Intelligent Methodology Using Machine Learning for Epileptic Seizure Identification Based on Time-Frequency Analysis of EEG Signals

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Abstract. The diagnosis of epilepsy is conducted through visual inspection of electroencephalogram (EEG) signal recordings. However, due to the variations in convulsive disorders, it can be challenging for clinicians to constantly monitor the patient for seizure type, especially because EEG records contain hours of signal. Nevertheless, these patterns present in EEG signals can also be identified through signal classification methods based on signal processing and machine learning approaches. In light of this, this study proposes the development of a methodology for epileptic seizure type classification based on analysis of time-frequency characteristics of EEG signals, using Continuous Wavelet Transform (CWT) and joint moments of time-frequency distribution. Epileptic seizure classification was performed using a convolutional neural network (CNN), employing k-fold cross-validation methods. Accuracy, sensitivity, specificity, and area under the curve (AUC) metrics were obtained to validate this algorithm. The achieved results for the CNN classifier were 96.54% accuracy, 96.54% sensitivity, 96.54% specificity, and AUC = 0.90%.

Keywords: Electroencephalogram Signal (EEG); Epileptic Seizures; Time-Frequency Feature Extraction; Machine Learning; Convolutional Neural Network (CNN).

1 Introduction

Epilepsy is a chronic brain syndrome characterized by abnormal electrical activities of neurons, potentially resulting in recurrent and spontaneous seizures. It is estimated that over 50 million people worldwide are diagnosed with epilepsy, making this neurological disorder one of the most common globally [1] [2]. To confirm the diagnosis of epilepsy, a non-invasive technique called Electroencephalography (EEG) is used. In this examination, multiple electrodes are placed on the individual's scalp to capture the electro-physiological activity from the brain, with each electrode corresponding to a distinct channel. The result of these measurements is the electroencephalogram (EEG), which consists of the set of signals recorded in each channel by the cranial electrodes [3].

Epileptic seizures detection is a fundamental step in the diagnosis of epilepsy and for seizure control. Moreover, the identification of different types of crises can help to determine the original location and pattern of seizures, enabling appropriate prescription of treatments, whether through medication or surgery [4]. This process involves visual observation of EEG recordings by experienced neurophysiologists in clinical practice. Through this visual analysis, it is possible to identify and classify the seizure present in the EEG signal. Typically, the recording is multi-channel, which makes the investigation a complex and time-consuming task. Humans become more susceptible to making errors due to fatigue when carrying out a demanding task such as analysis a signal on monitor for long periods. In this context, automate the process of analysis of signals obtained through EEG could result in more efficient diagnosis [4].

Automated detection systems, developed using signal processing techniques and machine learning, are excellent tools for analyzing complex, non-stationary, and nonlinear EEG signals [5]. Automated EEG analysis often involves extracting features from EEG signals in different domains, such as time, frequency, and time-frequency, as well as analysis of nonlinear signals. In frequency domain techniques, the spectra of EEG signals are obtained using Fourier Transform (FT) or Fast Fourier Transform (FFT), followed by feature extraction from the spectra. In joint time-frequency techniques, a two-dimensional (2D) time-frequency representation is obtained using Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT) [7]. In this way, appropriate discriminative features of transformed EEG signals are extracted. Generally, statistical features of first, second, and third orders, such as mean, variance, kurtosis, and skewness, are obtained independently. In this work, feature extraction related to joint moments of the generated time-frequency spectrogram (CWT) is performed.

After obtaining appropriate features, the final step involves applying a suitable classifier. In the literature, various classifiers are proposed for binary and multiclass classification of different subsets (classes) of EEG signals. For example, [8] investigated the use of different machine learning (ML) and deep learning (DL) based algorithms for epileptic seizure detection. The algorithms considered include conventional ML (ANN, SVM, and KNN), advanced DL (CNN/RNN/LSTM), and RF-based ML.

Thus, this study proposes the development of an automatic methodology to assist neurologists in classifying types of epileptic seizures based on EEG signal processing. Continuous Wavelet Transform (CWT) and Joint Moments are used for feature extraction in the time-frequency domain, in addition to employing a Convolutional Neural Network (CNN). The types of seizures studied in this investigation were non-specific generalized seizure (GNSZ), complex partial seizure (CPSZ), non-specific focal seizure (FNSZ), and tonic-clonic seizure (TCSZ).

