# Comparison of WPD, DWT and DTCWT for Multi-Class Seizure Type Classification

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**Abstract— Epilepsy is characterized by recurrent seizures that come in diverse types which are treated in a variety of ways. Electroencephalography (EEG) is a technique that is frequently used in medical settings to diagnose epileptic seizures. The accurate identification of seizures helps to provide optimal treatment and accurate information to the patient. This paper compares three wavelet-based feature extraction methods for multi-type seizure classification using EEGs. WPD, DWT, and DTCWT are used to extract features from EEG data, which are then classified using LightGBM. We evaluated the proposed methods on the TUH EEG Seizure Corpus v1.5.2, which is the world's largest available EEG epilepsy database. We also examined three different combinations of features on three different problems, each containing different seizure classes according to their medical definitions. The performance of our proposed method is measured according to the overall F1-score. For patient-wise cross-validation, EEG-based seizure type classification using WPD achieved the best results of weighted F1-score of 64%, 66.6% and 83.97% for 7-class, 5-class, and 2-class problems respectively. The results are compared with existing state-of-the-art techniques and our results established new benchmark results for this dataset.**

## I. Introduction

Epilepsy is the second most common type of brain disease in human beings. It is defined as "a sudden and recurrent brain malfunction and is a disease that reflects an excessive and hypersynchronous activity of the neurons within the brain" [1]. Over 60 million of the world population has epilepsy; whose characterized feature is recurrent seizures [2]. The seizures occur at unexpected times, affecting the brain's normal functioning. Patients with epilepsy suffer from unpredictable seizures, aberrant behavior, and even loss of consciousness. Patients would be vulnerable and unable to defend themselves against various and severe conditions during seizure attacks.

According to the World Health Organization (WHO), eighty percent of epileptic patients live in underdeveloped or developing nations with insufficient medical services [3]. Worryingly, the vast majority of those people remain undiagnosed and hence do not receive adequate treatment and care. Furthermore, those with epilepsy have three times more risk of premature death comparatively [4]. Roughly 66% of seizures can be controlled by medication, whereas about 8% only can be controlled by surgical intervention. While for the rest, no medical treatment exist [5].

An epileptic seizure often has periods of coordinated pulsations known as "epileptic paroxysms." Such seizures may be categorized as focal or generalized. In terms of the degree to which part of the brain is affected, focal seizures and generalized seizures are distinguished as different types of seizures. Focal seizures originate and occur in a single location of the brain. Focal seizures may be further categorized as simple or complex based on the patient's degree of consciousness. Generalized seizures, which impact the whole areas of the brain, are classified according to non-motor and motor symptoms enabling distinguishing absence, tonic, atonic, clonic, tonic-clonic, and myoclonic seizures. The nature of an epileptic seizure is determined by the brain region involved and the underlying fundamental epileptic condition [1].

Electroencephalography (EEG) is the most commonly used tool to diagnose seizures [6]. It provides rich information of the brain electrical activities which play an essential role besides clinical features in diagnosing the abnormality in the brain. EEG measures the current flows in the brain by placing a set of sensors on the scalp. This measurement is digitized and presented as a waveform (signals) [7]. By a careful examination of the signals, a neurologist can detect the abnormal signs related to epilepsy [8]. While it may be difficult to identify the specific type of seizures using EEG, clinical observation may be used to identify them. This involves incorporating information about the patient's medical history besides EEGs [8].

Accurate seizure type classification will support the epileptologist to provide the appropriate medication [9]. Correct classification is necessary as some seizure medications and equipment are only for the treatment of certain seizure types [10]. Doctors also use the classification to categorise patients for therapeutic interventions. Moreover, the classification evolves into a universal abbreviation for communication among professionals caring for epilepsy on a global scale. Seizure type classification may also be beneficial also for researchers in establishing a link between certain syndromes or etiologies [10].

