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Effectiveness of Multi Input Data and a Novel CNN Model for Epilepsy Classification

Chekhmane Ghezala*, Benali Radhwane

Biomedical Engineering Laboratory, Faculty of Technology, Abou Bekr Belkaid University, Tlemcen 13048, Algeria

Corresponding Author Email: ghezala.chekhmane@univ-tlemcen.dz

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ABSTRACT

Electroencephalogram (EEG) signals are crucial and promising tools used to diagnose of epilepsy through several sensor electrodes placed on the head scalp. Meanwhile, these signals are complex and difficult to analyze visually by neurologists and are considered time-consuming tasks. Recently, deep learning (DL) is the challenge in the epileptic disease classification. In this work, a novel CNN model is proposed to detect seizures based on signal processing methods and DL. Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) are applied to transform EEG signals from time domain to time-frequency (TF) domain. Then, the converted signals and augmentation of data are used as multi-input data (MID) for classification using CNN. Therefore, this CNN architecture established by using two layers for feature extraction and classification of MID. As results, the proposed MID-CNN model confirmed higher accuracy of 100% to distinguish between normal and seizures. Moreover, the comparison of this work with different studies in the literature review showed that the proposed MID-CNN model increases the performance of epileptic seizure classification than previous works. Finally, the effectiveness of using MID-CNN network is verified and can be used for clinical diagnosis of epileptic disease.

1. INTRODUCTION

Electroencephalogram (EEG) signals are the measurement of the neural activity, which can be recorded by sensor electrodes placed on the head scalp according to the international 10-20 system [1, 2]. Initially, this device was invented by Hans Berger in 1924 [3], which is considered one of the most useful and prominent tools for the diagnosis of epileptic disease. It was estimated that nearly about 1% of the population in the world is affected by epilepsy at any age. Thus, this disease is characterized by synchronous and excessive neuronal activity of the brain provoked by uncontrolled recurrent attacks [4, 5]. Therefore, the normal EEG signals composed of rhythms that are ranged from low to high-frequency bands recognized as Delta (δ) between 0.5 and 4 Hz, Theta (θ) between 4 and 8 Hz, Alpha (α) between 8 and 13 Hz, Beta (β) between 14 and 30 Hz, and Gamma (γ) more than 30 Hz [3, 4, 6]. Thus, up of these frequency bands are corresponds to the seizure onset (ictal state) [7]. In addition, normal EEG's amplitude sits on range of 10 and 100 µV, and the amplitude of abnormal EEGs is about 0.5 and 1.5 mV [8]. Previously, these patterns of frequency and amplitude generally are used for diagnosis of epileptic seizures which are visually analyzed by clinical experts to identify whether that patient has epilepsy or not. This inspection needs more clinical experiences and efforts. Therefore, this procedure is laborious and cumbersome tasks that it takes long time because of the EEG signals are complexity and nonstationary, especially for long-term EEG recordings. Moreover, EEG signals are contaminated by several artifacts and noises generated by muscles and eyes movements, cardiovascular activity and other non-physiological artifacts such as power line of 50 Hz [7, 8]. These limitations provide changes in their waveforms and disrupts the presence of epileptic disease which can make misdiagnosis. Recently, the evolution of artificial intelligence (AI) is the challenge in many fields including neuroscience research, such as the automatic detection of epileptic seizures. Machine learning (ML) has been applied for detection of seizures using EEG signals to improve the classification accuracy. The mechanism of ML based on manual extraction of statistical features by using different methods of signal processing. Then, the classification process is based on training of selected features and classified into different categories [9]. More recently, the potential of using deep learning (DL) in many research studies have been validated that achieved remarkable result and better analysis of data. DL facilitates learning of relevant patterns automatically for classifying epileptic seizures without manual feature extraction [10, 11]. Convolutional neural network (CNN) is one of the most successful DL architecture due to their capacity of learning spatial features. CNN unit was inspired from the visual cortex mechanisms, that it has the ability to extract complex patterns for making decisions [1, 8]. Furthermore, the basic structure of CNN network consists of layers including convolution layer, ReLU layer, pooling layer and fully connected layer. These layers learn input features and classified them to make final decision according to output classes [3]. CNN can be applied not only in a one-dimensional (1D-CNN) but also in two-dimensional (2D-CNN), because it has great potential in biomedical signal and image processing [12].

2. LITERATURE REVIEW

Previously, Aliyu and Lim [6] presented a framework based on long short-term memory (LSTM) and DWT for the classification of epileptic EEG signals. For dimensionality reduction of features, the optimal features are selected using correlation coefficient, P-value analysis (CCP) and principal component analysis (PCA). After that, the authors compared this framework with other classifiers of ML, including logistic regression (LR), support vector machine (SVM), K-nearest neighbour (K-NN) and decision tree (DT). Dhar et al. [8] applied different signal processing techniques including LBP, empirical mode decomposition (EMD), FFT, and DWT. For EEG classification, a comparison study is established between MultiSVM and CNN-RNN which is similar to RESNET50 style architecture. It is demonstrated that the proposed CNN-RNN perform better to detect seizures.

