figure 5(c): SVM + DWT with 35 features incorrectly classifies 49 non-seizure data as seizures, and 11 seizure data as non-seizures.

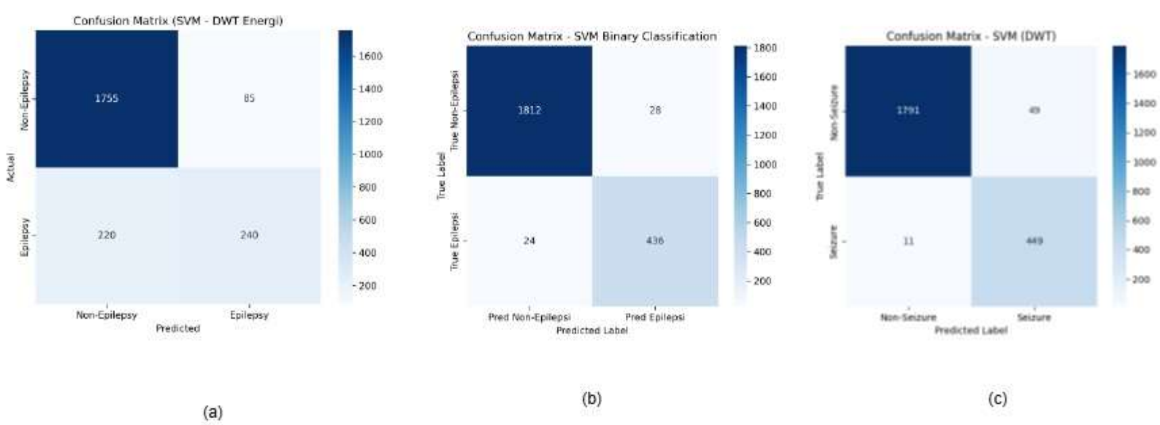

Figure 5: Confusion Matrix of SVM Classification with DWT

Figure 5 shows that using 25 features using DWT provides the most balanced performance (both sensitivity and specificity), while using 35 features is superior in seizure detection (low FN) but has a higher error rate (FP).

Figure 6(a): SVM + HHT with 10 features incorrectly classifies 32 non-seizure data as seizures, and 40 seizure data as non-seizures.

Figure 6(b): SVM + HHT with 20 features incorrectly classifies 26 non-seizure data as seizures, and 28 seizure data as non-seizures.

Figure 6(c): SVM + HHT with 30 features incorrectly classifies 23 non-seizure data as seizures, and 28 seizure data as non-seizures.

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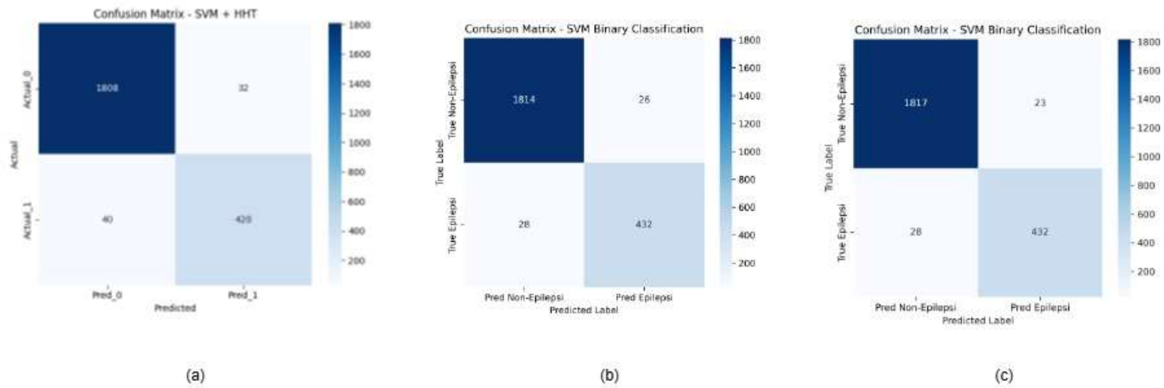

Figure 6: Confusion Matrix of SVM Classification with HHT

Figure 6 shows that performance increases with the addition of features. Using 30 features, HHT yields the best results due to the lowest and most balanced total error. Table 1 compares the performance of the Wavelet Transform, HHT, and STFT feature extraction methods. The best performance per method is shown by STFT-14 features (37), CWT-49 features (37), DWT-25 features (52), and HHT-30 features (51). Overall, the best method is between STFT-14 features and CWT-49 features, both with a total error of 37.

Table 1: Comparison of FP and FN confusion matrices.

