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EPILEPTIC EEG SIGNALS RHYTHMS ANALYSIS IN THE DETECTION OF FOCAL AND NON-FOCAL SEIZURES BASED ON OPTIMISED MACHINE LEARNING AND DEEP NEURAL NETWORK ARCHITECTURE

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Objective: Most studies in epileptic seizure detection and classification focused on classifying different types of epileptic seizures. However, localization of the epileptogenic zone in epilepsy patient brain's is paramount to assist the doctor in locating a focal region in patients screened for surgery. Therefore, this paper proposed robust models for the localization of epileptogenic areas for the success of epilepsy surgery. **Method:** Advanced feature extraction techniques were proposed as effective feature extraction techniques based on Electroencephalogram (EEG) rhythms extracted from Fourier Basel Series Expansion Multivariate Empirical Wavelet Transform (FBSE-MEWT). The proposed extracted EEG rhythms of δ , θ , α , β and γ features were used to obtain a joint instantaneous frequency and amplitude components using a sub-band alignment approach. The features are used in Sparse Autoencoder (SAE), Deep Belief Network (DBN), and Support Vector Machine (SVM) with the optimized capability to develop three new models: 1. FMEWT-SVM 2. FMEWT_SAE-SVM, and 3. FMEWT-DBN-SVM. The EEG signal was preprocessed using a proposed Multiscale Principal Component Analysis (mPCA) to denoise the noise embedded in the signal. Main results: The developed models show a significant performance improvement, with the SAE-SVM outperforming other proposed models and some recently reported works in literature with an accuracy of 99.7% using

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δ -rhythms in channels 1 and 2. *Significance:* This study validates the EEG rhythm as a means of discriminating the embedded features in epileptic EEG signals to locate the focal and non-focal regions in the epileptic patient's brain to increase the success of the surgery and reduce computational cost.

Keywords: EEG; time–frequency; SVM; SAE; DBN; MEWT; FBSE.

1. Introduction

Localization of epileptogenic regions is essential in drug-resistant epileptic patients screened for surgery. This task can be effectively realized using Electroencephalogram (EEG) signals from the human brain. It is a complex signal that consists of many neurons that are interconnected together.¹ EEG signals consist of and reveal essential clinical information that can be used in the analysis and diagnosis of brain disorders such as emotions recognition,^{2,3} measuring the depth of anesthesia,⁴ stroke-related disorders,⁵ depression,⁶ Parkinson's diseases,⁷ sleep-related disorders,⁸ brain death,⁹ and epileptic seizure.¹⁰ Epilepsy is a neurological disorder that occurs due to excessive electrical brain cell activities that need to be monitored appropriately and diagnosed because the effect of seizure may lead to loss of memory, uncontrolled motions, loss of consciousness, and jerking. It may even lead to death.^{11,12} Therefore, the quality of epilepsy patient's life was greatly affected by these effects as it is difficult for the clinician and patient to predict the occurrence of these seizures. The epileptic seizure patients were estimated to be around 50 million, most of whom are from low-income countries.¹³ Generally, epilepsy can be categorized into generalized and partial epilepsies. Focal epilepsy belongs to the partial class of epilepsy, with the brain region affected known as the epileptogenic zone. In contrast, non-focal seizures are recorded outside the epileptogenic zones.¹⁴

In general, clinicians observe the EEG record to detect the epileptic seizure and the regions affected by the seizure using visual monitoring and interpretation of the patient's EEG signal recording. This approach is tedious and time-consuming and also needs highly skilled personnel to interpret the EEG records correctly; even with experienced personnel, the longer time is taken, and difficulty to complete the task due to long EEG data recording may lead to fatigue and can render the monitoring and interpretation subjective and poor in accuracy.^{15,16} Therefore, the development of automated detection and classification for monitoring and diagnosis of epileptic seizures is paramount, especially at this time when the new generation of modern, portable, and smart devices popularly called the internet of medical things (IoMT) have been integrated into the health care system to monitor, detect, store, and transmit the data via the internet protocol system. A recent example of such a device was developed and reported in Ref. 17. They proposed a hand band low-power application-based seizure detection system that used a cloud to record and transmit the data. The performance of these devices largely depends on the algorithms developed to explore EEG signals' embedded characteristics, which also depends on the quality and robustness of the preprocessing, feature extraction, and classifiers

employed for the classification of seizures and non-seizure classes.¹⁸ Therefore, this work proposed efficient and robust feature extraction techniques and optimized seizure detection models that are suitable for intelligent and portable IoMT framework devices due to the optimized detection pipeline and reduced computational complexity.

The proposed methods developed in this work uses focal and non-focal EEG signal which reveal the electrical activity of the brain that a neurologist utilized to identify the brain's function, activities, and its different parts including the epileptogenic area. The focal EEG signal reveals the specific part of the brain that is affected (i.e., localized), while the non-focal signal indicates that several parts are involved (i.e., generalized). The traditional and manual techniques for the detection and interpretation of these signals are ineffective due to the missing of some valuable information about the signal.

This paper tends to carry out a comprehensive analysis of feature extraction, detection, and classification methods using several signal analysis domains for focal and non-focal EEG signals. The developed robust feature extraction was based on the advanced time–frequency approach based on the analysis of EEG rhythms combined with other signal processing domains. The extracted features were evaluated with the proposed efficient detection systems based on a hybrid method of optimized Support Vector Machine (SVM) classifier with deep learning architectures to explore and utilize the benefit of the two systems. Prior to feature extraction, the dataset was preprocessed using a proposed robust preprocessing technique based on the mPCA and DWT.

The rest of this paper is organized as follows: Sec. 2 is the literature review that highlights and discussed some relevant related works reported recently. Section 3 provides the detail of the model experimentation that consists of a dataset description and each stage in the block diagram of the proposed methodology. The result of the experiments was presented in Sec. 4, while Sec. 5 describes the discussion of the results presented and suggestions for future work. Finally, Sec. 6 offers the conclusion of the paper.

2. Literature Review

Many researchers have investigated and developed various techniques for detecting and classifying epileptic seizures using EEG signals, such as the works reported in Refs. 19 and 20. However, few studies focused on localizing the epileptogenic zone by classifying focal and non-focal EEG signal classes. Some of these works are reported in Ref. 21, which classified focal and non-focal EEG signals using weighted visibility graph entropy. Discrete wavelet transform (DWT), and its variants were used in the classification of focal and non-focal EEG signals, which includes DWT,^{22,23} tunable Q wavelet transform (TQWT),^{24,25} constant bandwidth TQWT,²⁶ wavelet packet transform,²⁷ and flexible analytic wavelet transforms (FAWT).^{28,29} Complex wavelet transform was used to develop a computer-aided (CAD) system using an adaptive

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neuro-fuzzy inference system (ANFISS) classifier as proposed in Ref. 30. In Ref. 31, the authors classified the focal and non-focal EEG signals using the neighborhood component analysis in the feature extraction stage and SVM classifier in the classification stage with the reported performance of 94.4%, 97.6%, and 96.1% as specificity, sensitivity, and accuracy respectively. Arunkumar *et al.*³² and Azami *et al.*³³ proposed a method for classifying focal and non-focal EEG signals using several entropy measures. Also, Ref. 34 reported the specificity, sensitivity, and accuracy of 95.0%, 95.0%, and 78.5%, respectively, when the differential entropy was employed in the feature extraction stage. The best classifier among the experimented classifiers was found to be a random forest classifier. A supervised approach was developed by Ref. 35 using a non-parametric statistical approach. Recently, some researchers who used convolutional neural network (CNN) architecture have applied deep learning algorithms to detect and classify focal and non-focal EEG signals, as reported in Refs. 36 and 37. Others are Ref. 38, which employed long short-term memory (LSTM) with bi-directional learning to classify focal and non-focal EEG signals with reported accuracy, sensitivity, and specificity of 99.60%, 99.55%, and 99.65%, respectively.

Recently, features from the sub-band of EEG signals have been investigated and extracted to distinguish between focal and non-focal EEG signals. The efficacy of the synchrosqueezing transform in reassigning the coefficients in the time–frequency matrix has shown better performance in the classification of ictal and non-ictal epileptic signals.³⁹ Wavelet transforms synchrosqueezing transform used to reassign energy and compensates for spreading the energy in time–frequency of the wavelet transform. Saminu *et al.*⁴⁰ proposed focal and non-focal detection models based on the wavelet transform Synchrosqueezing Transform (WT-SST) method with SVM, 1D-CNN, and 2D-DCNN as classifiers. This paper leverages the limitations associated with most of the reported works of either employing single domain feature extraction methods, using a single conventional classifier, or using a small dataset in Bern-Barcelona datasets. Also, most of the reported studies in the literature used an average of the raw EEG signals to decompose the signal into sub-bands. This paper tends to develop robust models that overcome the limitations associated with the previous work by creating a robust feature extraction technique from the combined statistical, nonlinear, and energy features. Advanced time–frequency features based on the extraction of EEG rhythms from sub-bands decomposed using proposed Fourier Basel Series Expansion Multivariate Empirical Wavelet Transform (FBSE-MEWT) have been proposed. The classification of focal and non-focal EEG signals is based on the EEG rhythm of δ , θ , α , β and γ subbands and the instantaneous frequency and amplitude components computed. The new model was developed based on the proposed new version of SVM classifiers that combine deep learning architectures of Sparse Autoencoder (SAE) and Deep Belief Network (DBN) with SVM machine learning classifiers. The proposed model was preprocessed with a new proposed preprocessing method called multiscale principal component analysis

combined with wavelet transform (mPCA-DWT) to deal with the non-stationary and nonlinear nature of EEG signals properly.