2 Epileptic seizures

Epilepsy is a neurological condition characterized by recurrent episodes of abnormal brain activity, known as epileptic seizures. This condition can manifest in various forms and present a wide range of types. One way to classify epilepsy is according to the Operational Classification of Seizure Types by the International League Against Epilepsy (ILAE) of 2017 [9]. According to the origin of the seizures, they can be focal, starting in a specific part of the brain, or generalized, involving the entire brain activity in a widespread manner. An epileptic seizure consists of the transient occurrence of signs resulting from excessive abnormal brain activity. In the focal aware seizure, the individual is conscious of themselves and their surroundings while experiencing the seizure. During a focal impaired awareness seizure, loss of consciousness occurs. In addition to classification regarding perception, seizures can be sub grouped into motor symptoms and signs seizures, affecting muscle activity, or non-motor at seizure onset. Focal seizures that evolve into bilateral tonic-clonic seizures originate in one hemisphere of the brain but spread to the entire brain as time progresses. Generalized non-motor onset seizures, also called absence seizures, only have a duration of a few seconds and are characterized by loss of awareness with the surroundings or the individual. It is worth noting that the ILAE 2017 classification may present specific subcategories in motor and non-motor symptoms seizures. Seizures of unknown onset may be labeled as unclassified, referring to situations where it is not possible to determine the onset of the seizure [9].

3 Signal processing in the time-frequency domain

Signal processing in the time-frequency domain encompasses a set of methods, techniques, and algorithms that analyze the information contained in a signal simultaneously in the time and frequency domains. This approach allows for a more comprehensive understanding of the signal's behavior over time and across different frequencies. One of the main advantages of signal processing in the time-frequency domain is its ability to capture information about the temporal evolution and spectral composition of the signal. While traditional techniques, such as the Fourier transform, provide information only about the frequencies present in the signal at a given moment in time, time-frequency representations enable visualization of how the different frequency components of the signal change over time. This joint approach to the temporal and spectral behavior of the signal provides a deeper and more comprehensive understanding of the signal under study. This is because the two classic variables representing the signal, time (t), and frequency (f), are used concurrently to represent the signal, allowing for a more complete and detailed analysis.

3.1 *Wavelet transform*

The Continuous Wavelet Transform (CWT) is a linear integral transform that can be employed in the analysis of features of non-stationary signals. It is useful for extracting information about variations in certain frequency bands and/or for detecting local structures present over [10]. Given a signal x, its integral transform is defined as:

$$X_{TCW}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t)\, \psi^*\left(\frac{t-\tau}{s}\right)\, dt \tag{1}$$

The transform of the signal $X_{TCW}(\tau, s)$ is a function that depends on the translation parameter τ and the scale parameter s. The mother wavelet function ψ^* indicates that the complex conjugate is used in the case of a complex wavelet. The signal's energy is normalized at each scale by dividing the wavelet coefficients by $1/\sqrt{s}$. This ensures that the wavelets have the same energy at all scales [11]. The wavelet function is contracted and dilated by changing the scale parameter s. Variation in scale s alters not only the central frequency f_c of the wavelet but also the length of the window. Thus, the scale s is used instead of frequency to represent the results of the Continuous Wavelet Transform. The translation parameter τ specifies the location of the wavelet in time; through this alteration, the wavelet can be shifted over the signal [11]. By keeping the scale s constant and varying the translation τ, the lines of the time-scale plane are filled; by varying the scale s and keeping the translation τ constant, the columns of the time-scale plane are filled. The elements in $X_{TCW}(\tau, s)$ are called wavelet coefficients, where each wavelet coefficient is associated with a scale (frequency) and a point in the time domain.

3.2 *Joint Moments of the Time-Frequency Distribution*

The moments of the time-frequency distribution provide an efficient way to characterize signals whose frequencies vary over time, i.e., are non-stationary [12][13]. The time-frequency distribution generated by time-frequency analysis techniques captures the behavior of signal frequency variations over time. However, treating these distributions directly as signal attributes can result in high computational burden and potentially introduce unrelated and undesirable characteristics.