Many variables complicate the diagnosis of seizure classification and make it a difficult task. Firstly, a detailed history from the patient and observers is always required for an appropriate clinical diagnosis, which can usually be harmed by erroneous and insufficient patient and carer information [8]. Secondly, the clinical and electrographic features are similar in some types of seizures [8]; it has been shown that it is difficult to discern between focal and generalized seizures, even for a highly trained neurologist [11]. Thirdly, inter-subject variability exacerbates the challenges of diagnosing an epileptic seizure, resulting in a wide range of presentations of the same type of seizure in various patients, and even in the same person over time. When a diagnosis cannot be established on the basis of symptoms and EEGs, video-EEG is commonly required [6]. Video-EEG monitoring entails patients being admitted to epilepsy monitoring facilities for many hours or days in order to capture spontaneous or provoked seizure occurrences [1]. As a result, neurologists must devote a significant amount of time and effort to manually analyze these lengthy recordings. With these difficulties in a sector that already suffers from a scarcity of qualified neurologists, computer-aided diagnostic (CAD) techniques offer a great deal of promise to assist in decision-making.

For the last two decades, most of the research has concentrated on automatic detection [12] and predication [13] of epileptic seizures using scalp EEG. However, seizure type classification received little attention due to the nonavailability of large clinical data and the difficulties inherent in this task [14]. Due to these problems, most of the previous research studies for the task of seizure classification were only for binary classification such as, focal vs non-focal classification [15–17] and normal vs abnormal EEG [18, 19]. Recently, there are few research studies that considered the problem of multi-type seizure classification especially after release of the Temple University Hospital EEG Seizure Corpus (TUSZ) [20].

For the problem of multi-type seizure classification, Wijayanto et al. [21] used empirical mode decomposition (EMD) for feature extraction and SVM for classification, and reported an accuracy of 95%. In [22], three different feature extraction methods: Independent Component Analysis (ICA), Mel Frequency Cepstral Coefficients (MFCC) and EMD, are utilized for the classification of 4-classes of seizures, achieving the accuracy of 91.4%. Recently, [23] applied the K-Nearest Neighbors (KNN) and XGBoost to classify between 7-types of seizures, achieving the F1-scores of 90.1% and 85.1% respectively. For the same problem, Aristizabal et al. [24] reported that the F1 of 94.5% using a deep learning model known as Neural Memory Networks (NMN). The author in [14] proposed a solution to the same seven-class problem using a deep learning network consisting of multiple convolutions connected with DensNets and reported the F1 of 96%. For an eight-class classification problem, the accuracy of 88.3% and 84.06% were reported in [25, 26] respectively, where both studies were based on convolution neural network (CNN) and transfer learning. Liu et al. [8] applied a hybrid bilinear model consisting of two feature extraction networks CNN and Long Short-Term Memory (LSTM), for the classification of 8-types of seizures. The study reported to achieve 97.4% F1-score.

Despite the positive performance shown in the preceding research studies, a common limitation of the previous research studies is that data from one patient is used for training and testing simultaneously. It is anticipated that these proposed solutions cannot be utilized in real-world scenarios as the performance considerably decreases if different patients' data is used for training and testing. In our literature survey, only two studies were found which considered the generalization of their proposed solutions to be evaluated across different patients. Both studies reported a significant reduction in overall performance. This indicates that there is a significant gap for improvement for better generalization capability.

To address the aforementioned issues, we propose a method to compare three different feature extraction methods based on three different wavelet based decomposition techniques to classify and determine the correct type of seizure. Additionally, we will look at three different classification problems. In the first problem, each label in the dataset is treated as a distinct seizure type. Whereas the second problem is more significant pathologically as it concerns the classification of specific seizure types. Similarly, the third problem deal with binary classification of two main seizures types. The main contribution of this paper consists of various steps that can be summarized as follows:

1) We examine the efficiency of a different combination of features that can finely classify the seizure type in a large-scale multi-class dataset.
2) We propose a robust method to reduce the feature space dimension without compromising the quality of features.
3) We compare three important signal decomposition techniques for multi-class seizure classification, which is done for the first time in the literature for selected large-scale dataset of TUSZ.
4) We evaluate our proposed approach across different patients, and compared its performance with other state-of-the-art methods. We found our proposed technique to provide better results compared to state-of-the-art methods.

