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Multi-Classification of Electroencephalogram Epileptic Seizures Based on Robust Hybrid Feature Extraction Technique and Optimized Support Vector Machine Classifier

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ABSTRACT

Epilepsy is a disease with various forms. However, limited dataset has confined classification studies of epilepsy into binary classes only. This study sort to achieve multi-classification of epileptic seizures through a robust feature extraction technique by comprehensively analyzing various advanced feature parameters from different domains, such as energy and entropy. The values of these parameters were computed from the coefficients of dilation wavelet transform (DWT) and modified DWT, known as dual-tree complex wavelet transform decomposition. The model was evaluated from the features of each of the parameters. The hybrid features were divided into three experiments to extract the meaningful features as follows: 1). features from combined energy features were extracted; 2). features from combined entropy features were also extracted; and 3). features from combined parameters as hybrid features were extracted. Finally, the model was developed based on the extracted features to perform a multi-classification of seven types of seizures using an optimized support vector machine (SVM) classifier. A recently released temple university hospital corpus dataset consisting of long-time seizure recordings of various seizures was employed to evaluate our proposed model. The proposed optimized SVM classifier with the hybrid features performed better than other experimented models with the value of accuracy, sensitivity, specificity, precision, and F1-score of 96.9%, 96.8%, 93.4%, 95.6%, and 96.2%, respectively. The developed model was also compared with some recent works in literature that employed the same dataset and found that our model outperformed all the compared studies.

Index Terms—Multi-classification, EEG, epileptic seizures, DTCWT, hybrid features, SVM

I. INTRODUCTION

An electroencephalogram (EEG) signal is a one-dimensional (1D) signal in a time domain that measures the changes in the brain's electrical activity. It is measured either from the scalp (EEG) or intracranial (ECoG) and recorded using electrodes to indicate the normal from abnormal conditions such as seizures and non-seizures conditions in epilepsy patients [1]. Epilepsy is a chronic brain disorder that happens due to abnormal excitation of brain cells, leading to unprovoked seizures. Some primary causes of seizures are low blood sugar levels, malformations, and oxygen shortage during childbirth [2, 3]. Epileptic seizures can happen at any time and cause a loss of consciousness, leading to injuries and even death. It is imperative to predict the occurrence of these seizures since it is challenging for a patient to predict when they will happen so that preventive measures can be taken to avoid loss of consciousness and even can sometimes lead to death [4, 5]. Early detection and identification of these seizures are vital and prevent patients from the effects associated with occurrence of seizures and help doctors in diagnosis and treatment. EEG measured during seizure occurrence is called ictal EEG, and due to the unpredictability nature of seizures, it is difficult to rely on only ictal EEG in differentiating between seizure and non-seizure epileptic signals [6]. Interictal EEG is also used to distinguish between an epileptic seizure and other conditions as it reveals the possible epileptic seizure occurrence to assist in diagnosis, monitoring, and treatment [7, 8].

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With the rapid development of intelligent internet of things (IoT) devices and the successful deployment of 5G networks, the integration of healthcare services for monitoring, diagnosis, and analysis of various diseases can never be overemphasized. Manual visual inspection and analysis of epileptic EEG signals is a traditional method of detection and classification by experts, which tends to be time-consuming, tedious, and prone to errors. Therefore, investigation of automatic methods that employ artificial intelligence is paramount to overcome the problem associated with visual inspection and variability nature among epileptic patients. Researchers have investigated and developed various methods to detect and classify epileptic seizures, as summarized and reviewed in [9]. However, with the advent of generating a massive amount of data in the form of signals, texts, images, and sounds, among others in healthcare management and the need for automated, smart, portable, wearable, and low-cost devices to improve patient diagnosis, the need for investigation and development of robust feature extraction techniques and classification models is also of great value.

This study investigates the advanced energy and entropy feature extraction parameters and evaluates their efficacy using optimized machine learning classifiers to find a suitable and effective model for detecting and classifying epileptic seizures. The study performed several experiments on the proposed feature extraction methods using a recently released EEG corpus from Temple University Hospital (TUH), which provides a vast and long-time publically available dataset for researchers.

A. Objectives and Contribution of the Study

The novelty and contribution of this study are highlighted as follows:

1. Investigation of various advanced energy and entropy features suitable for characterization of embedded epileptic seizures properties.
2. Decomposition of EEG epileptic seizure signals using a dilation wavelet transform (DWT) and an improved version of DWT known as dual-tree complex wavelet transform (DTCWT).
3. Extraction of valuable and relevant features from the decomposed signal sub-bands of several classes of seizures with long-time recording and a large number of data.
4. Performed a comprehensive experiment on the extracted features from our proposed technique and evaluated the multi-classification performance using an optimized SVM classifier. Different SVM types and their kernel function were also assessed.

B. The Organization of the Study

The remaining part of the study is organized as follows: section II provides relevant and related works that address similar problems to this study. Section III discusses model experimentation that describes all the stages of the proposed model. Results of the proposed model are given in section IV with the discussion of the obtained results. Finally, the conclusion of the paper was highlighted in section V.