On the other hand, obtaining low-dimensional time-frequency domain moments offer a method to capture the essential signal characteristics in a much smaller data package. The use of these moments significantly reduces the computational burden for feature extraction and comparison—a fundamental benefit for real-time operation [12][13][14].

The joint time-frequency moments of a non-stationary signal comprise a set of time-varying parameters that characterize the signal spectrum as it evolves over time [12][13][14]. In theory, the joint time-frequency moments of a signal, for the non-centralized case, can be directly obtained through (2):

$$\langle t^n \omega^m \rangle = \iint t^n \omega^m \rho(t, \omega)\ dt d\omega \tag{2}$$

Similarly, for the conditional spectral moment $\langle t^n \rangle_\omega$ of order n and for the conditional temporal moment $\langle \omega^m \rangle_t$ of order m of a signal, respectively (3) and (4),

$$\langle t^n \rangle_\omega = \frac{1}{P(\omega)} \int t^n \rho(t, \omega)\ dt \tag{3}$$

$$\langle \omega^m \rangle_t = \frac{1}{P(t)} \int \omega^m \rho(t, \omega)\ d\omega \tag{4}$$

So, it is possible to obtain the joint moments by (5)

$$\langle t^n \omega^m \rangle = \int t^n \langle \omega^m \rangle_t P(t)\, dt = \int \omega^m \langle t^n \rangle_\omega\, P(\omega) d\omega \tag{5}$$

In the presented equation, P(t) and P(ω) represent the time and frequency distributions, respectively, of the time-frequency distribution ρ (t, ω). Additionally, each moment is associated with a specific order set, with the first four orders being the statistical properties of mean, variance, skewness, and kurtosis [12][13].

4 Methodology

This study aims to develop an intelligent methodology for the identification of different types of epileptic seizures, including non-specific generalized (GNSZ), complex partial (CPSZ), non-specific focal (FNSZ), and tonic-clonic (TCSZ). The adopted approach involves extracting joint moments from the time-frequency distribution of the EEG signal, obtained through Continuous Wavelet Transform, using Convolutional Neural Networks (CNN). Figure 1 presents the schematic diagram of the proposed epileptic seizure classification to be developed.

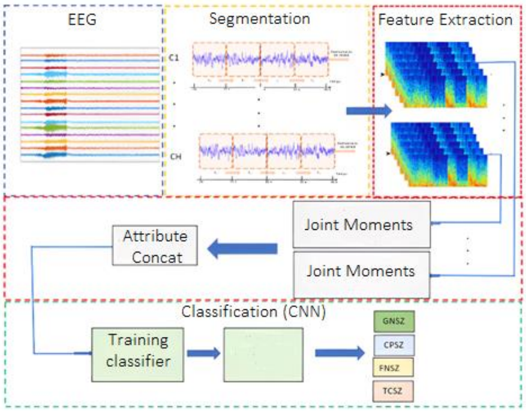

Fig. 1 Schematic diagram of the proposed methodology

4.1 *Database*

The EEG signals used in this study were obtained from the public database TUSZ (The TUH EEG Seizure Corpus), which is a subset of the database known as TUEG (The Temple University Hospital EEG Data Corpus), provided by the Temple University Hospital (TUH) in Philadelphia, Pennsylvania. TUSZ is recognized as the largest currently available open-source dataset, focused on epileptic patients, and offers high-quality annotations for different types of epileptic seizures, along with detailed patient metadata describing the clinical history [15].

The EEG recording sessions were conducted while patients were at rest, following established technical standards for clinical manifestations. Sampling rates vary in the database but are always at least 250 Hz. The electrodes were positioned on the patients' scalps according to the international 10/20 system, resulting in examinations with 22 channels [16].

4.2 *Preprocessing of EEG Signal*

For this study, we selected EEG signals from 60 patients who exhibited four different types of epileptic seizures: GNSZ, CPSZ, TCSZ, and FNSZ. These types of seizures were chosen due to their representativeness, as they involve a larger number of patients, providing a robust sample for analysis. Additionally, these categories encompass both focal and generalized seizures, covering a variety of epileptic manifestations, as discussed in other studies [17][18].