## II. Methods

### II-A. Dataset

We based our study on TUSZ v1.5.2 dataset [20], which is a subset of Temple University Hospital EEG Corpus (TUH EEG), the largest publicly available EEG dataset [27]. The TUSZ v1.5.2 dataset includes 3,050 seizure events, consisting of various seizure morphologies and recorded from over 300 different patients.

There are eight types of seizure events found in the TUSZ: Focal Non-specific Seizure (FNSZ), Generalized Non-specific Seizure (GNSZ), Simple Partial Seizure (SPSZ), Complex Partial Seizure (CPSZ), Absence Seizure (ABSZ), Tonic Seizure (TNSZ), Tonic-clonic Seizure (TCSZ) and Mayoclinc Seizure (MYSZ). The detailed distribution of the TUSZ v1.5.2 is presented in Table 1.

### *II-B. Prepossessing*

The TUSZ is derived from archival hospital data at Temple University Hospital (TUH), where clinical EEG data was extracted from CD-ROMs and made available in EDF format. Each set of data is not identical in terms of montage and sampling rate. As a result, we performed some initial procedures to generalize the input data prior to feature extraction. Firstly, the EEG segments which are exclusively responsible for seizures were extracted from the dataset. This was achieved using the annotated file provided in the dataset, including the start and the stop time of each seizure event. We have excluded the seizure type MYSZ due to its scarcity in the dataset. After extracting the seizure events, we used the transverse central parietal (TCP) montage to accentuate spikes activity [23]. Figure 1 presents the EEG channels considered in our study. Secondly, we re-sampled all recordings at 250Hz. Then, we cropped each extracted signal into equally non-overlapped segments such that each segment is of the length of two seconds. The events shorter than two seconds were excluded resulting in 20 events excluded from our study. Finally, we applied the method of Butterworth filter to filter out the noise; a passband filter in the range of 0.4 to 49.5 Hz is applied to the signals.

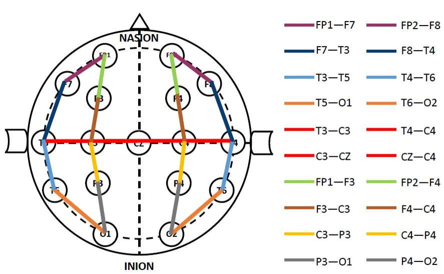


Figure 1. The 20 EEG-channels based on TCP montage with their locations on the scalp

Table 1. Seizure Type Statistics in the TUSZ v1.5.2

| Seizure Type | No. of seizure events | Duration (Seconds) | No. of patients |
|---|---|---|---|
| FNSZ | 1836 | 121139 | 150 |
| GNSZ | 583 | 59717 | 81 |
| CPSZ | 367 | 36321 | 41 |
| ABSZ | 99 | 852 | 12 |
| TNSZ | 62 | 1204 | 3 |
| TCSZ | 48 | 5548 | 12 |
| SPSZ | 52 | 2146 | 3 |
| MYSZ | 3 | 1312 | 2 |

### *II-C. Signal Decomposition Methods: WPD, DWT and DTCWT*

The Discrete Wavelet Transform (DWT) is one of the most well-known wavelet-based algorithms. By scaling and shifting the mother wavelet, DWT decomposes an input discrete-time signal $x[k]$ into a set of orthogonally correlated wavelets (coefficients). Starting with level of decomposition $j = 1$, a signal $x[k]$ is routed through two band-pass filters: high $h[.]$ and low $l[.]$. Each level outputs two downsampled components called Approximation $A$ and Detail $D$ coefficients, which are mathematically denoted as:

$$D_j[i] = \sum_k x[k] \cdot h[2 \cdot i - k] \tag{1}$$

$$A_j[i] = \sum_k x[k] \cdot l[2 \cdot i - k] \tag{2}$$

As illustrated in Figure 2, $A$ might be decomposed further into the next two levels, $Aj+1$ and $Dj+1$. The process is repeated until the required level of $j$ is attained.