3. Model Experimentation

The model presented in this work was proposed based on the following stages that combine to form a hybrid technique, as shown in Fig. 1. The proposed model's robustness and efficiency were evaluated with the popular benchmark datasets known as Bern-Barcelona datasets from the Bern University, Department of Neurology. The block diagram consists of the data acquisition stage which is the focal and non-focal EEG signal. After data acquisition, the EEG signal was preprocessed using the mPCA technique and then prepared for decomposition using the proposed MEWT decomposition technique. Instantaneous and joint instantaneous amplitude and frequency were computed before the features are extracted using various domains. The extracted features are then ranked to select the most relevant and useful features using a statistical approach. The features were passed to the proposed classifiers to classify the focal and non-focal EEG signals.

3.1. Dataset description

The Bern-Barcelona database consists of the datasets acquired intracranially from five longstanding pharmacoresistant temporal lobe epilepsy patients screened for surgery. It contains 3750 pairs of focal and non-focal EEG signals with two columns in each pair as x and y acquired from adjacent channels. The recording duration is over 80 h with an AD-TECH (Racine, WI, USA) device in a multichannel approach

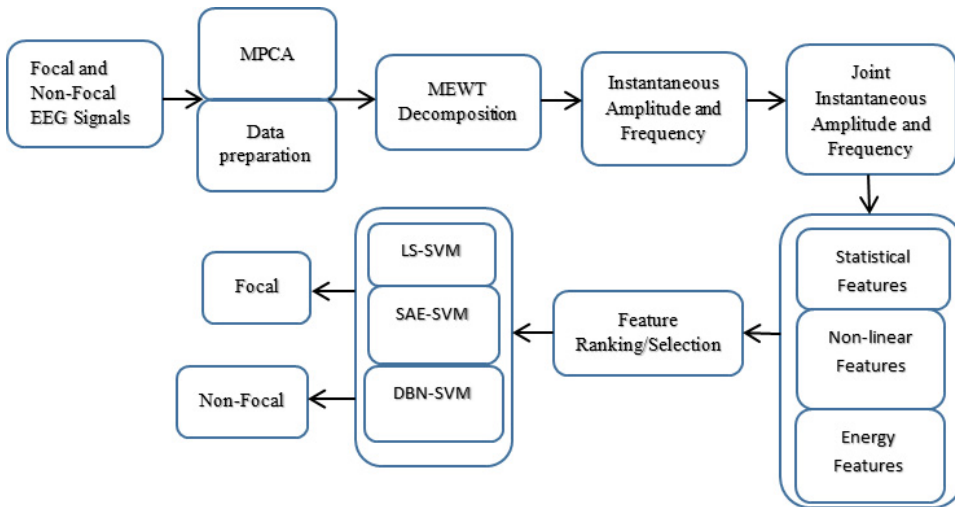


Fig. 1. Block diagram of the proposed model for the detection of focal and non-focal EEG signals.

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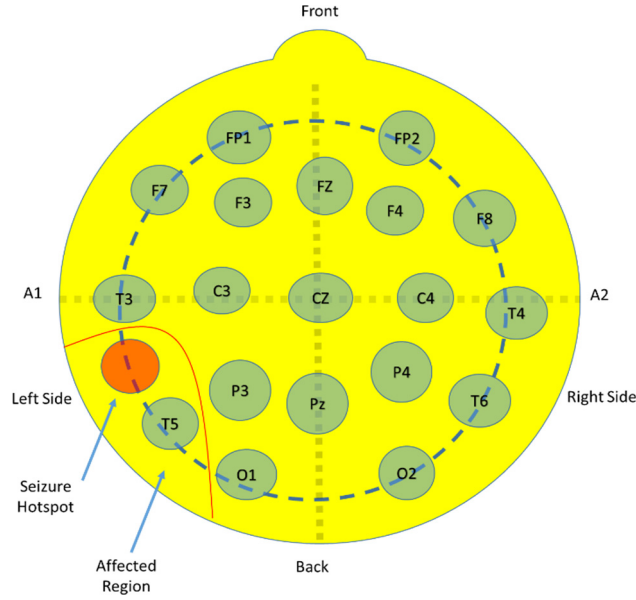


Fig. 2. Electrodes arrangement of EEG signal recording using 10–20 international system with seizure hotspot shown in red color.

with a sampling frequency of 512 Hz in 20 s, resulting in 10,240 samples. *Fz* and *Pz* are the reference electrode locations using 10–20 international standard recording arrangements. The recording electrode arrangement is shown in Fig. 2, with a red colour showing the seizure hotspots. The database contains two types of data sets: 50 and 3750 pairs of focal and non-focal EEG signals for small and large datasets. The proposed model was built based on large datasets, and 2048 samples were selected in this paper to investigate the model's efficacy properly. Details description of this dataset would be found in Ref. 41. Some of the reasons for using this dataset include 1. The dataset is available in the public domain 2. The data is sufficient to provide good statistical relevancy in characterizing discriminating features 3. The dataset provides strong evidence for comparing the model's performance as it has been used by most researchers in epileptogenic lesions localization.⁴² An example of part of the focal and non-focal EEG signal from the dataset is shown in Fig. 3.

3.2. Preprocessing

In the preprocessing stage, the EEG signals affected by various noises and artifacts during the acquisition process have been removed to prevent distorting the desired signals and jeopardizing the analysis of proper brain function. This work employed the multiscale principal component analysis combined with wavelet transform to utilize the benefit of the two approaches in dealing with nonlinear and non-stationary signals, such as EEG signals.^{43,44} The proposed model can be

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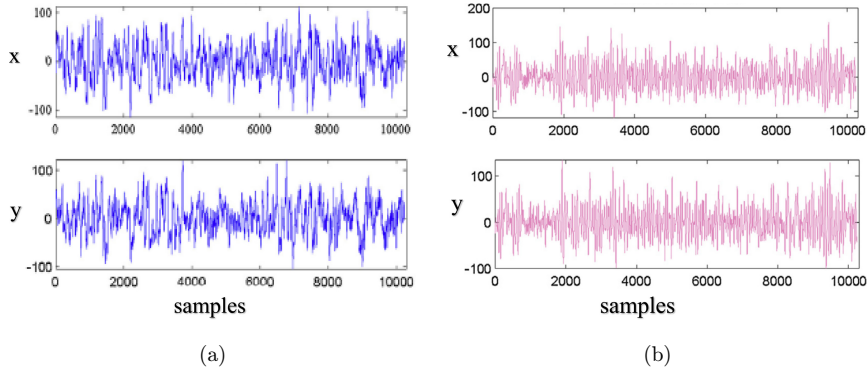


Fig. 3. Examples of pair of EEG signals are (a) focal EEG signals for x and y time series and (b) nonfocal EEG signals for x and y time series.

described linearly as:

$$z(n) = p(n) + q(n), \quad (1)$$

where $z(n)$ denotes the noisy EEG signals, $p(n)$ is the noise-free EEG signals and $q(n)$ represents the noise components.

The objective of the model is to separate and eliminate $q(n)$ from $p(n)$. The model which is depicted in Fig. 4 can be illustrated as follows:

- (i) Wavelet transform W is used to decompose each column of EEG signals Z at various levels j and produce $G_c Z$ and $H_c Z$ as details and approximation components matrices, respectively.

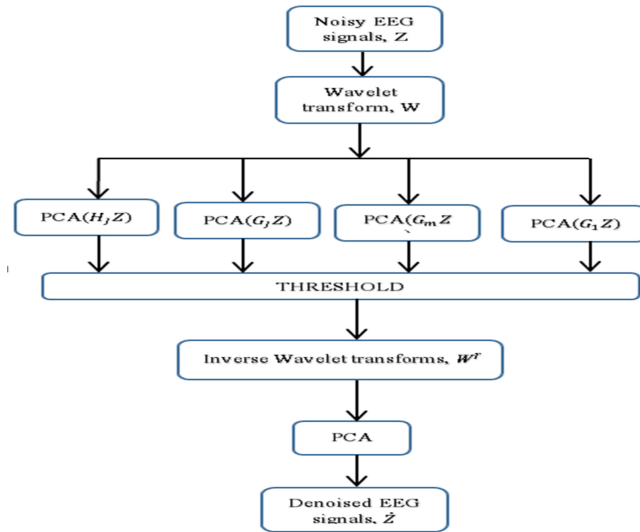


Fig. 4. Proposed mPCA for preprocessing the EEG focal and non-focal EEG signals.

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- (ii) PCA is then applied to the detailed components $G_c Z$. Using the Kaiser rule,⁴⁵ significant PCA components are computed based on the condition that their eigenvalues are higher than that of the remaining components and also that $1 \leq c \leq j$. Also, the principal components are chosen from the approximation matrices $H_c Z$ using the same condition.
- (iii) A new matrix is generated from the selected principal components obtained in (ii) after taking the inverse of wavelet transform W^T .
- (iv) Finally, PCA was carried out on the new matrix to obtain a clean signal $\hat{Z}$.

This mPCA method was adopted to remove the noise and artifacts in focal and non-focal EEG signals.

3.3. FBSE-MEWT decomposition

The FBSE-MEWT hybrid method was proposed and developed in this work to decompose and extract the EEG signals rhythms for each sub-bands from each channel. The EWT method⁴⁶ is used to analyze nonlinear and non-stationary signals such as epileptic EEG signals, the limitations associated with EMD and DWT of non-adaptive defects could be overcome using the EWT method decomposing the signal into different modes. The technique consists of building adaptive wavelet filters in the FBSE domain whose bandwidths vary based on the components of the input signal.⁴⁷ The summary of the FBSE-MEWT procedure is described as follows:

- (i) Transform the multichannel EEG signals into the FBSE domain.
- (ii) Divide the FBSE EEG signals spectrum into T segments according to the order range.
- (iii) Using the segmented FBSE spectrum, an empirical wavelet filter bank is designed using scaling and wavelet functions.
- (iv) Multivariate analysis as the extension of EWT is performed.