II. RELATED WORKS

Many works have reported their proposed techniques for automated epileptic seizure detection. These techniques were applied to extract different features that classifiers used in discriminating between epilepsy signal patterns such as normal rhythms, patterns prior to seizure occurrence (interictal), and abnormal spikes during the seizures (ictal). Various improvements have been achieved using different techniques such as the conventional time domain features [10], spectral analysis using Fourier transform [11], wavelet transforms and their variants [11-13], non-linear methods such as entropy estimators [14], statistical methods such as higher-order cumulants [15], time-frequency techniques [16, 17] among others. However, most of the reported works in literature used a binary classification in the classification of seizure and non-seizure and focal and non-focal seizures. This usage is due to the lack of publicly available datasets consisting of many classes of seizures and a large dataset. Recently, with the release of the TUH dataset consisting of eight types of seizures and a large number of clinical data, few researchers have started investigating and evaluating the performance of the different techniques on the dataset for multi-classification of various seizure classes. Saputro et al. [18] proposed a method for the classification of four seizure classes using the features extracted from Mel frequency cepstral coefficients (MFCC), empirical mode decomposition (EMD), and independent component analysis (ICA). The proposed models record accuracy of 91.4%. Wijayanto et al. (2019) reported an accuracy of 95.0% in their work when they employed an SVM classifier for the classification of various seizure types using the features extracted from empirical mode decomposition (EMD) [19]. XGBoost and k-NN were also utilized in [20] to classify seven types of seizures with a reported F1-score of 85.1% and 90.1%, respectively. Some authors use the TUH dataset with a deep learning approach to investigate the classification problem, such as the work reported in [21] with an F1-score of 96.0% by employing convolutional neural network (CNN) architecture. [22] achieved the F1-score of 94.5% when they proposed a deep learning structure called neural memory networks. CNN and Long-Short Term Memory (LSTM) networks are employed in [8] to classify various types of seizures. CNN network was also used in the work of [23-25].

Most of the works that addressed the detection and classification of epileptic seizures used a small number of the dataset in their work; others employed a binary classification as either seizure and normal classes or focal and non-focal classification. Few works in literature used the recent TUH dataset in their work, and there are still gaps to be filled in investigating the efficacy of the dataset for efficient detection and classification of epileptic seizures as it has more advantages over the commonly used available such as Bonn and Bern datasets. Also, investigating the model's performance with this dataset is paramount as it is suitable for realizing real-world practical devices that will be easily integrated into the recent internet of medical things (IoMT). Therefore, this work aimed to contribute to address the issues mentioned.

III. MODEL EXPERIMENTATION

The proposed model consists of dataset acquisition, pre-processing, signal decomposition, feature extraction, classification, and performance evaluation, as shown in Fig. 1.

A. Electroencephalogram Signals Datasets

One of the limitations of previous works in detecting and classifying epileptic seizures is the lack of adequate datasets that can be used to train, classify, and validate the seizures effectively. Most of the available datasets consist of a small number of data and short duration, which tend to be unsuitable for recent machine learning and deep learning networks. TUH recently provided a repository of

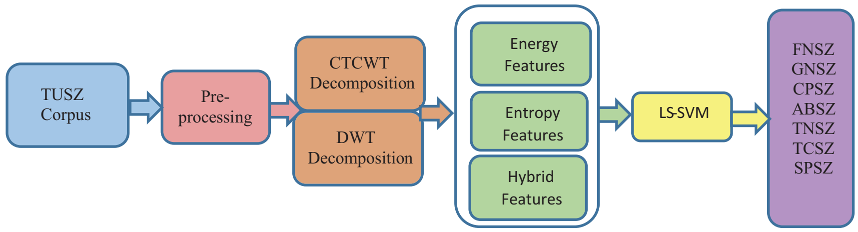

Fig. 1. Block diagram of the proposed model for multi-classification of seven types of seizures from Temple University Seizure Corpus (TUSZ) v.1.5.2

large epileptic seizure datasets, currently the largest publically available datasets. The dataset was acquired from over 300 patients, and after carefully screening and annotating, 3050 seizure events were identified and available in the dataset. Table I describes the detailed information about each seizure classes in the TUH database. More comprehensive information about the dataset distribution can be found in [26, 27]. Figure 2 shows an example of sample of seizure signals in TUH dataset.

B. Dataset Preprocessing

The TUH dataset is available in EDF format from the database, and the data are not the same in all the files regarding sampling rate and montage. The preprocessing procedure adopted in [28] was employed to generalize the data before extracting the features. Therefore, we used the annotated file provided in the dataset to extract the EEG segments associated with seizure activity. We then selected 250 Hz as sampling frequency to re-sample the entire signal data, while the transverse central parietal (TCP) montage approach accentuated the spike activity. The segments extracted are non-overlapped and made of 2 seconds each while discarding any event with less than 2 seconds. Finally, a filtering technique is used to remove the noise from the signals using a Butterworth filter of 0.4–49.5 Hz passband frequencies.