Initially, the signals from each channel were segmented into 10-second intervals and windowed using the rectangular function, without overlap, as described by [15]. This resulted in 1200 10-second segments of EEG signals for each type of seizure, totaling 4800 segments for analysis. As there is no consensus in the specialized literature regarding the ideal segment size for EEG signal analysis [15], we explored four different durations: 0.5 s, 1 s, 5 s, and 10 s, in order to determine the most suitable for our methodology.

4.3 *Feature Extraction of EEG Signal*

Prior to the feature extraction step, the set of matrices M^j was obtained from the T-th multichannel segment of the EEG signal, containing ch channels, of pattern j to be recognized, i.e., the classes GNSZ, CPSZ, FNSZ, and

TCSZ, as described in (6):

$$M^j = \{ X_1^j, X_2^j, X_3^j \dots., X_T^j \} \tag{6}$$

X is a matrix containing EEG signal samples of size $ch \times n$, where n is the number of samples per segment, given by the multiplication of the segment duration T=10s by the sampling frequency fa. Following the formation of set M^j, the feature extraction step is performed. In this phase, the Continuous Wavelet Transform Morse, Morlet, and Bump are applied to each row of matrix X belonging to set M^j, where each row of matrix X represents a channel of the EEG signal. Thus, for the T-th matrix of M^j, three sets of time-frequency energy distribution matrices are obtained for each TCW, represented by (7):

$$\zeta^j(t,f) = \left\{ \begin{bmatrix} W_1^{(t,f)} \\ W_2^{(t,f)} \\ \vdots \\ W_{ch}^{(t,f)} \end{bmatrix}_1, \begin{bmatrix} W_1^{(t,f)} \\ W_2^{(t,f)} \\ \vdots \\ W_{ch}^{(t,f)} \end{bmatrix}_2, \begin{bmatrix} W_1^{(t,f)} \\ W_2^{(t,f)} \\ \vdots \\ W_{ch}^{(t,f)} \end{bmatrix}_3, \dots, \begin{bmatrix} W_1^{(t,f)} \\ W_2^{(t,f)} \\ \vdots \\ W_{ch}^{(t,f)} \end{bmatrix}_T \right\} \tag{7}$$

Where

$$W_{ch}^{(t,f)}(M\ x\ n) = \begin{bmatrix} W_{s_1}1 & W_{s_1}2 & \dots & W_{s_1}n \\ W_{s_2}1 & W_{s_2}2 & \dots & W_{s_2}n \\ \vdots & \vdots & \ddots & \vdots \\ W_{s_M}1 & W_{s_M}2 & \dots & W_{s_M}n \end{bmatrix} \tag{8}$$

It is the time-frequency energy distribution matrix of the ch-th channel of the T-th segment. M is the number of analysis scales of the Continuous Wavelet Transform, s_M is the M-th scale of the TCW, and $W_{s_M n}$ is the n-th coefficient of the TCW at scale s_M.

Once the set $\zeta^j(t,f)$ is formed, four joint time-frequency moments are generated from the ch-th matrix $W_{ch}^{(t,f)}$ of the T-th segment: joint mean - μ(t,f) (9), joint variance – $\sigma^2_{(t,f)}$ (10), joint skewness – λ(t,f) (11), and joint kurtosis – κ(t,f) (12). Thus, four sets of statistical metrics are obtained for the different TCW:

$$\mathcal{M}^j_{\mu_{(t,f)}} = \{ Md_1^j, Md_2^j, Md_3^j, \dots, Md_T^j \} \tag{9}$$

$$\mathcal{V}^j_{\sigma^2_{(t,f)}} = \{ Var_1^j, Var_2^j, Var_3^j, \dots, Var_T^j \} \tag{10}$$

$$\mathcal{A}^j_{\lambda_{(t,f)}} = \{ Ass_1^j, Ass_2^j, Ass_3^j, \dots, Ass_T^j \} \tag{11}$$

$$\mathcal{K}^j_{\kappa_{(t,f)}} = \{ Curt_1^j, Curt_2^j, Curt_3^j, \dots, Curt_T^j \} \tag{12}$$