The details of the steps followed to execute the FBSE-MEWT were presented and explained in the following steps:

(1) Step 1: Bessel functions zero and first order $J_0(\cdot)$ and $J_1(\cdot)$, respectively, was used to transform the multichannel EEG signals $x^m(n)$ as in Eq. (2) to FBSE domain, m being the number of channels. The coefficients of FBSE (FC) for the m th EEG signal channel is denoted as in Eq. (3)

$$x^m(n) = \sum_{k=1}^N FC_k^m J_0\left(\frac{\alpha_k(n)}{N}\right), \quad n = 0.1, \dots, N-1, \quad (2)$$

$$FC_k^m = \frac{2}{N^2 [J_1(\alpha_k)]^2} \sum_{n=0}^{N-1} n x^m(n) J_0\left(\frac{\alpha_k(n)}{N}\right), \quad (3)$$

α_k is Bessel function zero order positive roots of $J_0(\cdot) = 0$, with $k = 1, 2, \dots, N$. The roots' a' are obtained by Newton's Raphson approach and derived with Taylor series

expansion such that $J_0(a) = 0$. After the simplification of the Taylor series, the roots of the equation are obtained as

$$J_0(a) = J_0(a_p) + (a - a_p)(\Delta J_0(a_i)), \quad (4)$$

where p represents the number of iterations.

The relationship between F_k, F_s , represented as the EEG signals frequency and EEG signals sampling frequency, respectively, with $J_0(\alpha_k)$ for k th order of FBSE coefficients can be described as

$$\alpha_k = \frac{2\pi F_k N}{F_s}, \quad (5)$$

where $\alpha_k = k\pi$ and Eq. (5) can be expressed as

$$k = \frac{2F_k N}{F_s}, \quad (6)$$

Hence, the FBSE coefficients order k can be described in terms of discrete frequency Ψ_k as

$$k = \frac{\Psi_k N}{\pi}. \quad (7)$$

Therefore, to cover the whole range of EEG signals frequency, the order k can vary from 1 to N . This order shows that good spectral resolution has been achieved from the FBSE spectrum of EEG signals and can also be conveniently utilized to reconstruct the EEG signals from FBSE coefficients perfectly.

Step 2: $M - 1$ intermediate order range was adaptively detected; after that, the FBSE spectrum was segmented into N contiguous segments depending on the chosen order range by applying a boundary detection approach to obtain the boundary frequencies $\{\Omega_i\}_{i=0,\dots,N}$ where first $(\Omega_0) = 0$ while $(\Omega_N) = \pi$. The FBSE spectrums can be written as $[0 \ \Omega_1], [\Omega_1 \ \Omega_2], \dots, [\Omega_{N-1} \ \pi]$. In this work, the order range was fixed as $[0-32]$, $[32-64]$, $[64-102]$, $[102-240]$, and $[240-600]$. From Eq. (6), the order ranges are transformed into frequencies as $[0-4]$, $[4-8]$, $[8-13]$, $[13-30]$, and $[30-75]$, which corresponds to the EEG rhythms of the delta, theta, alpha, beta, and gamma.

Step 3: Empirical wavelet filter banks were then designed on each band using scaling and wavelet functions based on the concept of Littlewood–Paley and Meyer wavelets.⁴⁶ The empirical scaling functions $\hat{S}_k(v)$ and wavelet functions $\hat{W}_k(v)$ are described as⁴⁸:

$$\hat{S}_k(\Omega) = \begin{cases} 1, & \text{if } |\Omega| \leq (1 - \beta)\Omega_k \\ \cos\left(\frac{\pi\phi(\beta, \Omega_{k+1})}{2}\right), & \text{if } (1 - \beta)\Omega_k \leq |\Omega| \leq (1 + \beta)\Omega_k, \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

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$$\hat{W}_k(\Omega) = \begin{cases} 1, & \text{if } (1 + \beta)\Omega_k \leq |\Omega| \leq (1 - \beta)\Omega_{k+1} \\ \cos\left(\frac{\pi\phi(\beta, \Omega_{k+1})}{2}\right), & \text{if } (1 - \beta)\Omega_{k+1} \leq |\Omega| \leq (1 + \beta)\Omega_{k+1} \\ \sin\left(\frac{\pi\phi(\beta, \Omega_{k+1})}{2}\right), & \text{if } (1 - \beta)\Omega_k \leq |\Omega| \leq (1 + \beta)\Omega_k \\ 0, & \text{Otherwise} \end{cases}, \quad (9)$$

$$\phi(\beta, \Omega_k) = \alpha \left(\frac{(|\Omega| - (1 - \beta)\Omega_k)}{2\beta\Omega_k} \right). \quad (10)$$

To avoid overlap between functions, the β is appropriately selected in Eqs. (8) and (9). Also, to ensure a tight frame condition in $L^2(\mathfrak{R})$ is satisfied of empirical wavelet functions as well as empirical scaling functions, Eqs. (8) and (9) should meet Eq. (11) as

$$\beta < \min_k \alpha \left(\frac{(v_{k+1} - v_k)}{v_{k+1} + v_k} \right), \quad (11)$$

The arbitrary function $\alpha(z)$ is described as Eq. (12)

$$\alpha(z) = \begin{cases} 0, & \text{if } z \leq 0 \\ \alpha(z) + \alpha(1 - z) = 1, & \text{for all } z \in [0, 1] \\ 1, & \text{if } z \geq 1 \end{cases}. \quad (12)$$

The inner product of EEG signals wavelet functions and scaling functions is used to compute the details and approximate coefficients for each EEG channel which corresponds to rhythms of the EEG signals. The rhythms, which are time-frequency signals of EWT extracted based on the Hilbert transform using sub-bands filters, result in instantaneous amplitude and frequency.

Step 4: The EWT extension of multivariate analysis for multichannel EEG signals is to extract the amplitude and frequency modulated components denoted as A.F.s for every channel, and the aim is from multichannel signals to derive matched mono-component signals. Two conditions need to be met to achieve the multivariate approach. 1. The extracted sub-bands should be equal in each channel, and 2. The frequency range in each sub-bands indexed in every channel should be the same.⁴⁹ Therefore, to satisfy the multivariate analysis requirements, let us calculate the mean spectrum magnitude of multivariate time series signal $\dot{z}(t)$ as

$$\dot{Z}(f) = \frac{1}{N_c} \sum_{n=1}^{N_c} |\dot{Z}_n(f)| \quad (13)$$

and

$$\dot{z}(t) = [\dot{z}_1(t), \dot{z}_2(t), \dots, \dot{z}_k(t)] \quad (14)$$

where $\dot{Z}(f)$ is the Fourier spectrum of the n -th channel signal $\dot{z}(t)$. While N_c is the number of channels with n varying from 1 to N_c . We then employed the boundary

search approach reported in Ref. 46 onto $\dot{Z}(f)$ to obtain the generated adaptive filter banks.

The multivariate signal $\dot{z}(t)$ after its decomposition can be defined in Eqs. (15)–(17). It can also be described in terms of amplitude and frequency modulated components A.F.s as follows:

$$\dot{z}(t) = \begin{bmatrix} z_1, AF_1(t) & z_1, AF_2(t) & \cdots & z_1, AF_N(t) \\ z_2, AF_1(t) & z_2, AF_2(t) & \cdots & z_2, AF_N(t) \\ \vdots & \vdots & \ddots & \vdots \\ z_M, AF_1(t) & z_M, AF_2(t) & \cdots & z_M, AF_N(t) \end{bmatrix} \quad (15)$$

$$\dot{z}_{+(m, AF_n)}(t) = \dot{z}_{m, AF_n}(t) + j\mathcal{H}(\dot{z}_{m, AF_n}(t)) \quad (16)$$

Another expression of equation (16) is

$$\dot{z}_{+(m, AF_n)}(t) = \dot{A}_{(m, AF_n)}(t) e^{j\phi_{m, AF_n}(t)}. \quad (17)$$

The instantaneous amplitude of $\dot{A}_{(m, AF_n)}(t)$ can be expressed as

$$\dot{A}_{(m, AF_n)}(t) = \sqrt{(\dot{z}_{m, AF_n}(t))^2 + (\mathcal{H}(\dot{z}_{m, AF_n}(t)))^2}. \quad (18)$$

Instantaneous phase $\phi_{m, AF_n}(t)$ can be described as follows

$$\phi_{m, AF_n}(t) = \arctan\left(\frac{\mathcal{H}(\dot{z}_{m, AF_n}(t))}{\dot{z}_{m, AF_n}(t)}\right). \quad (19)$$

Instantaneous frequency of $\phi_{m, AF_n}(t)$ can also be defined as

$$\dot{F}_{m, AF_n}(t) = \frac{d}{dt}(\phi_{m, AF_n}(t)). \quad (20)$$

Hence, using the instantaneous amplitude $\dot{A}(t)$ as well as instantaneous frequency $\dot{F}(t)$, we can conveniently describe the multivariate signal $\dot{z}(t)$ by these parameters, as follows:

$$\dot{A}(t) = \begin{bmatrix} \dot{A}_1, AF_1(t) & \dot{A}_1, AF_2(t) & \cdots & \dot{A}_1, AF_N(t) \\ \dot{A}_2, AF_1(t) & \dot{A}_2, AF_2(t) & \cdots & \dot{A}_2, AF_N(t) \\ \vdots & \vdots & \ddots & \vdots \\ \dot{A}_M, AF_1(t) & \dot{A}_M, AF_2(t) & \cdots & \dot{A}_M, AF_N(t) \end{bmatrix}, \quad (21)$$

$$\dot{F}(t) = \begin{bmatrix} \dot{F}_1, AF_1(t) & \dot{F}_1, AF_2(t) & \cdots & \dot{F}_1, AF_N(t) \\ \dot{F}_2, AF_1(t) & \dot{F}_2, AF_2(t) & \cdots & \dot{F}_2, AF_N(t) \\ \vdots & \vdots & \ddots & \vdots \\ \dot{F}_M, AF_1(t) & \dot{F}_M, AF_2(t) & \cdots & \dot{F}_M, AF_N(t) \end{bmatrix}. \quad (22)$$