C. Feature Extraction

For the successful detection and classification of epileptic seizures, the accuracy and precision of classifiers must be considered, which depend on the quality of features extracted that characterize the signal's property. This work proposed a robust feature extraction technique that is highly efficient, reliable, and low in complexity. It is suitable for portable and low-cost automatic computer-aided devices (CAD), especially in our current IoMT devices and networks. The proposed feature extraction technique consists of a combination of energy and entropy features. The model consists of signal decomposition using dilation wavelet transform (DWT) and its modified version known as DTCWT. After the decomposition, energy and non-linear parameters were computed to explore the nonlinearity and complex nature of EEG brain's signals and reduce the signal dimension for low complexity and redundancy reduction.

1) Dilation Wavelet Transform Decomposition

Wavelet transform decomposition is an effective and efficient approach to analyze biomedical signals due to its capability of representing the signals into the time-frequency resolution of the signal sub-bands. DWT is highly suitable for analyzing non-stationary signals such as EEG epileptic seizure signals. The EEG signals $x(n)$ can be expanded and decomposed into several sub-bands corresponding to the DWT level of decomposition. In DWT, the mother wavelet and level of decomposition were chosen. Daubechies mother wavelet is selected in this work because it was proven in the literature to have similar morphology to EEG signals and performed well in our previous studies [29, 30]. The DWT is given as

$$x(m,s)=\int x(t)\psi^{*}_{m,s}(t)dt \quad (1)$$

where

$$¤_{m,s}(t)=2^{m/2}\psi\left(2^{m}-s\right) \quad (2)$$

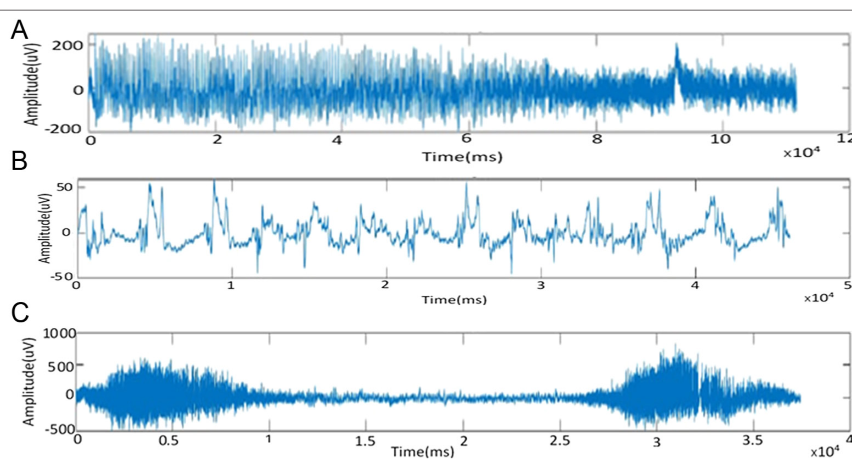

Fig. 2. Type of seizure EEG signals in TUH dataset (A) GNSZ (B) FNSZ, and (C) TCSZ. EEG, electrocardiogram; TUH, temple university hospital; FNSZ, focal non-specific seizure; GNSZ, generalized non-specific seizure; TCSZ, tonic clonic seizure.

With $\psi(t)$ stands as the mother wavelet function, which uses an integer scaling function *s* and position function *m* to produce a set of orthogonally correlated wavelets. We choose the decomposition level as 5, and the discrete signal $x(k)$ is passed through two bandpass filters denoted as h[.] and g[.] for high and low pass filters, respectively. At each level of decomposition, the outputs of these filters, known as details and approximations coefficients, are downsampled. The mathematical representation of the components is given as

$$D_j(i) = \sum_k x[k].h[2.i-k] \tag{3}$$

$$A_j(i) = \sum_k x[k].g[2.i-k] \tag{4}$$

Approximation coefficients A_j+1 can be decomposed into the next level of $A_j(i)+1$ and D_j+1. The decomposition is repeated to the next level until the desired chosen level j is reached.

DWT recorded many successes over the decades in analyzing and applying physiological signals such as EEG, Electromyography (EMG), Electrooculography (EOG), and Electrocardiography (ECG), among others. However, a few drawbacks of this approach include a lack of phase shifts, poor directionality, inadequate information by its components at a high-frequency scale, and shift display variance. Therefore, many researchers proposed several improvements to DWT to address the limitations of DWT, such as wavelet packet decomposition (WPT), tunable Q-factor wavelet transform (QTWT), rational dilation wavelet transform (RDWT), and stationary wavelet transform (SWT) among others. This work employed an efficient DWT extension called dual-tree complex wavelet transform (DTCWT) to extract the features from our datasets. This DWT improvement was proposed by Kingsbury [31] and later developed by Selesnik et al. [32]. This approach extends DWT by including two additional low pass filters and two high pass filters at each level; this will produce four components corresponding to four filters instead of two as in DWT, as shown in Fig. 3. DTCWT eliminates DWT shortcomings of directionality and minor shift variance.