Where

$$Md_T^j = \begin{bmatrix} \mu_{(t,f)}{}^1 \\ \mu_{(t,f)}{}^2 \\ \vdots \\ \vdots \\ \mu_{(t,f)}{}^{ch} \end{bmatrix}_{chx1} \quad (13) \qquad Var_T^j = \begin{bmatrix} \sigma^2_{(t,f)}{}^1 \\ \sigma^2_{(t,f)}{}^2 \\ \vdots \\ \vdots \\ \sigma^2_{(t,f)}{}^{ch} \end{bmatrix}_{chx1} \quad (14) \quad Ass_T^j = \begin{bmatrix} \lambda_{(t,f)}{}^1 \\ \lambda_{(t,f)}{}^2 \\ \vdots \\ \vdots \\ \lambda_{(t,f)}{}^{ch} \end{bmatrix}_{chx1} \quad (15) \quad Curt_T^j \begin{bmatrix} \kappa_{(t,f)}{}^1 \\ \kappa_{(t,f)}{}^2 \\ \vdots \\ \vdots \\ \kappa_{(t,f)}{}^{ch} \end{bmatrix}_{chx1} \quad (16)$$

Therefore, the attributes extracted from the channels of each segment, given in equations (13), (14), (15), and (16), are aggregated by concatenating the mean of the attribute sets. Thus, each class GNSZ, CPSZ, FNSZ, and TCSZ is characterized by the set $\mathcal{VC}^j$ composed of the attribute vector $\mathcal{VC}^j$, whose elements are the integration indices of the time-frequency moments $Ec_{\mu_{(t,f)}}, Ec_{\sigma^2_{(t,f)}}, Ec_{\lambda_{(t,f)}}, Ec_{\kappa_{(t,f)}}$(17):

$$\mathcal{VC}^j = \{ Ve_1^j, Ve_2^j, Ve_3^j, \dots, Ve_T^j \} \tag{17}$$

4.4 *Classification*

After the extraction and vectorization of the time-frequency characteristics, the data were analyzed to identify possible anomalies, trends, and patterns. We used the K-fold method to randomly divide the datasets into 10 subsets, each with approximately the same number of samples. Eighty percent of the dataset was allocated for training the CNN model, allowing us to assess the algorithm's robustness in the face of data changes. The remaining twenty percent was reserved as a test set to evaluate the model's validity. Our proposed pattern classification model aims to classify an input signal into four categories: GNSZ, CPSZ, FNSZ, and TCSZ. We developed the CNN model using the Python language, with the Keras programming interface and the TensorFlow library. Initially, we established a base model with convolutional networks and proceeded to evaluate its performance, adjusting hyperparameters such as the number of filters and kernel size to different values. Hyperparameter tuning was performed using the GridSearch algorithm from the Scikit-learn library, seeking the best combination of values for each of them. Based on this tuning, we designed the 18-layer CNN model, composed of CNN-1D convolutional layers, BatchNormalization, Flatten, and MLP layers, as illustrated in Figure 2.

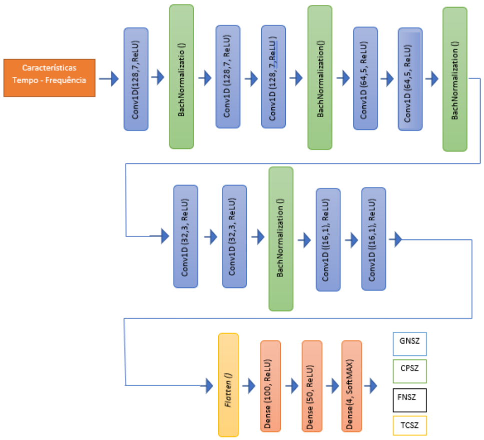

Fig. 2 CNN Classifier Model

The performance of the proposed CNN model in discriminating the classes was evaluated using metrics such as accuracy, sensitivity, specificity, precision, area under the ROC curve (AUC), and confusion matrix.