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The instantaneous frequencies at any oscillatory levels are adequately separated, which is described as $\dot{F}_m, AF_n(t) > \dot{F}_m, AF_{n-1}(t)$ and this is from the instantaneous amplitudes and frequencies represented as columns (21) and (22), denoted as $\{\dot{F}_n\}_{n=1,\dots,N}$. These instantaneous amplitudes and frequencies were then combined from all the channels and referred to as joint instantaneous amplitudes and frequencies denoted as $\dot{A}_n^{\text{comb}}(t)$ and $\dot{F}_n^{\text{comb}}(t)$, respectively. They were defined mathematically as:

$$\dot{F}_n^{\text{comb}}(t) = \frac{\sum_{m=1}^M [\dot{A}_m, AF_n(t)]^2 \dot{F}_m, AF_n(t)}{\sum_{m=1}^M [\dot{A}_m, AF_n(t)]^2}, \quad (23)$$

$$\dot{A}_n^{\text{comb}}(t) = \sqrt{\sum_{m=1}^M [\dot{A}_m, AF_n(t)]^2}. \quad (24)$$

After obtaining the joint instantaneous frequency and amplitude for each frequency rhythm, we adopted the approach proposed in Ref. 50 to produce the multivariate time–frequency coefficients

$$\dot{T}_n^{\text{comb}}(f, t) = \dot{A}_n^{\text{comb}}(t) \delta[f - \dot{F}_n^{\text{comb}}(t)]. \quad (25)$$

Lastly, for all the oscillatory levels, $\dot{T}_n^{\text{comb}}(f, t)$ can be described as

$$\dot{T}_n^{\text{comb}}(f, t) = \dot{T}^{\text{comb}}(f, t) \quad \text{for } n = 1, \dots, N. \quad (26)$$

Time–frequency components computed from the instantaneous frequency and amplitudes components were extracted using the proposed FBSE-EWT method for each EEG rhythm from all the channels. Various experiments were conducted using several features from different domains to comprehensively analyzed and explored the benefits of single and hybrid models. The frequency response of the empirical wavelet filter banks designed on each band using scaling and wavelet functions is shown in Fig. 5.

3.4. Feature extraction/ranking

To classify focal and non-focal EEG signals for localization of the epileptogenic zone, relevant and significant features that characterize the properties of the signal must be extracted and fed to the classifiers for good discrimination of the target signal classes. For the first time, this work investigates many features from different domains such that the most significant features were used for the classification. The domains considered are statistical parameters, time domain features, frequency domain features, time–frequency features, nonlinear entropies features, and energy features.

Using all the features extracted may increase the redundancy of some features that are not relevant to the epileptic seizure. Also, it may increase the computational complexity of the model and classifiers. Therefore, a feature selection technique must be employed to select the most significant features.⁵¹ This work used the

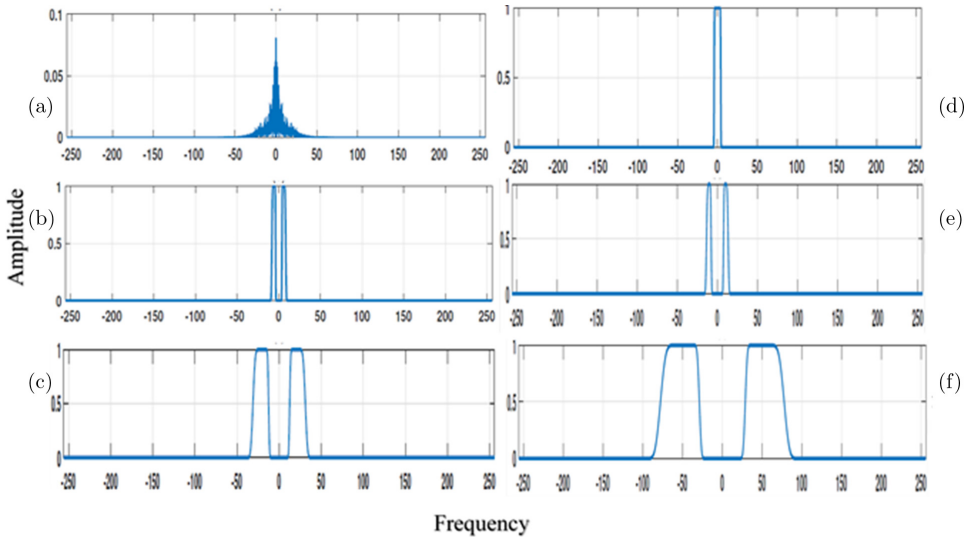


Fig. 5. Empirical filter bank (a) Epileptic EEG signal spectrum (b)–(f) frequency response of filters design in the frequency range of delta, beta, theta, alpha, and gamma, respectively.

Kruskal–Wallis statistical test to rank the features into statistical probability (p) values. Kruskal–Wallis statistical test measures the difference in the means of different features. If the value is less than the p -value of 0.05, it indicates a significant variation in the focal and non-focal features under consideration.²⁴

3.5. Classification of focal and non-focal EEG signals

3.5.1. LS-SVM classifier

SVM classifier is one of the popularly utilized classifiers in epileptic seizure analysis due to its effectiveness and simplicity, and it can handle both linear and nonlinear analysis. It is also very suitable in binary classification, such as for focal and non-focal seizure signals. To improve the robustness of SVM, LS-SVM was proposed⁵² to solve constraint conditions associated with SVM by transforming the quadratic programming problems into linear equations. LS-SVM decision function can be interpreted as⁵³

$$q(f) = \text{sign} \left(\sum_{i=1}^d q_i l_i \text{Ker}(f, f_i) + b \right), \quad (27)$$

q is the class label of the i th input feature vector f_i , d is the feature vector total dimension, the bias term is donated as b , while the Lagrange multiplier is as l_i .

LS-SVM operates on the type of kernel function which determines the decision accuracy of the classifier.⁵³ Therefore, this work investigates different types of kernel functions to optimize the classifier's performance.

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3.5.2. SAE-SVM classifier

Another classifier considered in this work is the hybrid structure of the SAE and SVM classifier. In this classifier, the features were extracted by the SAE part, while the classification was performed on the SVM part. At the SAE stage, the optimization function that needs to be minimized to find the weight matrix W_l^q and bias vector b_l^q for l th subbands with $l \in \{\delta, \theta, \alpha, \beta, \gamma\}$ is given as⁵⁴

$$J(W_l, b_l) = \sum_{i=1}^{Tr} \|\tilde{S}_l^i - S_l^i\|_2^2 + \frac{\lambda_1}{2} \|W_l^q\|_2^2 + \lambda_2 \sum_{j=1}^{\theta_{Tr}} KL\left(\frac{\rho^l}{\tilde{\rho}_j^l}\right), \quad (28)$$

where λ_1, λ_2 are denoted as regularisation indices, S_l^i and $\tilde{S}_l^i$ represents the actual and predicted subbands of i th EEG signals. Tr is the total number of training instances. K.L. is defined as the Kullback-Leibler divergence, ρ^l . $\tilde{\rho}_j^l$ is the desired and estimated sparsity of the l th subband and the j th hidden neuron of the l th subband. At level 2, which consists of the input layer to the hidden layer, q is set as 1; at level 2, with the hidden layer to the output layer, q is set as 2. The feature vector H_l at the hidden layer for the l th layer can be obtained after calculating the weight matrices W_l^1 and b_l^1 for the l th subband during the training of SAE. H_l can be expressed as

$$H_l = f(W_l^T S_l + b_l). \quad (29)$$

Sigmoid is used as the activation in both levels. After extracting features from SAE, various kernel functions were experimented to classify focal and non-focal EEG signals. The dimension for the weight matrix is $W_l \in R^{456 \times 2048}$ and $b_l \in R^{456}$.

3.5.3. DBN-SVM classifier

To further improve the performance of SVM classifiers and investigate the performance of combined conventional machine learning classifiers with deep neural network architectures, we combined DBN and SVM to characterize focal and non-focal EEG signals using the extracted features from modified empirical wavelet transform. DBN structure extracts the features from the deep structure and probabilistic generation model, eliminating the issue associated with conventional multilayer neural networks of training difficulties. DBN's structure consists of Restricted Boltzmann Machines (RBM) layers characterized by hidden variable input data distribution. The RBM has lower and high levels, with the output of lower levels as the input to the high-level RBM. The combination of the DBN-SVM structure improves the convergence rate as the SVM has a higher convergence rate than DBN. In contrast, the DBN has fault tolerance, higher nonlinear fitting, and is robust in mapping arbitrarily complex mapping nonlinear relations.⁵⁵

The DBN-SVM model utilized supervised and unsupervised learning, with DBN performing unsupervised learning while SVM served as a classifier. DBN consists of four hidden layers, and the input layer nodes are five times the channels selected,

which is computed from the empirical formula as described in Eq. (30)

$$y = \sqrt{z + y} + a, \quad (30)$$

where y is the number of nodes in the output layers, “ z ” is the number of nodes in the previous layers, and “ a ” is a constant. SVM is connected to every node in the DBN output layer to classify focal and non-focal EEG signals.

The proposed DBN–SVM model trained and tested the FBSE-MEWT features as described below:

- Step 1: unsupervised training employed by DBN on the FBSE-MEWT features to compute the weights parameters;
- Step 2: supervised training classification is performed by SVM when the DBN top-level output is connected to SVM, with each layer corresponding to the classification using the features for a particular EEG class.
- Step 3: backpropagation algorithm is employed to provide feedback on the error to the DBN top layer; the error is obtained from the expected output of the training and the SVM actual output. Therefore, the correlation weight is adjusted for the DBN top layer and the SVM layer;
- Step 4: the tuning process is used to fine-tune the RBM below the DBN top-level layer.