2) Non-linear Features

Entropy and energy features were extracted from the DWT- and DTCWT-decomposed EEG signals further to explore the nonstationarity and non-linear dynamics of the signals. The following are the entropy and energy parameters selected in this study.

a) Stein's Unbiased Risk Estimation and Threshold Entropies

For EEG signal $x(n)$, SURE entropy can be described as

$$SURE_{en} = N - \#\{i \text{ such that } |x_i| \le \epsilon\} + \sum_i min(x_i^2, \epsilon^2) \tag{5}$$

where *N* is the number of samples of the signals

$$TH_{en}(x_i) = \begin{cases} 1, |x_i| > \varepsilon \\ 0, \text{otherwise} \end{cases} \tag{6}$$

Therefore,

$$TH_{en} = N - \#\{i \text{ such that } |x_i| > \varepsilon\} \tag{7}$$

where x_i is the signal's sample, ε represents the positive threshold.

The average values of $SURE_{en}$ and TH_{en} are calculated from the decomposed signal in each EEG signal subband.

b) Shannon Wavelet Entropy

Shannon wavelet entropy ShW_{en} is calculated as follows

$$ShW_{en} = \sum_n x_i(n) log x_i(n) \tag{8}$$

c) Centered Correntropy

Correntropy measures the correlation in the non-linear domain. It extracts the EEG signal characteristics from the decomposed components. It can be defined as

$$CC(k) = \frac{1}{N-k+1} \sum_{n=k}^{N} k_\sigma(x(n) - x(n-k)) \tag{9}$$

where *N* is the length of *x(n)*, *k* is the delay factor, and k_σ is the Gaussian kernel function with respect to σ bandwidth. The mean correntropy is given as

$$CC_{mean} = \frac{1}{N^2} \sum_{k=1}^{N} \sum_{n=k}^{N} k_\sigma(x(n) - x(n-k)) \tag{10}$$

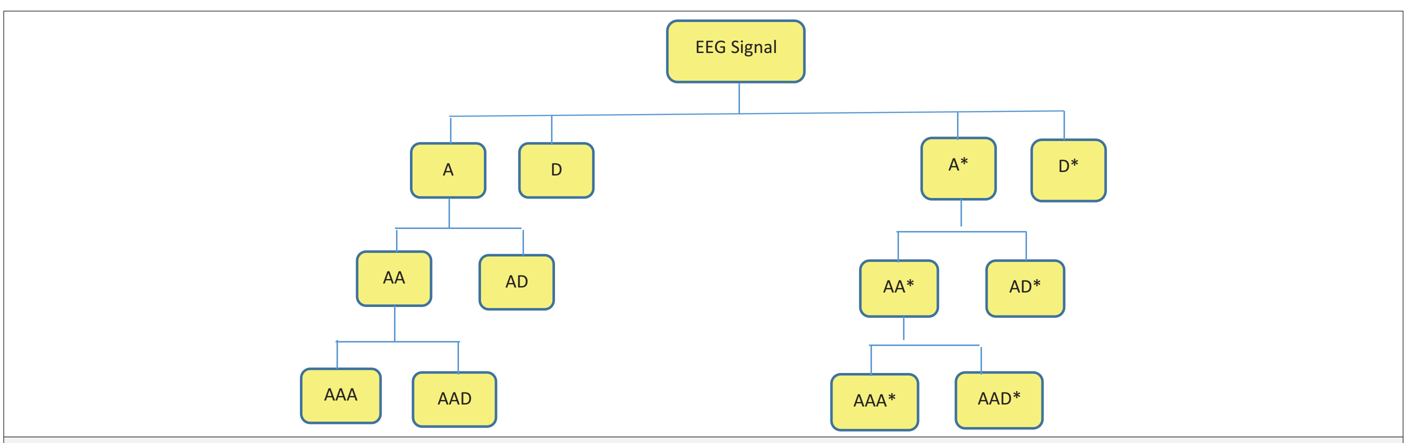

Fig. 3. DTCWT structure of three scale level decomposition. DTCWT, dual-tree complex wavelet transform.