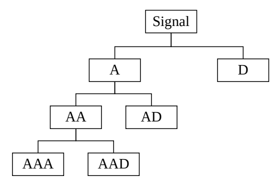


Figure 2. The structure of three scale level of DWT

Despite DWT having many successful applications, it has a few disadvantages. Most notably, its components provide inadequate information in the high-frequency range. Moreover, it has shifts display variance, poor directionality and lacks phase shift. Many improvement are proposed to address the drawbacks of DWT. Wavelet Packet Decomposition (WPD) is an expanded variant of DWT. It compensates for the major shortcoming of DWT, which only decomposes the signal's low-frequency components. WPD decomposes both low and high-frequency components, resulting in a full wavelet binary tree, as seen in Figure 3. For j-level of decomposition, WPD will produce $j^2$ components, whereas the DWT's output is only $j+1$. Thus, WPD has more frequency resolution than DWT, which captures important information in higher as well as lower frequency components.

Another useful extension of DWT is dual-tree complex wavelet transform (DTCWT) which was initially proposed by Kingsbury [28] and developed later by Selesnick et al. [29]. It uses extra double low-pass filters and two high-pass filters to produce four components at each scale real and imaginary parts. DTCWT can be seen as two parallel DWTs as shown in Figure 4. Therefore, DTCWT overcome the DWT limitations of minor shift variance and directionality.

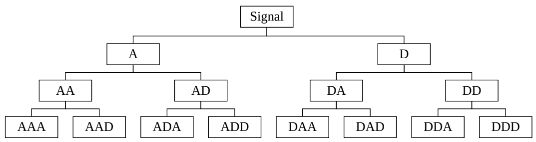


Figure 3. The structure of three scale level of WPD

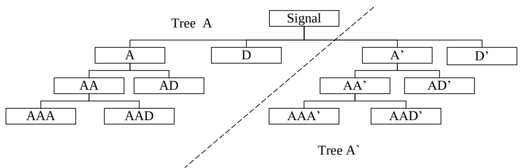


Figure 4. The structure of three scale level of DTCWT

### II-D. Feature Extraction

The decomposition techniques of DWT, WPD and DTCWT produce a set of coefficient components. We decompose the EEG signals into four levels in all the methods, using PyWavelets for both DWT and WPD, and DTCWT's Python's library [30]. Each method produces different number coefficients. For example, DWT produces four detail coefficients and one approximation coefficient. Similarly, the output of DTCWT can be seen as two parallel DWTs, real and imaginary tree. In this research, we choose to take the real and the imaginary coefficients as unique coefficients of DTCWT. For WPD, the obtained coefficients are 16, which are the output of the last level. Table 2 shows the number of obtained coefficients from each of the decomposition methods. After the decomposition, we computed six statistical features from each of the obtained coefficients [17, 31]:

1) Mean absolute values $F1$,
2) Average power $F2$,
3) Standard deviation $F3$,
4) Ratio of the absolute mean values of adjacent coefficients $F4$,
5) Skewness $F5$,
6) Kurtosis $F6$.

In three different experiments, this research examines three sets of features which are:

- Experiment 1: feature_set (*F1,F2,F3,F4.*)
- Experiment 2: feature_set (*F1,F2,F5,F6.*)
- Experiment 3: features_set (*F1–F6.*)

Table 2. Number of features in each decomposition technique

| Method | No. of sub-bnds | No. of features | | |
|---|---|---|---|---|
| | | EXP1 | EXP2 | EXP3 |
| DWT | 5 | 20 | 20 | 30 |
| WPD | 16 | 64 | 64 | 96 |
| DTCWT | 9 | 36 | 36 | 54 |

#### II-D1. Feature Aggregation

The feature extraction process resulted in a feature matrix $M_n \in \mathbb{R}^{(S_i \times E \times F)_n}$, $n \in N$ where $N$ is the number of EEGs containing the seizure events, $S_i$ is the analyzed 2 seconds cropped segment, $i$ is the number of segments per EEG event, $E$ is the number of EEG channels and F is the feature vector. The median of all segments that belong to the same events was calculated because it has been shown to be a successful aggregation function in [18, 19]. At the end, we obtained a single feature vector of length $F$ for each seizure event $M_n \in \mathbb{R}^{(E \times F)_n}$. The aggregation function aided in reducing the size of the feature space without impacting feature quality.