3.5.4. Performance measures

The proposed model is evaluated using standard performance measures for validation and comparison with other related works. These performance metrics are sensitivity, specificity, accuracy, precision, and F1-score. These parameters are defined based on the true positive (T.P.), which can be described as the number of focal EEG signals correctly identified by the model and the baseline annotation file. True negative (T.N.) is the number of non-focal EEG signals accurately determined by the model. False positive (F.P.) is defined as the number of incorrectly focal EEG signals identified by the model. In contrast, false negatives (F.N.) can be described as the number of incorrectly non-focal EEG signals determined by the model. Mathematically, the performance parameters were defined as follows:

$$\begin{aligned} \text{Sensitivity} &= \frac{TP}{TP + FN} \\ \text{Specificity} &= \frac{TN}{TN + FP} \\ \text{Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN} \\ \text{Precision} &= \frac{TP}{TP + FP} \\ \text{F1_Score} &= 2 \frac{\text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \end{aligned}$$

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The values of T.P., T.N, F.P., and F.N. are extracted from the confusion matrix to compute the above performance parameters. Also, to validate and further evaluate the classifier efficiency in discriminating between focal and non-focal EEG signals, other performance parameters were deployed, such as the receiver operating characteristic (ROC) curve and accuracy and loss curve computed from the training performance of our proposed deep learning models.

4. Experimental Results

In assisting doctors and clinicians in the localization of epileptogenic zone in epileptic patients screened for surgery, this paper investigated and carried out a comprehensive analysis of detection and classification models to characterize focal and non-focal EEG signals. Various features from different domains were extracted and experimented with proposed robust feature extraction using the FBSE-MEWT technique and proposed classifiers. The models proposed in this paper involve the datasets from the Bern-Barcelona publically available dataset, which consists of focal and non-focal EEG signals. The dataset was obtained from five pharmacoresistant temporal lobe epilepsy patients screened for surgery. The dataset consists of two channels corresponding to two pairs of signals denoted as x and y . We selected 2048 samples of data in each class, denoised the data using the proposed mPCA technique, and then applied our proposed enhanced FBSE-MEWT to extract the signal sub-bands. At each sub-bands, comprehensive feature extraction is performed with a large number of features from different domains.

The complete dataset with 7500 focal and non-focal EEG records for each class was selected randomly to form the complete feature vector in the .txt file for training and test operation. The dataset features are divided into 70% and 30% standard training and test records based on a hold-out approach when classifying using the LS-SVM classifier. While for SAE-SVM and DBN-SVM networks, the features were partitioned into 80% for training and 20% for testing. Furthermore, the 80% set for training was divided into 70% and 30% for training and validation records, respectively. In training and test instances, 5-fold cross-validation was employed in this study to acquire a fair output and prevent overfitting during the training and test operation. Before feeding the extracted features to a classifier, feature ranking was conducted to select only significant features that passed the statistical t -test. SPSS software was used to compute the p -value of the feature. The learnable features whose p -value is less than 0.05 were chosen because they are statistically significant. Those those with a value greater than 0.05 were discarded and dropped from the learnable features.

This paper proposed five different models to effectively evaluate the efficacy of proposed hybrid features combined with proposed classifiers as described below:

Confusion matrices were computed in Figs. 6(a)–6(f) for each experiment to ensure the accurate and acceptable results were obtained, the average accuracy and

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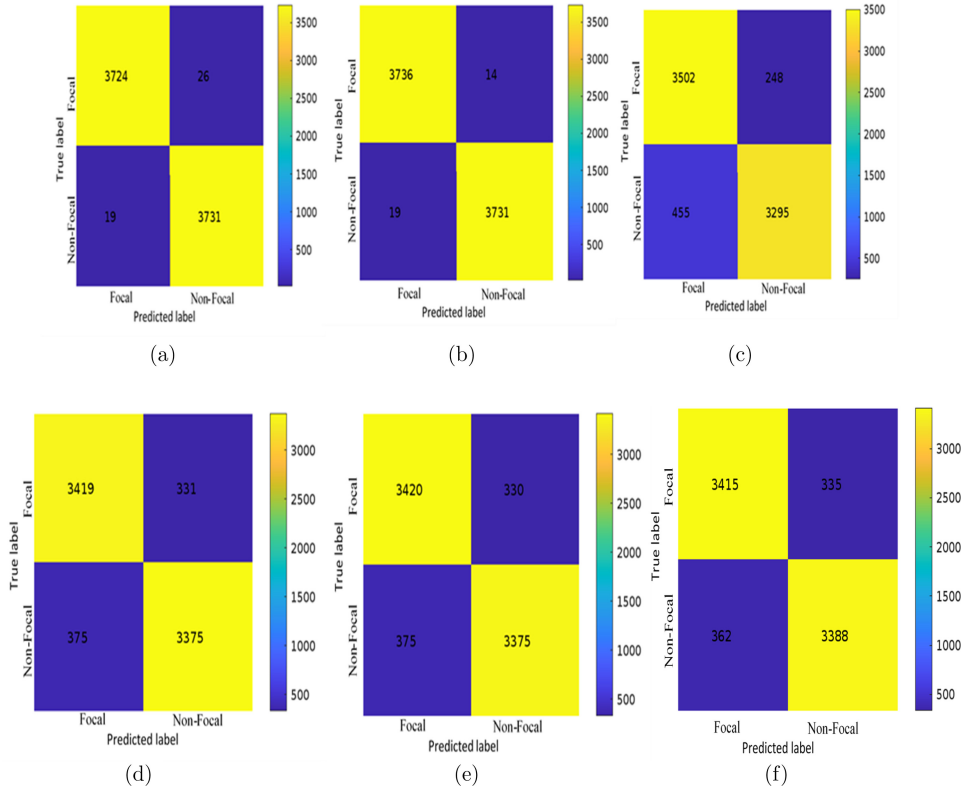


Fig. 6. Confusion matrix computed using 5-fold cross-validation (a) Hybrid-LS-SVM (b) Hybrid-SAE-SVM (c) Hybrid-DBN-SVM (d) FMEWT-LS-SVM (e) FMEWT-SAE-SVM and (f) FMEWT-DBN-SVM.

other performance metrics are calculated based on the confusion matrix values. The diagonal boxes show the TPs for each focal and non-focal class, respectively.

4.1. Focal and non-focal classification results for hybrid features and SVM classifier (Hybrid_SVM)

The proposed hybrid features extracted from different domains, such as regular and higher order statistical parameters, nonlinear, and energy features, were prepared as a learnable feature in this experiment. This work experimented with various SVM classifiers using the proposed hybrid features. The performance of each kind of SVM is depicted in Fig. 7. From this figure, it was clearly shown that the LS_SVM classifier is superior in performance accuracy, sensitivity, and specificity of 91.2%, 89.4%, and 89.4%, respectively, compared to the accuracy of 84.2% and 86.9% obtained using the SMO_SVM and QP_SVM, respectively. We optimized the LS-SVM classifier by investigating its performance using various kernel functions such as RBF, linear and quadratic functions as shown in Table 1 to explore the performance of LS SVM further and get the optimal performance.

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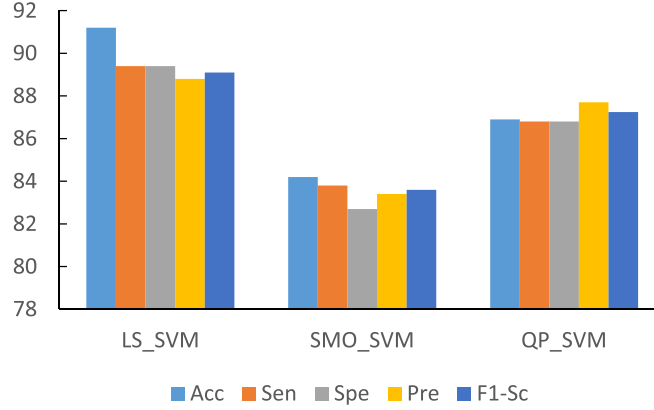


Fig. 7. Performance of different SVM classifiers using hybrid features.

Table 1. Performance of various SVM kernel function classifiers using hybrid features.

Kernel function	Sen (%)	Spe (%)	Acc (%)	Prec (%)	F1-Sc (%)
Linear	87.3	87.3	86.1	86.6	86.9
Quadratic	85.6	85.7	87.0	85.4	85.5
Polynomial	89.4	89.4	91.2	88.8	89.1
rbf	85.3	84.2	82.5	83.2	84.2

4.2. Focal and non-focal classification results for FBSE-MEWT features and SVM classifier (FMEWT_SVM)

In this experiment, the learnable features extracted from the proposed FBSE-MEWT feature extraction technique, consisting of computed EEG signals rhythm for focal and non-focal classes for both channel (1) and channel (2), were computed. These features were prepared and fed to the LS-SVM classifier to classify each sub-band rhythm. LS SVM classifier was chosen from the performance evaluation of various types of SVM conducted in Sec. 5.2 different kernel functions were also tested and evaluated, as shown in Table 2, to find the optimal value and analyze the characteristics of EEG signals in each rhythm for focal and non-focal classes. The most optimal model was deployed to classify each EEG band rhythm for channels (1)

Table 2. Performance of various SVM kernel functions in FMEWT_SVM model.