5 RESULTS

The results of the CNN model training can be observed in Table 1. The model achieved an accuracy of 96.54%, precision of 96.54%, sensitivity of 96.54%, specificity of 96.54%, and an AUC of 90%. These numbers demonstrate the effectiveness of the model in classifying epileptic seizures with high accuracy and consistency.

TABLE 1 - CNN MODEL RESULTS.

Metrics	Value (%)
Accuracy	96,54
AUC (Area Under Curve)	90,00
Sensitivity	96,54
Precision	96,54
Specificity	96,54

Fig. 3 Confusion Matrix for Classification of the Proposed CNN Model

The confusion matrix presented in Figure 3 illustrates the classification results of the CNN model for the four classes of epileptic seizures: GNSZ, CPSZ, FNSZ, and TCSZ. The values in the diagonal cells indicate the percentage of correct classifications, while the values off the diagonal represent the percentage of incorrect classifications. It is noted that the model achieved high rates of correct classification for all classes, with 98.29% for GNSZ, 97.28% for CPSZ, 98.67% for FNSZ, and 91.92% for TCSZ. Although the lowest rate of correct classification was observed for the TCSZ class, the model still achieved considerable performance in this category.

For comparative analysis, the results of the proposed model were compared with those of other studies that used the same TUSZ database for the classification of epileptic seizures. Table 2 presents the performance of different intelligent algorithms, highlighting metrics such as accuracy (acc.), sensitivity (sen.), specificity (spec.), precision (pre.), F1 Score (F1), and area under the ROC curve (AUC). It is observed that the CNN model proposed in this study outperforms most of the algorithms presented and exhibits performance comparable to high-performance models based on Long Short-Term Memory (LSTM) networks. These results emphasize the effectiveness and robustness of the proposed model in the classification of epileptic seizures.

TABLE 2 - PERFORMANCE OF DIFFERENT INTELLIGENT ALGORITHM MODELS

AUTHORS	CLASSIFIERS	METRICS (%)
Golmohammadi et al., 2017 [19]	CNN/LSTM	sen 30.83 spec 97.10
Wijayanto et al., 2019 [20]	SVM	acc 95
Vanabelle et al., 2019 [17]	Gradient Boosting	sen 71,6; pre 40.01
Saputro et al., 2019 [21]	SVM	spec 76,41
Stragier; Vanabelle; Tahry, 2021 [22]	XGBoost	sen 90.25 spec 97.83 acc 91,4
Abou-Abbas et al., 2022 [23]	Random Forest	sen 61.4 spec 89.6 F1 37.2
Thuwajit et al., 2022 [24]	CNN	AUC 95 pre 91 F1 S 91
He et al., 2022 [25]	GAT + BiLSTM	acc 98.02 sen 97.7
Ayodele et al., 2020 [26]	CNN	spec 99.06 auc 97.8 sen 72,5

6 Conclusion

This study presented a methodology for the accurate identification of epileptic seizures, using a convolutional neural network (CNN) model to categorize EEG signals according to the type of seizure, based on features extracted in the time-frequency domain. The results obtained demonstrated a high rate of correct classification for all classes of seizures studied: GNSZ, CPSZ, FNSZ, and TCSZ.

The application of deep CNNs to differentiate and classify epileptic seizures based on time-frequency features, including continuous wavelet transform and joint moments, proved highly effective in the accurate identification of epileptic seizures. This method offers a promising approach for early diagnosis and the development of personalized therapies for patients with epilepsy.

The results obtained in this study provide solid evidence that the use of advanced signal processing techniques and machine learning can aid in the diagnosis and treatment of epilepsy. This approach not only assists medical professionals in making more accurate diagnoses but also offers the opportunity for prescribing more appropriate therapies tailored to the individual needs of each patient.

Furthermore, by eliminating the unpredictable nature of epileptic seizures, this method contributes significantly to improving the quality of life of patients affected by this debilitating medical condition. The accurate prediction of epileptic seizures enables faster and more effective intervention, reducing the risks associated with these events and providing greater safety and well-being to patients and their caregivers.

Ultimately, this study represents a significant advancement in the field of epilepsy, highlighting the potential of signal processing and machine learning approaches to improve the diagnosis, treatment, and quality of life of patients affected by this complex neurological condition.

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