### II-E. Classification

A recent study For EEG binary classification [18] indicated that LightGBM is one of the most effective classifiers based on decision trees in terms of time and performance. Therefore, we used the LightGBM machine learning algorithm for classification in this study. LightGBM is a gradient-boosting decision trees framework that utilizes a tree-based learning algorithm. It is efficient in memory usage, trains quickly, and produces accurate results [32]. Hyperopt [33] was utilised to determine the optimal hyperparameters for LightGBM.

## III. Results and Discussion

### III-A. Performance Evaluation

It can be observed from Table 1 that TUSZ multi-class dataset has an issue with class imbalance. In comparison to the other classes, FNSZ, GNSZ, and CPSZ classes have higher number of occurrences in the data. With this asymmetrical class distribution, the accuracy alone cannot adequately describe the performance of the utilized methods. As a result, the performance of our methods is evaluated using the average weighted F1-score.

Moreover, two separate cross-validation scenarios are used to evaluate performance comparison between the feature extraction methods. The first scenario is seizure-wise cross-validation, where the dataset is randomly divided into five-folds, which is the method used in all prior studies using the same dataset [8, 14, 23, 24]. In general, five-fold cross-validation involves randomly allocating the proportional distribution of classes throughout the whole dataset into five-folds. The second scenario is patient-wise cross-validation, in which the data is divided into three folds; in each fold, the data were divided into training and testing subsets, ensuring that seizures in the training and testing subsets are from distinct patients.

### III-B. Experimental Results

This section compares the obtained results for each of the experiments for three different wavelet-based feature extraction methods.

### III-B1. *Evaluation at the Seizure Level*

In this evaluation, we evaluated our three decomposition methods for seizure-wise cross-validation for both seven-class and five-class problem. Table 3 presents the obtained results for each experiment for all three methods. For the seven-class problem, it is clear that the best-obtained results among the three signal decomposition methods were %89.9 and %89.8, which were both achieved by DTCWT in Experiment 1 and 3, respectively. Similarly, WPD-based feature extraction provided the second-best results with a slightly small difference, achieving the weighted F1-score of 89.6%in Experiment 1 and 89.2% F1-score in Experiment 3. At the same time, using DWT, the best result was 89.2% in experiment 3. Overall, Experiment 2 was the worse case in all decomposition techniques, providing the F1-score of 87.6%, 86.7%, and 86.0% for WPD, DTCWT, and DWT, respectively. Figures 5, 6 and 7 present the classification performance in terms of F1-score for each class for all three classification problems. The results in Table 3 demonstrate that in all decomposition techniques, the combination of features in Experiment 1 and 3 significantly outperform the combination of features used in Experiment 2. Moreover, although DTCWT-based features provided the best results in two experiments, WPD's results in all experiments show very competitive results that are only lower by a very small margin than the best-obtained result.

For the classification of five classes when only the specific seizure types are considered, the best-achieved results among the three decomposition techniques were 95.8% and 95.3% in Experiment 1 and 3 respectively, using DTCWT. WPD and DWT-based features in Experiment 1 have almost similar performance, achieving 95.1% F1-score. Similar to the seven-class classification problem, the feature set in Experiment 2 across all decomposition techniques did not perform well among the three, providing 94.5%, 93.3% and 91.9% using WPD, DTCWT and DWT, respectively.

From the results in Table 3, it is important to mention that WPD based feature extraction show more stable performance among the three experiments as the results have a tiny difference that is less than 1 point between the top and worse combination of features. On the other hand, the findings from the three experiments employing DTCWT and DWT indicate a larger gap between the top and the worst feature sets, ranging between 2.5 and 3.2 points for DTCWT and DWT, respectively.