Kernel function	Sen (%)	Spe (%)	Acc (%)	Prec (%)	F1-Sc (%)
Linear	88.0	88.0	87.1	87.6	87.8
Quadratic	86.7	86.7	85.0	85.8	86.2
Polynomial	91.5	91.5	92.1	92.3	91.9
RBF	89.3	88.2	89.5	89.2	89.2

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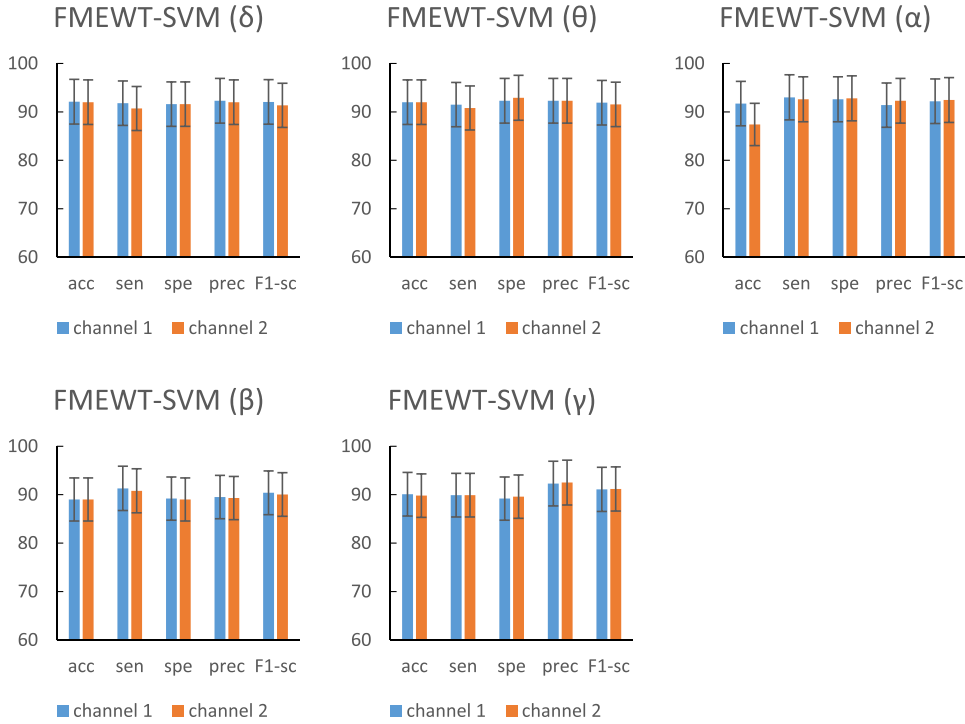


Fig. 8. Performance of Delta, Theta, Alpha, Beta, and Gamma EEG rhythms in the classification of focal and non-focal EEG signals using FMEWT-SVM model for the channel (1) and channel (2).

and (2). As shown in Fig. 8, the performance of the model for each δ , θ , α , β and γ EEG rhythms was provided. δ , θ , and α rhythm learnable features show higher classification performance for both channels, whereas β -rhythm shows the worst performance of discriminating focal and non-focal EEG signals.

4.3. Focal and non-focal classification results for FBSE-MEWT features and SAE-SVM classifier (FMEWT_SAE-SVM)

Features from the proposed FBSE-MEWT were extracted and used to classify focal and non-focal EEG signals with the proposed SAE-SVM as a classifier. The proposed model of FMEWT_SAE-SVM was developed to explore the efficacy of the improved EWT method by extracting the instantaneous frequency and amplitudes of EEG rhythm. The best-optimized SVM classifier obtained from the performance of each SVM kernel function was used in the analysis of our proposed model. Table 3 shows that the polynomial kernel function performed better than the remaining kernel function examined. Therefore, two approaches were conducted in this model. First, hybrid features extracted from various domains and raw focal and non-focal EEG signals were each experimented with and evaluated with the proposed SAE-SVM classifier. The performance of this model in terms of accuracy, sensitivity, specificity,

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Table 3. Performance of various SVM kernel functions using FMEWT_SAE-SVM model.

Kernel function	Sen (%)	Spe (%)	Acc (%)	Prec (%)	F1-Sc (%)
Linear	97.1	97.3	96.1	96.8	96.9
Quadratic	96.6	95.6	95.6	96.4	96.4
Polynomial	99.5	99.5	99.7	99.3	99.4
Rbf	98.7	99.2	99.2	99.5	99.1

precision, and $F1$ -score is 90.9%, 89.9%, 89.2%, 92.3, and 91.1%, respectively. Second, the EEG sub-band rhythm extracted from the proposed FBSE-MEWT feature extraction technique for each δ , θ , α , β and γ EEG rhythms was evaluated and presented in Fig. 8. From Fig. 9 and Table 3, it is seen that there was an improvement in the characterization of focal and non-focal EEG signals when compared to the hybrid-SVM model with accuracy, sensitivity, specificity, precision, and $F1$ -score of δ rhythm for channel 1 gives 99.7%, 99%, 99.2%, 99.5%, and 99.2%, respectively.

4.4. Focal and non-focal classification results for FBSE-MEWT features and DBN-SVM classifier (FMEWT-DBN-SVM)

This work also further investigates the performance of deep learning networks combined with conventional machine learning classifiers to enhance the

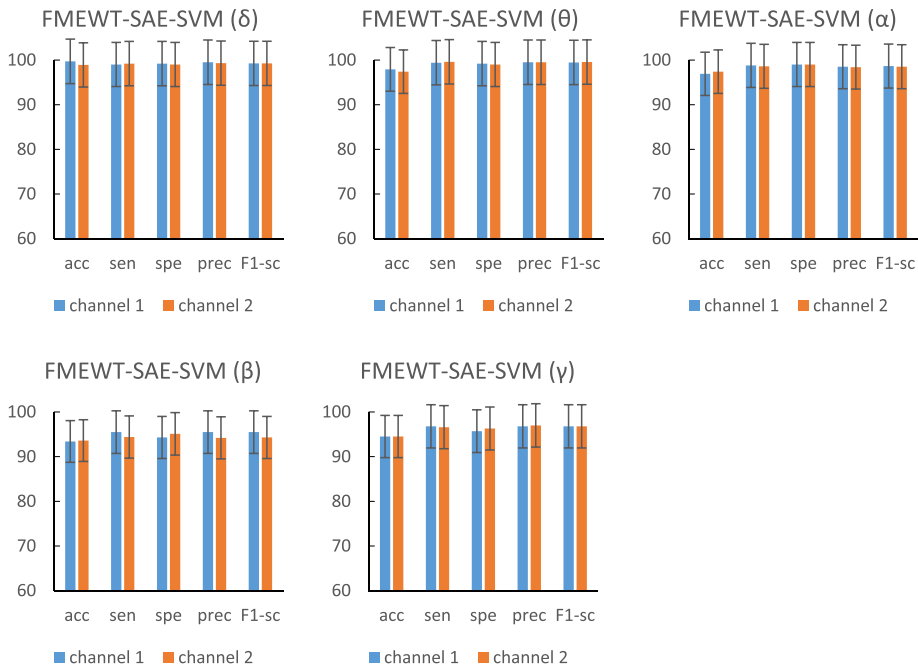


Fig. 9. Performance of Delta, Theta, Alpha, Beta, and Gamma EEG rhythms in the classification of focal and non-focal EEG signal using FMEWT-SAE-SVM model for channel (1) and channel (2).

characterization ability of proposed models in detecting and classifying focal and non-focal EEG signals. Raw EEG signals were tested first in the DBN-SVM model so that the DBN architecture extracts the features used by the SVM classifier in classification. After that, the proposed hybrid features from statistical, nonlinear, and time-frequency domains were prepared as learnable features. These features serve as the input to DBN architecture which further extracts the feature used by the SVM classifier. This model ensures that the most robust features that further distinguished the hidden EEG signals characteristics were adequately captured and explored for increasing the CAD system performance that helps identify parts of the brain such as the epileptogenic zone as well as functions and activities of the brain. The performance of this model in terms of accuracy, sensitivity, specificity, precision, and $F1$ -score is given as 89.2%, 89.0%, 89.0%, 89.2%, and 89.1%. The performance of FMEWT_DBN-SVM with various kernel functions was also evaluated and presented in Table 4. It was depicted that the polynomial kernel function outperformed linear, quadratic, and RBF functions with accuracy, sensitivity, and specificity of 99.6%, 99.5%, 99.5%, 99.3%, and 99.4%, respectively. This model's performance was evaluated and presented using various EEG rhythms for channels (1) and (2), as depicted in Fig. 10. It can be seen that the δ, θ rhythms show an improved performance in detecting the epileptogenic lesions with an accuracy of 99.6% for both channels.

Figure 11 shows the simulation result of accuracy and loss curves for the DBN network. These values are also standard indexes used to assess the learning performance of the datasets. As shown in Fig. 6(a), the loss quickly decreases as the number of epochs increases and vice-versa. Also, the accuracy keeps increasing with the increase of epochs. This indicates the proposed DBN-SVM structure's effectiveness in detecting and classifying focal and non-focal EEG signals.

4.5. Performance of proposed models based on ROCs

Another vital performance measure for evaluating the classifier's efficiency is the ROC curve. ROC curve usually assesses the performance of two-dimensional problems, as in the case of our problem of classification of focal and non-focal EEG signals. Figure 12 shows the ROC curve of all five models developed by computing the area under the curve (AUC), which ranges from 0 to 1, indicating the classifier's efficiency. A higher value of AUC indicates the better capability of the classifier to

Table 4. Performance of various SVM kernel functions using FMEWT_DBN-SVM model.

Kernel function	Sen (%)	Spe (%)	Acc (%)	Prec (%)	F1-Sc (%)
Linear	97.2	95.5	96.1	96.7	96.9
Quadratic	95.0	94.3	93.0	94.4	94.7
Polynomial	99.5	99.5	99.6	99.3	99.4
rbf	99.3	99.2	99.5	99.5	99.4

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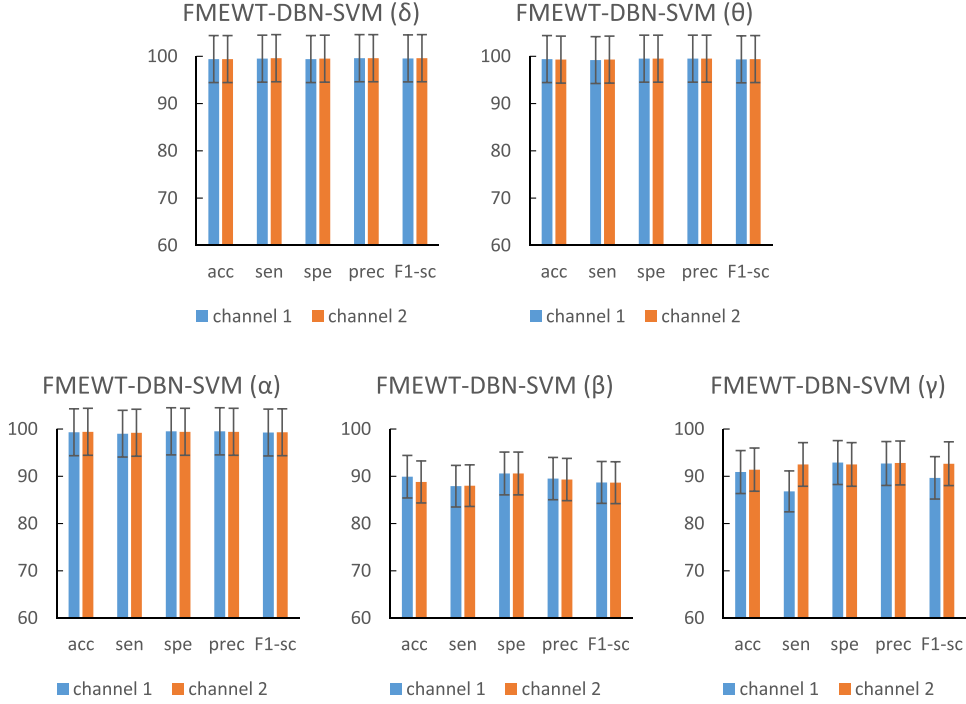


Fig. 10. Performance of Delta, Theta, Alpha, Beta, and Gamma EEG rhythms in the classification of focal and non-focal EEG signal using FMEWT-SAE-SVM model for channels (1) and (2).

distinguish between two classes of focal and non-focal EEG signals. As shown in Fig. 12, the AUC values for the FMEWT-SAE-SVM model and FMEWT-DBN-SVM model for all the EEG rhythms are greater than 0.9, which shows the improved classification ability of the proposed models.