Method	Number of Features	False Positive	False Negative	Total Error
STFT (Figure 3a)	5	37	127	164
STFT (Figure 3b)	4	39	39	78
STFT (Figure 3c)	9	20	22	42
STFT (Figure 3d)	14	16	21	37
CWT (Figure 4a)	6	66	17	83
CWT (Figure 4b)	49	16	21	37
DWT (Figure 5a)	5	85	220	305
DWT (Figure 5b)	25	28	24	52
DWT (Figure 5c)	35	49	11	60
HHT (Figure 6a)	10	32	40	72
HHT (Figure 6b)	20	26	28	54
HHT (Figure 6c)	30	23	28	51

3.2 AUC-ROC curve

ROC-AUC is used to describe how effective the model is in classifying epilepsy and non-epilepsy classes [25]. 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 classification, in this case epilepsy and non-epilepsy. Figure 7, figure 8, figure 9, and figure 10 show the AUC values of each model. Figure 7 shows the AUC value of the SVM classification model and STFT feature extraction with AUC values of (a) 5 features AUC value = 0.954, (b) 4 features AUC value = 0.993, feature 9 AUC value = 0.995, and feature 14 = 0.997.

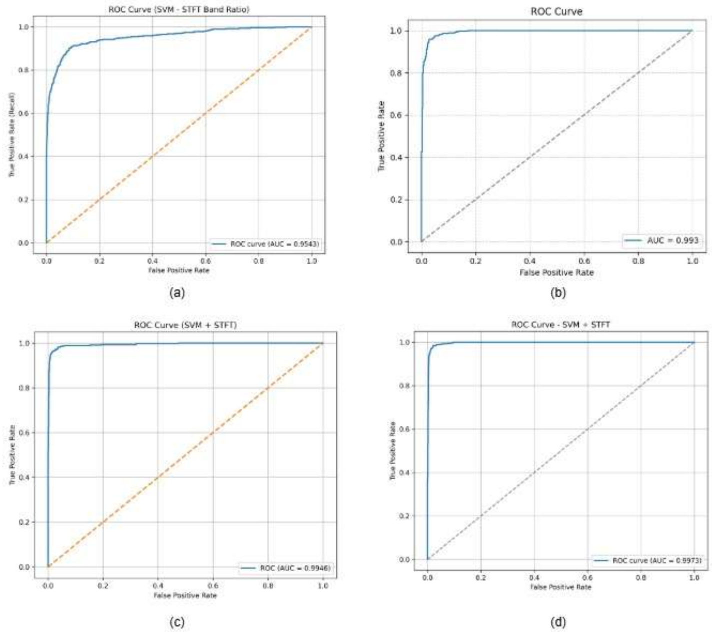

Figure 7: ROC-AUC curve values for SVM and STFT classification types

Figure 7 shows that the more features used, in this case 14 features from the STFT feature extraction, the higher the AUC value. This indicates the model's near-perfect ability to differentiate seizure and non-seizure data. Figure 8 shows the AUC values of the SVM classification model and CWT feature extraction, with AUC values of (a) 6 features (AUC = 0.99), and (b) 49 features (AUC = 1.00).

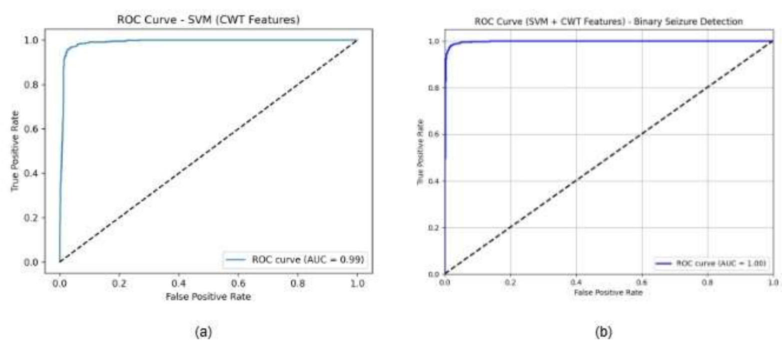

Figure 8: ROC-AUC curve values for SVM and CWT classification types.

Figure 8 shows that increasing the number of features from 6 to 49 during the feature extraction process with CWT can improve model performance from very good to excellent. Figure 9 shows the AUC values of the SVM classification model and DWT feature extraction, with AUC values of (a) 5 features (AUC = 0.88), (b) 25 features (AUC = 0.996), and (c) 35 features (AUC = 1.00).