Table 3. Performance comparison of F1-score (%) for different feature extraction methods at the seizure level and patient level

| | | WPD | | | DTCWT | | | DWT | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Validation | EXP1 | EXP2 | EXP3 | EXP1 | EXP2 | EXP3 | EXP1 | EXP2 | EXP3 |
| 7 classes | Seizure-wise | 89.6 | 87.6 | 89.2 | **89.9** | 86.7 | 89.8 | 88.4 | 86.0 | 89.2 |
| | Patient-wise | 63.1 | 63.4 | **64** | 63.2 | 59.44 | 63.9 | 58.6 | 59.7 | 63.3 |
| 5 classes | Seizure-wise | 95.1 | 94.5 | 94.9 | **95.8** | 93.3 | 95.3 | 95.1 | 91.9 | 94.3 |
| | Patient-wise | 62.3 | **66.6** | 65.9 | 65.4 | 60.9 | 65.7 | 61.4 | 62.2 | 63.4 |
| 2 classes | Seizure-wise | 92.73 | 92.123 | 93.06 | **93.29** | 91.64 | 93.24 | 92.54 | 91.72 | 93.04 |
| | Patient-wise | 82.61 | 80.19 | **83.97** | 81.26 | 75.98 | 80.23 | 77.47 | 77.089 | 81.52 |

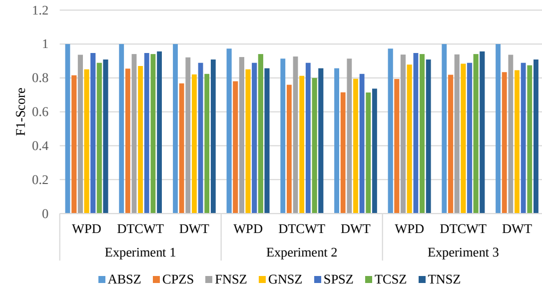


Figure 5. The classification results for the seven-class problem

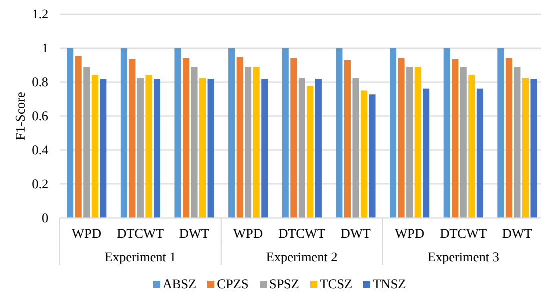


Figure 6. The classification results for the five-class problem

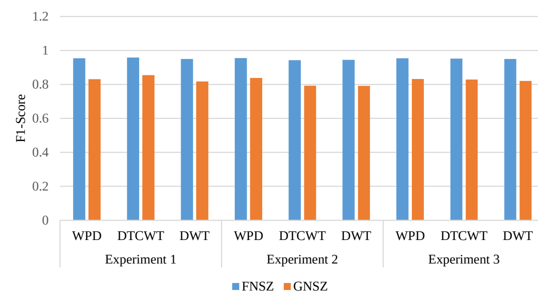


Figure 7. The classification results for the two-class problem

For the classification between Focal seizures and generalized seizures, the results in Table 3 show a similar pattern for the seven-class and five-class problems. The best-obtained results are 93.29% and 93.24%, both achieved through DTCWT in two different experiments 1 and 3 respectively. WPDs' results come after DTCWT with a very small margin and more stable performance over all of the experiments. Like WPD, the top-performing feature set for DWT is in Experiment 3.

In summary, at the seizure level, we have observed that DTCWT and WPD based feature extraction are superior to DWT. Moreover, the combination of features in Experiment 1 is a very discriminative set of features compared to the features used in Experiment 2, which obviously has a noticeable impact on the results of Experiment 3. Moreover, the use of all features from Experiment 1 and 2 combined in Experiment 3 has shown a slightly improved results.

### III-B2. *Evaluation at the Patient Level*

This evaluation scenario is more challenging as the data used for testing is always from new patients whose data has never been used in the training phase; in other words, the data used for training is generalized to unseen patient data. Again in this evaluation scenario, we compare the obtained results for each of the decomposition methods for three different experiments: seven-class, five-class, and two-class problems.

Interestingly, for each of the decomposition methods, the best performing feature set is when we utilized all of the six features (Experiment 3). The best-obtained results were 64% and 63.9% achieved by WPD and DTCWT respectively. DWT, on the other hand, provided the results of F1-score of 63.3%, which is still not very low as compared to the top-performing methods. Overall, the performance of WPD-based features demonstrates a more stable performance in every experiment.