Therefore, centered correntropy CC_k can be computed as

$$CC_k = CC(k) - CC_{mean} \tag{11}$$

d) Mean Teager-Kaiser Energy

The ability of mean Teager-Kaiser energy (MTKE) to track minor fluctuations in EEG signals for both amplitude and frequency, which can extract meaningful information from the signals, makes it a suitable choice parameter to extract signal properties in this study. MTKE can be mathematically expressed as

$$MTKE = \log\left(\frac{1}{N}\sum_t \left| x(t)^2 - x(t+1) * x(t-1) \right|\right) \tag{12}$$

e) Log Energy Entropy

Taking the square of the signal enables us to obtain complete information about the signal. Therefore, Log energy entropy helps us better discriminate our EEG signals. Log energy entropy is defined as

$$LE_{en} = \sum_t \log(x(t)^2 \tag{13}$$

D. Experimental Protocol

In this section, we describe the experimental procedures for developing our model. The EEG epileptic seizures were decomposed using both DWT and DTCWT to generate a set of coefficients. This study chose five decomposition levels, and each approach produces different component coefficients. In the DWT method, for example, five detail coefficients and one approximation coefficient were combined as features, while the DTCWT approach is considered a two-parallel DWT. The features presented in subsection B of section III were calculated on each decomposed coefficient from the two decomposed approaches. Non-linear and energy features are significant features that can characterize and discriminate our different epileptic EEG signals. Therefore, we divided the experiments based on the combination of computed features as follows:

1. Features were computed and extracted from five advanced energy and entropy parameters as follows: SURE, Shannon wavelet entropy, centered correntropy, mean Teager-Kaiser energy, and log energy entropy.
2. Combined hybrid features are divided into three experiments as follows:
   a) experiment 1 involves entropy features,
   b) experiment 2 involves energy features, and
   c) experiment 3 consists of the combination of all the feature sets.

The feature matrix $F_m \in \mathbb{R}^{(s_i \times E \times F)_n}$ $m \in N$ where N is the number of seizure events in the EEG signals, s_i is the cropped segment of EEG signals, *i* is the number of segments in each EEG signal event, and *E* is the number of channels in EEG signals. In each similar event, we have computed the median as it is proven to be a feature collection function [33]. This collection function helps us reduce the feature space size without scarifying the feature quality. Finally, for every seizure event, a single feature vector $F_m \in \mathbb{R}^{(E \times F)_n}$ of length, *F* is obtained. Therefore, the number of feature matrix is 300, 200, and 500 for experiments 1, 2, and 3, respectively.

E. Classification

The concept of artificial intelligence (AI) is in which vast knowledge and intelligence acquired by human experts are translated and built into machines and computers so that they can learn and perform the function of human experts. Several types of machine learning models which are part of AI have been proposed in the literature to detect and classify epileptic seizures, such as artificial neural network (ANN), support vector machine (SVM), k-means clustering, naive Bayes, logistic regression, etc. [9, 34]. These ML algorithms overcome human limitations such as variations in interpretations, time consumption, and fatigue.

This work deployed one of the famous and most commonly employed classifiers in literature in the classification of images, imagine speech decoding, emotion recognition, and motor imagery. SVM is highly suitable for binary classification in focal and non-focal epileptic seizures. In the SVM classifier, higher dimensional feature space is used to generate a hyperplane to provide a decision boundary and assign a class to new input data by maximally separating clusters of labeled input data. It is very effective and simpler in computation and can also deal with linear and non-linear classification problems. The SVM classifier was proposed to perform a multi-classification of seizure-type classes using features extracted from different domains.

IV. EXPERIMENTAL RESULTS

As seen in Table I, the TUH dataset consists of different types of seizures with class imbalance. Therefore, the model's performance was validated using seizure-wise cross-validation. The dataset is divided into ten-folds randomly as adopted in [22, 25], who employed the same datasets in their studies. The multi-classification of seizure classes listed in Table I was experimented based on the models developed in this study. The learnable features extracted were prepared and divided into standard 70% and 30% for training and test sets, respectively.

Due to the class imbalance of the seizure classes, the performance of the models was not evaluated based on accuracy alone; instead,

TABLE I. TUSZ 1.5.2. SEIZURE TYPE CLASSES

Type of Seizures	Seizure Events	Duration (sec)	Patients
FNSZ	1836	12 1139	150
GNSZ	583	59 717	81
CPSZ	367	36 321	41
ABSZ	99	852	12
TNSZ	62	1204	3
TCSZ	48	5548	12
SPSZ	52	2146	3
MYSZ	3	1312	2

FNSZ, focal non-specific seizure; GNSZ, generalized non-specific seizure; CPSZ, complex partial seizure; ABSZ, absence seizure; TNSZ, tonic seizure; TCSZ, tonic clonic seizure; SPSZ, simple partial seizure; ATSZ, atonic seizure; MYSZ, myoclonic seizure.

other performance evaluation metrics have been deployed, such as F1-score, sensitivity, specificity, and precision. The mathematical expression of these metrics is given as:

$$\text{Sensitiivity} = \frac{TP}{\text{TP} + \text{FN}}$$

$$\text{Specificity} = \frac{TN}{\text{TN} + \text{FP}}$$

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

$$\text{Precision} = \frac{TP}{\text{TP} + \text{FP}}$$

$$\text{F1\_Score} = 2\frac{\text{Precision*Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

where TP is true positive; TN is true negative; FP is false positive; and FN is the false negative values.