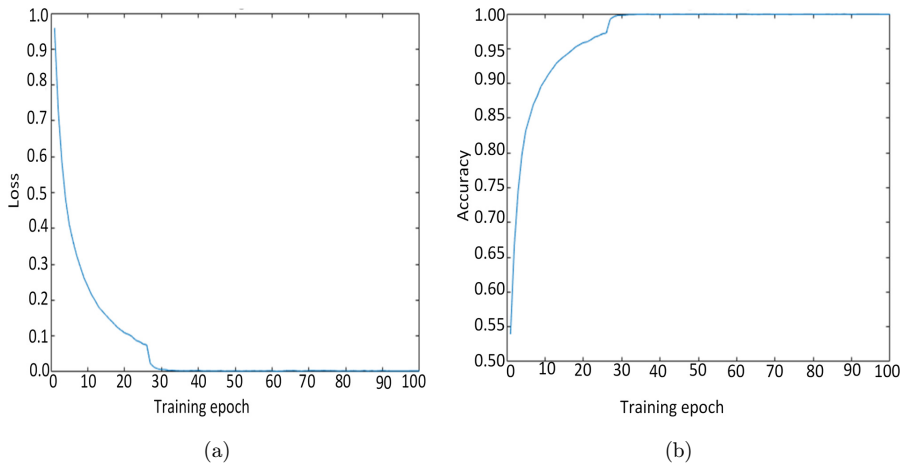


Fig. 11. Training (a) loss and (b) accuracy for DBN network architecture.

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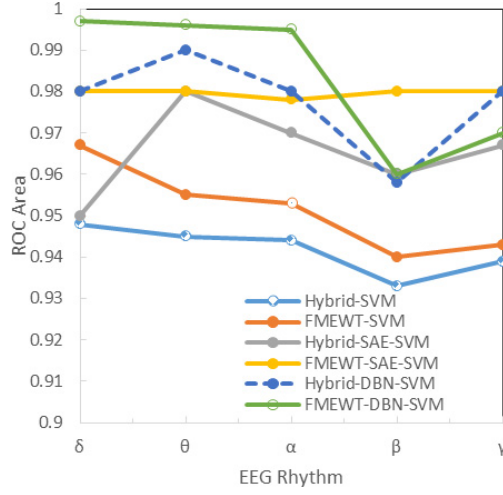


Fig. 12. ROC area for each developed model.

In this paper, we have also computed the ROC curve based on the trade-off between true positive rate (sensitivity) and false positive rate (specificity) to validate further and estimate how the classifiers distinguished the focal and non-focal classes well. Figure 13 clearly shows how the ROC curves for classifiers that used our proposed FMEWT features are very close to the upper left corner. This shows the excellent separation of classes by the classifiers with values of 0.91, 0.95, and 0.96 for LS-SVM, SAE-SVM, and DBN-SVM, respectively, as shown in Fig. 13.

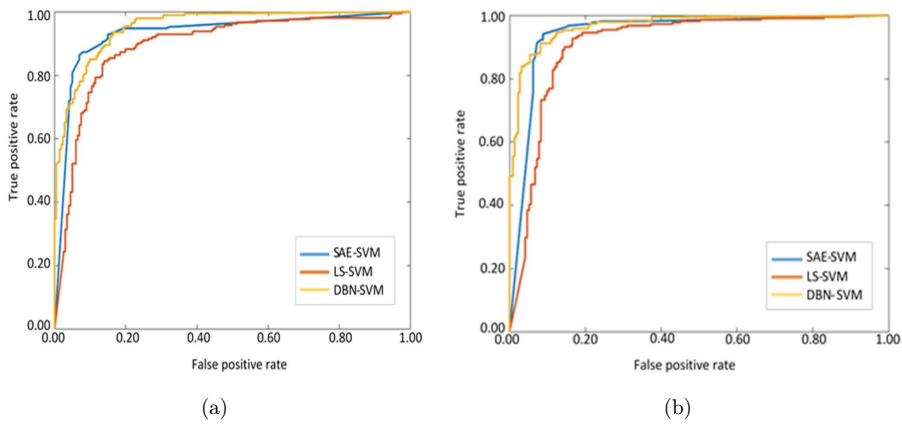


Fig. 13. ROC curve of the proposed method (a) based on the hybrid features (b) based on the FMEWT features.

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4.6. Computational complexity

Apart from evaluating the proposed models with performance metrics, it is also highly imperative to assess the models using execution time to investigate the suitability of the models in real-time scenarios. Also, to realize the practical implementation of the models in clinical settings that can augment the desire for the development and implementation of IoMT devices, the computational complexity should be evaluated and considered in the performance of developed algorithms. Therefore, this work investigates and computes the time taken by each of the models proposed to execute the algorithms, which includes preprocessing time, signal decomposition, feature extraction, and classification during the testing of the models, as shown in Fig. 14.

4.7. Performance comparison of proposed models

This section observed the performance of the proposed extracted features and developed classifiers. Each model's best classifier performance was selected with the different features extracted. Table 5 shows the performance of hybrid learnable features extracted from other domains and classified with LS-SVM, SAE-SVM, and

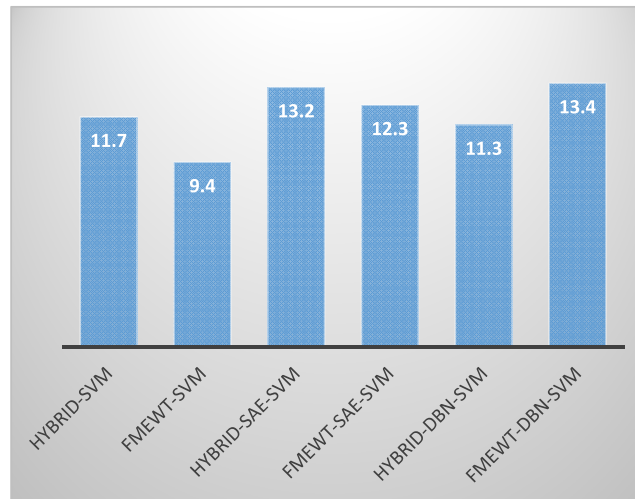


Fig. 14. Time complexity in seconds computed for each developed model.

Table 5. Comparison of developed models using hybrid features.

Classifier	Sen (%)	Spe (%)	Acc (%)	Prec (%)	F1-Sc (%)
Hybrid-SVM	89.4	89.4	91.2	88.8	89.1
Hybrid-SAE-SVM	90.9	89.9	89.2	92.3	91.1
Hybrid-DBN-SVM	89.0	89.0	89.2	89.2	89.1

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Table 6. Comparison of developed models using FBSE-MEWT features.

Classifier	Sen (%)	Spe (%)	Acc (%)	Prec (%)	F1-Sc (%)
FMEWT-SVM	91.5	91.5	92.1	92.3	91.9
FMEWT-SAE-SVM	99.5	99.5	99.7	99.3	99.4
FMEWT-DBN-SVM	99.5	99.5	99.6	99.3	99.4

DBN-SVM. It was indicated that the SAE-SVM and DBN-SVM have higher performance accuracy with an accuracy of 89.2%. These metrics show our proposed SAE-SVM's and DBN-SVM's robustness in characterizing focal and non-focal EEG signals. Also, the features extracted from the proposed FBSE-MEWT method of EEG rhythms that are classified using LS-SVM, SAE-SVM, and DBN-SVM are compared, as shown in Table 6. It was seen that the proposed SAE-SVM and DBN-SVM model performs better than LS-SVM.

4.8. Comparison of proposed models with some recent works in the literature

To ensure that the proposed methods developed in this work are effective and robust, we compared the results obtained in this work with some recently published works in the literature carried out by researchers. Studies that used the same database used in this work were selected in this comparison. Table 7 compares the proposed models with recent results using accuracy as the performance metric. The type of feature

Table 7. Comparison of this work with recent works that used the same database as our proposed models.