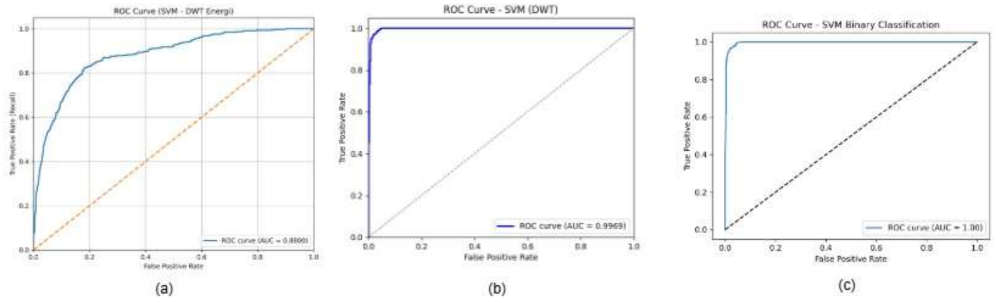

Figure 9. ROC-AUC curve values for SVM and DWT classification types.

Figure 9 shows that the more DWT features used, the more significant the classification performance improvement, reaching perfection at 35 features. Figure 10 shows the AUC values of the SVM classification model and HHT feature extraction, with AUC values of (a) 10 features: AUC = 0.994, (b) 20 features: AUC = 1.00, (c) 20 features: AUC = 1.00.

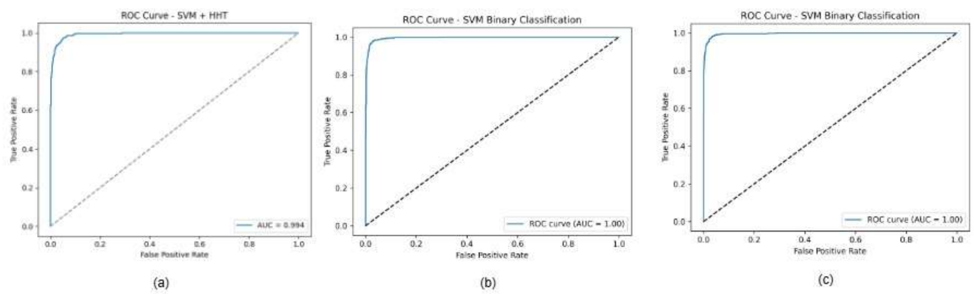

Figure 10: ROC-AUC curve values for SVM and HHT classification types.

Figure 10 shows that the SVM + HHT model, starting with 20 features, has an AUC value of 1.00, indicating that the model can distinguish between seizure and non-seizure data. Therefore, the more features used, the better the model performance will be. Table 2 shows the difference values for each performance model. By comparing them, we can determine the best performance for detecting epilepsy and non-epileptic symptoms.

Table 2: Comparison of AUC values of SVM models with various feature extraction methods.

Method	Number of Features	AUC Value	Description
STFT	5	0.954	Good
	4	0.993	Very High
	9	0.995	Very High
	14	0.997	Almost perfect
CWT	6	0.990	Very High
	49	1.000	Perfect
DWT	5	0.880	Still low compared to others
	25	0.996	Almost perfect
	35	1.000	Perfect
HHT	10	0.994	Very High
	20	1.000	Perfect
	30	1.000	Perfect

Table 2 shows that feature extraction using DWT (35 features), CWT (49 features), and HHT (≥20 features) was able to achieve AUC = 1,000 (perfect). Feature extraction using STFT was also very good, especially on 14 features with AUC = 0.997, although not perfect. Feature extraction using DWT with few features (5 features) had the lowest performance (AUC = 0.880). Figure 11 is a comparison of AUC values displayed in graphical form.

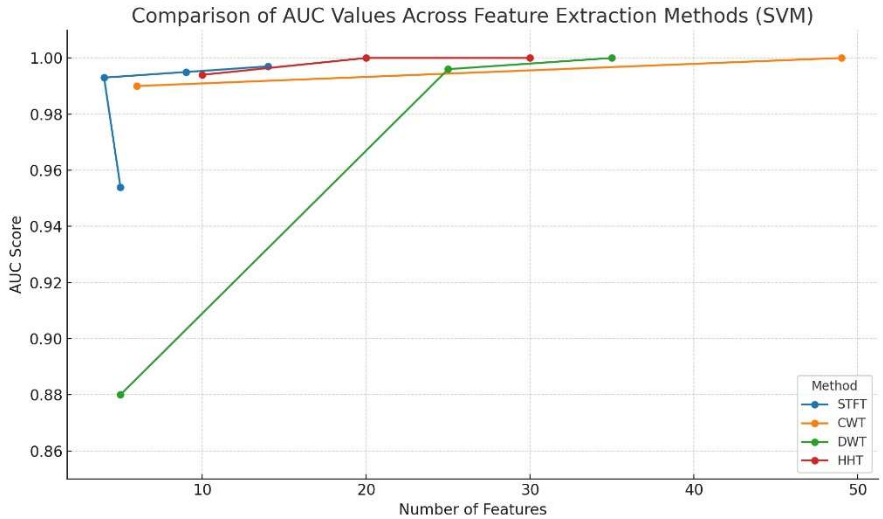

Figure 11: Comparison of AUC values with different feature extractions

3.3 Classification Report

This study presents a classification evaluation report based on Accuracy, Recall, Precision, MCC, Kappa, and F1-score for each category (seizure and non-seizure). Table 3 presents this report and indicates that the proposed method produces effective results in EEG classification.