A. Performance Evaluation of Dilation Wavelet Transform Features

A comprehensive performance analysis of features extracted from DWT decomposition was performed using different experimental scenarios. Energy, entropy, and hybrid features that consist of combined energy and entropy are experimented as experiments 1, 2, and 3, respectively. The feature from each experiment is used to classify seven seizure classes using different SVM classifiers. To obtain the most optimal classifier among the SVM types and its kernel function, we performed several experiments on various types of SVM and the kernel function, as shown in Table II and Fig. 4, respectively. From Table II, LS-SVM shows better performance than SMO-SVM and QP-SVM, with an accuracy of 77.4%. SVM kernel functions were also experimented with LS-SVM. It was established in Fig. 4 that the polynomial kernel function shows a better performance compared to other kernel functions.

After optimizing the SVM classifier, we developed our model using the LS-SVM classifier with a polynomial kernel function. The proposed features were extracted from DWT decomposition, and the model is experimented based on the performance of each SURE, Shannon wavelet entropy, centered correntropy, mean Teager-Kaiser energy, and log energy entropy, and the performance of hybrid features is divided into three experiments: energy features, entropy features, and all the combined features, as shown in Fig. 5 and Table III, respectively.

Table III was computed from the confusion matrix calculated from the TP, FP, FN, and TN values. The values of confusion matrix were normalized, while the average values of accuracy, sensitivity, specificity, precision, and F1-score are computed and presented in Table III. The test sets were evaluated using a ten-fold cross validation to validate and evaluate the performance of the DWT-Hybrid-LS_SVM

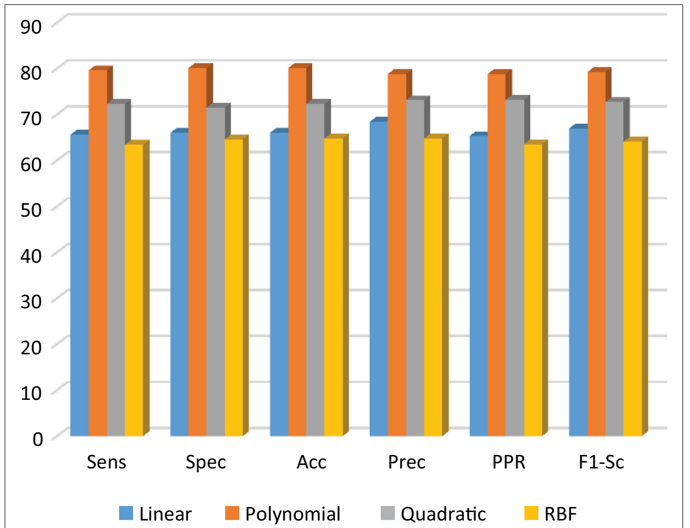

Fig. 4. Performance of different SVM kernel functions. SVM, support vector machine.

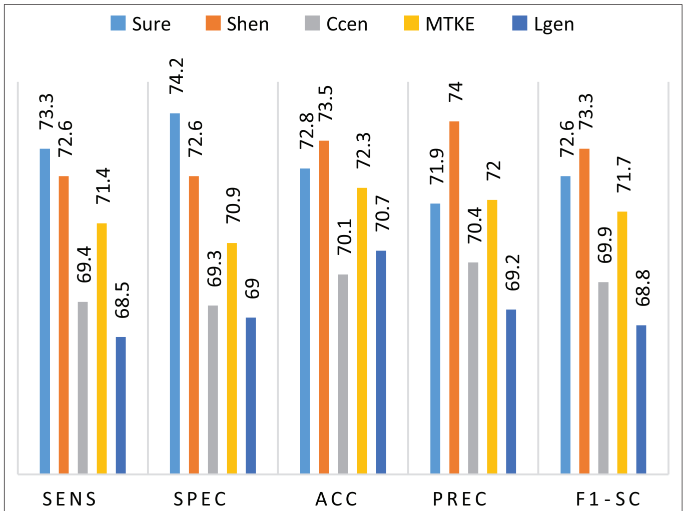

Fig. 5. Performance of SURE, Shannon wavelet entropy, centered correntropy, mean Teager-Kaiser energy, and log energy entropy features computed from DWT decomposition with LS-SVM model. DWT, dilation wavelet transform; SURE, Stein's unbiased risk estimation.

TABLE II. PERFORMANCE OF DIFFERENT TYPES OF SVM MODEL

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
QP-SVM	65.5	62.5	62.5	61.8	62.1
LS-SVM	77.4	78.5	79.0	78.3	78.4
SMO-SVM	68.5	67.8	68.2	68.1	67.9

SVM, support vector machine.