For the five-class problem at the patient level, the obtained results show a similar pattern to seven-class problem except for WPD based feature. The best-obtained results were the F1-score of 66.6% and 65.9% achieved by WPD in Experiment 2 and 3, respectively. The F1-score of 65.7% and 65.4% were the second-best achieved results; both were obtained using DTCWT in Experiment 3 and 1 respectively. DWT-based features demonstrate lower performance compared to the other decomposition techniques. Importantly, DTCWT based features in Experiment 1 and 3 show very close results compared to WPD-based features. However, in Experiment 2, DTCWT always provided low results as compared to WPD. For a two-class problem, the numbers in Table 3 demonstrate the superiority of WPD-based features compared to the other two decomposition techniques.

### III-C. *Comparison with Previous Studies*

To demonstrate our proposed technique's success, we compare our findings to those of previously published research. In the literature, there are few studies that considered the problem of seizure type classification as shown in Table 4. It is tricky to compare our proposed methods with the studies in Table 4, as each of the studies chooses a different number of classes for classification and different evaluation criteria. Moreover, most of the published studies utilized the older version of TUSZ dataset (TUSZ v1.4.0), which has fewer samples than the existing version. In addition, the majority of previous research studies only considered seizure-wise cross-validation technique in which the data are split into training and testing subsets without considering the patient's specific data. This is a common limitation for most of the previous research studies as this technique leads to the data from one patient being present during training and testing phases, which may lead to a good performance at the seizure level and a lower performance at the patient level. Fortunately, [14, 23] are the only published studies that considered the generalization of their proposed models to be evaluated on unseen patients data.

Table 4. Performance comparison of previous works with proposed method for Multi-type seizure classification

| Method | No. of seizure classes | Performance Evaluation(%) Seizure_wise | Patient_wise |
|---|---|---|---|
| Inceptionv3[25] | 8* | 88.3 Accuracy | – |
| AlexNet[26] | 8* | 84.06 Accuracy | – |
| CNN+LSTM+MLP[8] | 8 | 97.40 F1-score | – |
| SeizureNet[14] | 7 | 95 F1-score | 62 F1-score |
| NMN[24] | 7 | 94.5 F1-score | – |
| K-NN[23] | 7 | 90.1 F1-score | 40 F1-score |
| XGBoost[23] | 7 | 85.1 F1-score | 54.2 F1-score |
| **Proposed method using WPD** | 7 | 89.6 F1-score | **64 F1-score** |
| **Proposed method using DTCWT** | 7 | 89.9 F1-score | **63.9 F1-score** |
| **Proposed method using DWT** | 7 | 89.2 F1-score | **63.3 F1-score** |

*Including non-seizure EEG class.

It can be observed from Table 4 that it is challenging when a model is tested on data from new patients. All proposed methods in Table 4 showed a very low performance at the patient level while achieving very good results at the seizure level. However, our proposed method in all three wavelet-based feature extraction, namely, DWT, DTCWT and WPD, show better results when tested on data from new patients. For the seven-class problem, Asif et al., [14] reported the best result of 62% F1 score at the patient level using a deep learning framework, SeizureNet, with ensemble learning and multiple DensNets. Roy et al., on the other hand, stated that their proposed FFT-based feature extraction and XGBoost yielded the results 54.2% F1-score. Our proposed methods outperform the state-of-the-art result by more than 2%, achieving the results of 64%, 63.9% and 63.3% F1-scores using WPD, DTCWT and DWT, respectively.

## IV. CONCLUSIONS

In this paper, we have investigated three different wavelet-based feature extraction methods for the task of multi-type seizures classification using EEGs. We have explored these feature extraction techniques in three different experiments with different sets of statistical features. Moreover, we have investigated different seizure types classifications based on their medical categorization in 7-class, 5-class and 2-class problems. The finding of the experiments indicates that the WPD and DTCWT based features are more superior to DWT. The results demonstrate better classification results by the proposed wavelet-based technique as compared to the existing studies for patient-wise cross-validation. Our proposed technique also show better generalization capability using the world's largest available seizures dataset, achieving F1-scores of 64%, 66.6% and 83.97% for 7-class, 5-class, and 2-class problems respectively. In future, we plan to employ deep learning techniques to learn from the wavelet-based extracted features for better comparison and classifications.

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