Author	Year	Feature extraction	Type of classifier	Accuracy (%)
Bhattacharyya <i>et al.</i> ²⁵	2017	Fuzzy Entropy, FAWT	LS-SVM	84.67
Sharma <i>et al.</i> ⁵⁶	2017	Entropies, WFB	LS-SVM	94.25
Gupta <i>et al.</i> ²⁹	2017	Entropy, FAWT	LS-SVM	94.40
Sharma <i>et al.</i> ⁵⁷	2018	Time-domain, IMFs	LS-SVM	84.01
Bhattacharyya <i>et al.</i> ⁵⁸	2018	RPS, EWT	LS-SVM	90.0
Acharya <i>et al.</i> ⁵⁹	2018	Nonlinear Features	LS-SVM	87.93
Zhao <i>et al.</i> ⁶⁰	2018	Entropies	CNN	83.0
Arunkumar <i>et al.</i> ³²	2018	Entropies	Exemplars classifier	99.0
Siddharth <i>et al.</i> ⁶¹	2019	SM-SSA	SAE-RBFN	99.1
Gupta and Pachori ⁶²	2019	Entropies, IMFs	LS-SVM	83.18
Subasi <i>et al.</i> ⁶³	2019	WPT	Random Forest	99.2
Daoud and Bayoumi ⁶⁴	2020	DCAE	MLP	93.2
Fraïwan and Alkhodari ³⁸	2020	B-LSTM	B-LSTM	99.60
Sue <i>et al.</i> ⁶⁵	2021	STFT	CNN	94.3
Saminu <i>et al.</i> ⁴⁰	2022	DWT, hybrid	1D-CNN	99.4
Saminu <i>et al.</i> ⁴⁰	2022	Hybrid Features	LS-SVM	99.3
This study	2022	FBSE-MEWT	LS-SVM	92.1
This study	2022	FBSE-MEWT	SAE-SVM	99.7
This study	2022	FBSE-MEWT	DBN-SVM	99.6

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extraction and classifier employed to characterize the studies' focal and non-focal EEG signals are shown in the table.

5. Discussion

This work aims to develop a computationally novel and robust model that improves the performance of localization of epileptogenic zone algorithms using focal and non-focal EEG signals. A comprehensive analysis of the effectiveness of various features from different domains investigated the hybrid structure of deep learning and conventional machine learning networks. The following are the achieved objectives of this work.

- (1) Preprocessing the EEG signals is one of the essential stages to improving the quality of focal and non-focal detection systems. This paper proposed an efficient preprocessing technique to eliminate noise and artifacts from the EEG signal. It is a hybrid technique that consists of DWT and PCA, as described in the section. The selection of this method is based on testing some traditional preprocessing techniques such as spatial and temporal filtering and BPF. It was believed that the proposed mPCA performs better than the tested techniques.
- (2) Relevant and significant feature extraction methods based on the time domain, frequency domain, time–frequency domain, nonlinear, and energy were investigated to extract the most suitable features for detecting focal and non-focal EEG signals. The statistical approach ensured that the features were ranked correctly and selected in the analysis of the models.
- (3) To deal with the non-stationary and nonlinear nature of EEG signals, this paper leverages the efficacy of the proposed MEWT as the extension of EWT. The result from MEWT decomposition in $\delta, \theta, \alpha, \beta$ and γ subbands for each EEG channel was aligned in frequency scale. Joint instantaneous components are chosen from each subband, and the relevant features are extracted for the analysis, detection and classification of focal and non-focal EEG signals.
- (4) The features are selected and ranked based on the Kruskal Wallis statistical test to choose only suitable feature sets used by proposed classifiers. This approach reduces the classifier's computational complexity.
- (5) The performance of the SVM classifier was improved and optimized with the development of robust classifiers that integrate the advantage of deep learning networks with SVM. Two classifiers were proposed, SAE–SVM and DBN–SVM, to further characterize the embedded features hidden in EEG signals and improve the classification accuracy.

This work has considered models' parameters that determine the classification performance of the classifier. The two key parameters that determine the classification performance are the regularization parameter and bandwidth denoted as γ and σ^2 , respectively. The relationship between the model simplification aspect and the

decrease in error in the training data is determined by the regularization parameter. Mapping between the inputs and the features is determined by the bandwidth parameter. To avoid overfitting issues and effective performance in the proposed model we investigate the parameter tuning methods that provides a better solution without affecting the convergence rate. For deep learning architectures, the weight matrix W , bias vector b , and regularization parameter λ , are properly selected and tuned to achieve the best performance.

The performance of different experiments was evaluated for each EEG rhythm in channels (1) and (2) with Bern-Barcelona focal and non-focal EEG signals. 5-Fold cross-validation was employed in the classification stage to evaluate the capability of proposed preprocessing, feature extraction, feature ranking, and classification techniques that characterize the pathological signs of epileptic seizure signals. The proposed method was assessed using the performance metrics such as F1-score, precision, specificity, sensitivity, and accuracy. Based on the presented results in Sec. 4, the LS-SVM classifier with features extracted from proposed FBSE-MEWT EEG rhythms yields an average value of 92.0%, 92.3%, 91.5%, 91.5%, and 92.1% for F1-score, precision, specificity, sensitivity, and accuracy respectively with δ -rhythm learnable features for channel 1. The improved performance was recorded due to combined SAE and SVM with FBSE-MEWT features with an average value of F1-score, precision, specificity, sensitivity, and accuracy of 99.4%, 99.3%, 99.5%, 99.5%, and 99.7%, respectively. This result shows that the proposed feature extraction and combined SAE-SVM classifier improved the models' accuracy, indicating better categorization of focal and non-focal EEG signals. Moreover, the integrated deep learning architecture with machine learning classifier proves that a high classification value could be achieved because, based on the results obtained in this paper, SAE-SVM and DBN-SVM have a slight difference in their performance with δ -rhythm learnable features outperforms θ , α rhythm. In contrast, β -rhythm learnable features show the worst performance for channels 1 and 2.

Other performance parameters employed in this work to evaluate the performance of proposed techniques are ROCs and computational complexity. The AUC values obtained in this paper for both FMEWT-SAE-SVM and FMEWT-DBN-SVM models are higher than 0.9, indicating better performance. The computational complexity of the proposed models was evaluated to assess the time taken for the system to execute the algorithm so that the models can be assessed based on the real-time and possible realization of the models in a clinical setting. Though the combined deep learning and machine learning classifiers provide a very high-performance accuracy, they exhibit high execution time compared to other models, such as FMEWT-LS-SVM.

The preprocessing stage is a crucial stage that can improve the performance of focal and non-focal EEG detection systems. Therefore, this work aimed to investigate and propose an advanced technique for removing artifacts and noise in the EEG signals. The method that combines the efficacy of DWT and mPCA shows a high discrimination capability of the noise embedded in the epileptic signals. The

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performance of this method was compared with other advanced preprocessing techniques, such as the work reported by Refs. 66 and 67, which employed the variational mode extraction (VME) with DWT and smoothed nonlinear energy operator (SNEO), respectively.

Besides comparing the performance of the models developed in this paper, as reported in Tables 5 and 6, we have also compared the performance of our work with recently published work that used the same Bern-Barcelona database in their studies. TQWT was used as the feature extraction approach to classify focal and non-focal EEG signals with multivariate EEG signals.²⁵ Another work was reported in Ref. 62 to classify focal and non-focal EEG signals using empirical mode decomposition (EMD) to decompose the signal into intrinsic mode functions. LS-SVM was used in the classification stage with an accuracy of 83.13%. Entropy features were extracted from the modes of EEG signal that are also extracted from the designed wavelet filter bank. The features were used in the LS-SVM classifier to classify focal and non-focal EEG signals. The performance accuracy reported in this study is 94.25%.⁵⁶ Arunkumar *et al.*³² analyzed several types of entropies such as fuzzy, sample, and approximate. The extracted entropies features were then used to classify focal and non-focal EEG signals with various classifiers. They reported that the Non-Nested Generalised Exemplars classifier outperforms other tested classifiers with an accuracy of 99.0%. Recently, some authors focused on investigating deep learning networks' advantages in characterizing focal and non-focal epileptic EEG signals. Daoud and Bayoumi⁶⁴ designed a deep convolutional autoencoder to classify focal and non-focal EEG signals and reported an accuracy of 93.2%. Hybrid structures consisting of deep learning and machine learning networks were proposed in Ref. 65. The model consists of short-time Fourier transform features combined with CNN architecture. The reported accuracy from this hybrid network is 94.3%.

Localization of epileptogenic lesions in drug-resistant epileptic patients screened for surgery has been a significant area of research in recent times. However, few research works exist in the literature that investigates the problem. Even with the existing one, some limitations exist, such as using a small number of a dataset, employing a single domain in feature extraction, analysis using the average value of the channels, and employing either conventional machine learning classifiers or deep learning networks alone, among others. This work comprehensively analyzed various features from different types of domains. The work also analyzed the performance of deep learning networks combined with hand-crafted features and the combined conventional machine learning classifier and deep learning networks for successful surgery operations. The success of this work can be seen from the improved performance obtained compared to other studies in the literature.

Despite the highly promising results obtained in this work, the experimental models were developed with some limitations, such as (1) The experiment was conducted based on seizure-specific cross-validation as the dataset does not contain patient-specific information. (2) Though we utilized the whole data in the Bern dataset, the volume of the data needs to be increased for developing a real and

practical clinical model. (3) The experiment was conducted offline, not online real-time scenario.

6. Conclusion

A robust and novel feature extraction and classification technique for the localization of epileptogenic lesions in drug-resistant epilepsy for successful operation is proposed in this paper. The experimental results presented in this paper depicted that focal and non-focal epileptic EEG signals detection and classification have improved the performance of the models. Learnable Features of EEG rhythms have been extracted using a fully data adaptive technique suitable for decomposing nonlinear and non-stationary EEG signals into distinct sub-band known as FBSE-MEWT and experimented with three different proposed classifiers such as LS-SVM, SAE-SVM, and DBN-SVM. Classification of focal and non-focal EEG signals using FBSE-MEWT with LS-SVM, SAE-SVM, and DBN-SVM gives an accuracy of 92.1%, 99.7%, and 99.6%, respectively. The algorithms presented in this paper are computationally efficient as the execution time shows their suitability in real time and potential application for IoMT devices. Among the models proposed in this paper, SAE-SVM and DBN-SVM offer better performance than recently related works. Despite the high level of accuracy recorded in this work, feature work should consider several deep-learning structures, such as transformer models. Other hybridization networks should also be investigated, and additional datasets should be explored in both the public and non-public domains.

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