TABLE III. PERFORMANCE OF DWT-HYBRID-LS_SVM MODEL

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
Experiment 1	87.9	86.8	89.2	89.5	88.1
Experiment 2	87.4	86.6	89	89.3	87.9
Experiment 3	89.0	91.3	89.2	89.5	90.4

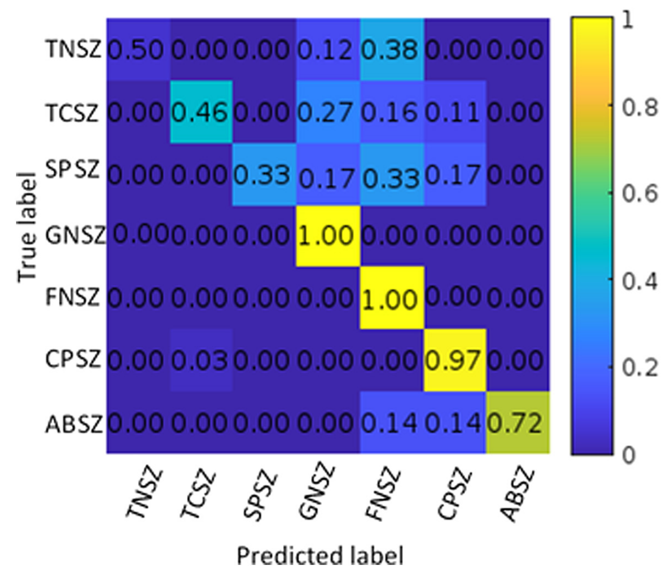

Fig. 6. Confusion matrix of seven type of seizures based on multi-classification problem using a TUH seizure corpus with ten-fold cross validation for DWT-Hybrid-LS_SVM model. TUH, temple university hospital.

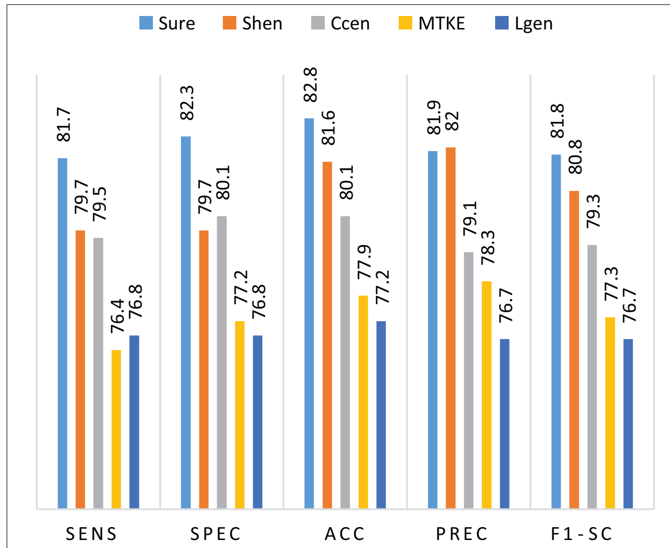

Fig. 7. The performance of SURE, Shannon wavelet entropy, centered correntropy, mean Teager-Kaiser energy, and log energy entropy features was computed from DTCWT decomposition with the LS-SVM model. DTCWT, dual-tree complex wavelet transform; SURE, Stein's unbiased risk estimation; SVM, support vector machine.

model in each experiment. Figure 6 depicts example of confusion matrix for experiment 3 of the proposed model.

B. Performance Evaluation of Dual-Tree Complex Wavelet Transform Features

To evaluate the performance of our proposed models based on the features extracted from DTCWT decomposition, we used the same experimental scenarios as in subsection A of section IV. Features from SURE, Shannon wavelet entropy, centered correntropy, mean Teager-Kaiser energy, and log energy entropy are used to evaluate the performance of LS-SVM. Hybrid parts were divided into three experiments, as described in subsection A of section IV. The performance of both models is shown in Fig. 7 and Table IV. It was demonstrated that the proposed hybrid features performed better than the single features with a value of accuracy, sensitivity, specificity, precision, and F1-score of 96.9%, 96.8%, 93.4%, 95.6%, and 96.2%, respectively

Also, we have calculated the confusion matrix in normalized values for the classification of seven class seizure types based on the DTCWT-Hybrid-LS_SVM model. Example of confusion matrix computed based on experiment 3 of the proposed model is shown in Fig. 8.

The model proposed in this study is also compared with recent literature works that used the same dataset for the multi-classification of various types of seizures. As shown in Table V, our proposed method significantly improves the characterization of various types of seizures.