Table 3: Comparison of model performance evaluations of various features.

Method	Number of Features	Accuracy	Precision	Recall	F1-Score	MCC	Kappa
STFT	5	0,928696	0,9	0,723913	0,80241	0,766232	0,759531
	4	0,966087	0,915217	0,915217	0,915217	0,894022	0,894022
	9	0,981739	0,956332	0,952174	0,954248	0,942845	0,942842
	14	0,983913	0,964835	0,954348	0,959563	0,949545	0,949523
CWT	6	0,963913	0,870334	0,963043	0,914345	-	-
	49	0,983913	0,964835	0,954348	0,959563	-	-
DWT	5	0,867391	0,738462	0,521739	0,611465	0,546076	0,534351
	25	0,977391	0,939655	0,947826	0,943723	-	-
	35	0,973913	0,901606	0,976087	0,93737	-	-
HHT	10	0,968696	0,929204	0,913043	0,921053	0,901586	0,901532
	20	0,976522	0,943231	0,93913	0,941176	-	-
	30	0,977826	0,949451	0,93913	0,944262	-	-

Table 3 shows that all methods above 96%, except for feature extraction with the DWT method with 5 features, can be categorized as very good. Feature extraction with the STFT method (14 features) and CWT (49 features) produced the highest accuracy, namely 98.39%, this result exceeds previous research using the SVM method as a classifier. Feature extraction using the DWT method with 5 features had the worst performance, namely 86.74%.

3.4 Summary of Method Performance

Table 4 summarizes the results, advantages, disadvantages, and potential clinical applications of each EEG feature extraction method tested.

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Table 4: Summary of Method Performance

Method	Best Features	Strengths	Weaknesses	Potential Application
STFT	14 features	- High accuracy (98.39%) - Near-perfect AUC (0.997) - Relatively efficient (fewer features)	- Performance drops with fewer features (4–5) - Less flexible than CWT in frequency resolution	Real-time seizure detection, portable EEG systems with limited computational resources
CWT	49 features	- High accuracy (98.39%) - Perfect AUC (1.0) - Very detailed time–frequency representation	- Requires many features (higher computational complexity)	Detailed clinical detection, laboratory or offline systems with sufficient resources
DWT	25–35 features	- Perfect AUC (1.0) with 35 features - Good in seizure detection (high sensitivity)	- Very poor performance with few features (5 features, AUC = 0.88) - Higher False Positive rate at high feature levels	Pre-screening of epilepsy, less ideal for real-time or low-resource devices

4. CONCLUSION AND FUTURE WORK

This study aimed to detect epileptic and non-epileptic seizures using EEG signals through a structured process, including pre-processing, feature extraction (STFT, WT, and HHT), and classification with SVM. The findings demonstrate that the proposed framework achieves high performance, not only in terms of accuracy but also across critical evaluation metrics such as recall, precision, and F1-score. These results highlight the importance of a comprehensive evaluation beyond accuracy alone, particularly in healthcare applications where both seizure and non-seizure recognition are equally vital.

The comparative analysis reveals that STFT offers a balance between accuracy and efficiency, CWT provides high-resolution but computationally intensive analysis, DWT shows good sensitivity yet instability with fewer features, and HHT effectively captures nonlinear EEG dynamics. These insights underscore that the choice of method should be aligned with the intended application, whether in real-time systems, offline diagnostic tools, or advanced research settings.

Implications: This study contributes a structured evaluation framework that can guide future developments in EEG-based seizure detection, particularly in designing clinically reliable diagnostic support systems.

Future Work: Despite the promising results, limitations remain, such as reliance on a single dataset, potential computational overhead for certain methods, and lack of deployment in real clinical workflows. Future research will address these limitations by:

- Extending experiments to larger, multi centre datasets to ensure generalizability.
- Exploring deep learning and hybrid models for automated feature learning.
- Optimizing algorithms for real-time and low-resource environments.
- Conducting clinical validation studies to assess usability in real-world healthcare settings.

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