TABLE IV. PERFORMANCE OF DTCWT-HYBRID-LS_SVM MODEL

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
Experiment 1	93.4	95.5	94.3	95.5	95.5
Experiment 2	93.6	94.4	95.1	94.2	94.3
Experiment 3	96.9	96.8	93.4	95.6	96.2

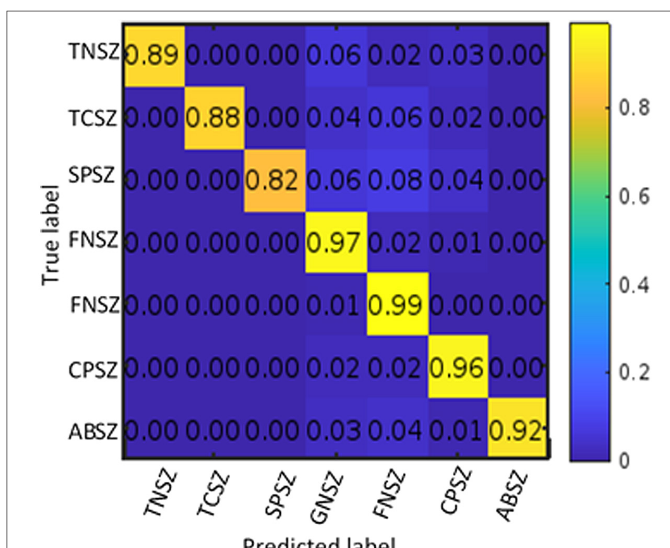

Fig. 8. Confusion matrix of seven type of seizures based on multi-classification problem using a TUH seizure corpus with ten-fold cross validation for DTCWT-Hybrid-LS_SVM model. TUH, temple university hospital; DTCWT, dual-tree complex wavelet transform.

V. DISCUSSION

This study presents a comprehensive analysis of the detection and classification of epileptic seizures by proposing robust feature extraction techniques and an optimized SVM classifier. Five advanced feature parameters were investigated on the recently released TUSZ

TABLE V. COMPARISON OF THE PROPOSED MODEL WITH SOME RECENT WORKS THAT USED THE SAME DATASET

Author	Year	Feature Extraction	Type of Classifier	Performance (%)
Sriraam et al. [23]	2019	STFT	CNN	Acc = 84.14
Saputro et al.[18]	2019	Non-linear	SVM	Acc = 91.40
Roy et al. [20]	2020	Correlation coefficient	XGBoosr	F1 = 85.10
Roy et al. [20]	2020	Correlation coefficient	K-NN	F1 = 90.10
Asif et al.[21]	2020	-	SeizureNet	F1 = 95.00
Aristizabal et al. [22]	2020	-	CNN	F1 = 94.50
This study	2022	DWT-hybrid features	LS_SVM	Acc = 89.0,F1= 90.4
This study	2022	DTCWT-hybrid features	LS-SVM	Acc = 96.9, F1=96.2

STFT, short-time Fourier transform; CNN, convolutional neural network; SVM, support vector machine; XGBoost, eXtreme gradient boosting; K-NN, k-nearest-neighbor; LS-SVM, least-squares SVM; DWT, discrete wavelet transform; DTCWT, dual-tree complex wavelet transform.

dataset, consisting of extensive data and many types of seizure classes. Based on the results presented in subsections A and B of section IV, it was seen that the SURE and Shannon entropy shows a better capability of distinguishing the types of seizure events in EEG epileptic seizure signals, as shown in Figs 5 and 7 of DWT and DTCWT, decomposition, respectively. Also, among the experiments conducted on hybrid features, a hybrid feature that combined all the five investigated parameters shows a higher performance than other energy and entropy hybrid features. It clearly shows that combining the efficacy of various non-linear features would improve the characterization of multiple types of seizures. Therefore, this work has proven efficient and effective in developing a model suitable for use in recently developed IoMT devices and practical implementation of the developed algorithms in clinical settings.

The proposed DTCWT-Hybrid-LS_SVM model developed in this study provides higher performance than other studies that used DTCWT to discriminate between epileptic and non-epileptic patients. However, the complex problem of dealing with big data, long-term duration, and many seizure classes could not be well addressed with some standalone techniques. The hybrid features combine the advantages of various domains that characterized and explored the embedded properties of seizure EEG signals, this has been proven in our proposed model which detected and classified seven seizure classes of long-term duration datasets including specific and non-specific focal and generalized seizures. The most commonly employed techniques proposed in the literature to extract features for discriminating epileptic EEG signals include a fast Fourier transform (FFT) [20] which has a poor resolution in the time domain and good resolution in the frequency domain. To overcome the limitations of FFT, short-time Fourier transform (STFT) was proposed [24, 25]. However, STFT used a fixed window length, leading to this method's inability to catch sharp signal events [35]. To overcome the limitations associated with these methods, we proposed a hybrid technique to extract meaningful and relevant features by smoothing the EEG signals as evident in the higher results obtained compared to other techniques.

VI. CONCLUSION

Multi-classification of epileptic seizures is very tedious and highly challenging due to the variability nature of the epileptic patients' EEG signals. As opposed to most previous works, this work proposed a multi-seizure classification of seven types of seizures recorded and annotated at TUH, containing a vast and long-time recording of seizures. The proposed model in this study performed very well and improved the classification accuracy compared to other recently reported studies in the literature, with a value of 96.9% obtained based on the proposed hybrid feature technique and optimized LS-SVM classifier. Future works should investigate other methods such as deep learning architectures, more features, hybridization of various features, and machine learning with deep learning models. Time complexity would also be investigated further to validate the model on recently developed IoMT devices.

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