Sun et al. [11] proposed a multi-input feature deep learning network (MDFLN) that two types of CNN are used (1D-CNN and 2D-CNN), for feature extraction from time domain and TF domain. After that, Bidirectional long short-term memory (BLSTM) network is used to distinguish between seizure and nonseizure events. Boonyakitanont et al. [12] compared between Artificial Neural Network (ANN) and CNN for EEG signals classification by using multiple feature selection implemented based on Fourier transform and Discret Wavelet Transform (DWT) in time, frequency, and time-frequency domains. Pan et al. [13] presented hybrid input formats of EEG signals including original EEG data, Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT) and DWT. Then, different types of features are fed into CNN network with feature fusion for the classification EEG. Hossain et al. [14] applied two-dimensional (2D) convolutional neural network (2D-CNN) to classify spectral, spatial and temporal features of EEG channels, for cross-patient seizure detection. The proposed system consists of four layers, two max-pooling layers and fully connected layer. Furthermore, Alharthi et al. [15] used KAU dataset and the CHB-MIT dataset for data integration Then, the datasets are preprocessed by DWT and classified by the proposed algorithm which combined one-dimensional CNN (1D-CNN) and bidirectional LSTM (BiLSTM) networks.

Xu et al. [16] combined one-dimensional convolutional neural network with long short-term memory (1D-CNN-LSTM) for automatic recognition of epileptic seizures. The raw EEG signals are pre-processed and normalized. Then, the combined 1D-CNN-LSTM is implemented. Mao et al. [17] applied Continuous Wavelet Transform (CWT) for processing of EEG signals. Then for classification, a comparison of three types of CNN is examined which are AlexNet, GoogleNet and the proposed CNN which is composed of three convolutional layers. Furthermore, Ru et al. [18] focused on data augmentation based on the Adversarial and Mixup Data Augmentation (AMDA) method. Then, 1D-CNN and gated recurrent unit (GRU) network and attention mechanism (AM) are combined (AM-1D CNN-GRU) for epilepsy detection. Khurshid et al. [19] proposed a deep neural network (DNN) to improve the performance of epileptic disease recognition. Nie et al. [20] established new approach based on fully-convolutional nested long short-term memory (FC-NLSTM) model, and FFT for feature extraction to classify epilepsy. Hassan et al. [21] presented hybrid network NeuroWave-Net based on combination of convolutional neural networks (CNN) and long short-term memory (LSTM) architectures for neurological diagnostics. In addition, Zhang et al. [22] used DWT for decomposition of EEG signals, and the classification approach for seizure detection and prediction was implemented with the combination of convolutional neural network and gated recurrent unit-attention mechanism. Irwan et al. [23] used multi-segments of EEG signal and STFT to convert these segments into spectrograms which are passed through CNN as inputs for classification, and the number of layers is used was three layers. Malekzadeh et al. [24] used a band-pass filter and Tunable-Q Wavelet Transform (TQWT) for removal artifacts and decomposition of the EEG signals from Bonn and Freiburg datasets. Then, various linear and nonlinear features are extracted from TQWT sub-bands. For classification, CNN-RNN approach is investigated.

The previous studies achieve higher accuracy for epilepsy classification. However, they are developed algorithms based on one method for processing of EEG dataset, that a small number of parameters are input to DL which cannot provide efficient information, and composed of many layers for learning of data [17, 23]. Other models are employed features in frequency domain of EEG signals which are lucking from patterns. Additionally, a view features and multi-inputs for DL are trained and tested for classification of EEG signals. However, it utilized many methods of processing of data and significantly high number of convolution layers for extraction of features [8, 11, 13]. These models are considered complex systems and need suitable methods for automatic analysis of EEG signals [25, 26]. On the other hand, several classifiers are combined that they increase the implantation time of features training [15, 16, 18, 22]. Thus, it is demonstrated that the CNN perform better than LSTM in such studies [6]. Although, previous works proved the usefulness of DL models for seizure detection, and many features extraction methods employed focused on improvement of classification performance. However, there are several works evaluated frameworks composed of a simple architecture of CNN, which processed a big data of the EEG signals through these models, and they can't learn high level of data [11]. Moreover, most of articles in the literature review are insufficient and presented low accuracy. In order to overcome and outperform these limitations for evidence analysis of EEG signals, and to achieve higher accuracy of classification and detection of seizures. Thus, to reduce the high computational and complexity architecture of the previous frameworks, that need long time which affects the classification performance of the model. This work established a novel MID-CNN model to classify input images with a data augmentation defined by multi-input data (MID) which are more powerful features. Furthermore, the purpose of this work is to enhance the performance accuracy. MID is investigated by using only two methods such as STFT and CWT to convert EEG signals into time-frequency domain, that these models integrate the advantages of both STFT and CWT to ensure more accurate information in time-frequency domain and augmentation of data. Then, the developed deep network based on MID-CNN network with a minimum and optimal number of convolution Layers is detailed to determine the ability and robustness of the model. Moreover, to prove the efficiency of this algorithm employing DL, it was compared with two classifiers of SVM including linear SVM (LSVM) and quadratic SVM (QSVM) that these classical classifiers of ML are based on manual extraction of features. The main contributions of this paper can be listed and presented as follows:

(1) Two classifiers of ML were examined by using SVM such as LSVM and QSVM. After decomposition with DWT of EEG signals, different features are extracted from sub-bands in time-frequency and nonlinear domains, and are classified by using LSVM and QSVM. However, this step is added in this study to compare the obtained results with the proposed algorithm and show how it can perform better than ML algorithms.

(2) The new proposed MID-CNN algorithm is established and developed for epilepsy detection by using time-frequency methods. First, Short Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) are applied for preprocess of EEG signals, and after transformation they are called spectrograms and scalograms. After that, these features will be selected and fed into MID-CNN network composed of two layers.

(3) The classification approach will be then evaluated by implementation of many indicators that they can determine the performance of this work.

The remainder paper organized as follows. Section three described the dataset used in this work. Then, section four detailed different methods and classification approach including the new MID-CNN model. Later, in section five, the obtained results are evaluated by implementation of various indicators and analyzed in the discussion. Finally, the paper concludes by conclusion in section six.

3. MATERIALS

3.1 Dataset description

Bonn University dataset consists of five sets of healthy subjects and epileptic patients denoted by A, B, C, D, and E [14, 27]. Each set contains 100 single-channels of EEG recordings with duration of 23.6 s and 4097 of samples. All EEG signals were recorded with the same 128-channel amplifier system using an average common reference [24, 28]. The descriptions of this database are summarized in Table 1. Sets A and B were recorded from healthy subjects using surface EEG (Figure 1) with their eyes open and closed, respectively. Sets C, D and E were obtained from epileptic patients using intracranial EEG electrodes (Figure 2). The EEG signals of sets [28].

Table 1. Data set of university of Bonn [27, 28]

Set	Z	O	N	F	S
Subjects	Healthy	Healthy	Epilepsy	Epilepsy	Epilepsy
EEG Recording	Surface	Surface	Intracranial	Intracranial	Intracranial
State	Open eyes	Closed eyes	Interictal	Interictal	Seizure
Channels	100	100	100	100	100
Samples	4097	4097	4097	4097	4097
Duration (s)	23.6	23.6	23.6	23.6	23.6

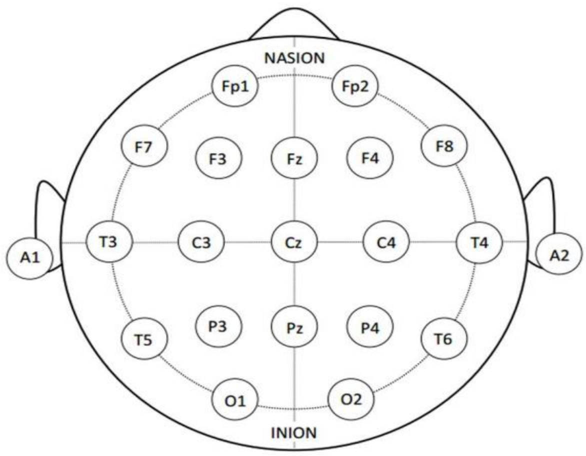

Figure 1. International10-20 electrode placement system [1]. The letter (C) indicates to central lobe, the letter (F) indicates to frontal lobe, the letter (O) indicates occipital lobe, the letter (P) indicates to parietal lobe, the letter (T) indicates to temporal lobe, the letter (A) indicates anterior and the letter (z) indicates to zero [29, 30]

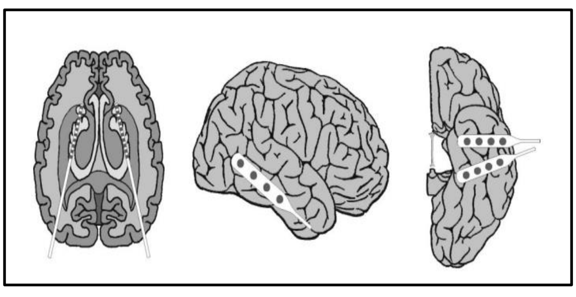

Figure 2. Intracranial EEG electrode placement [27]

4. METHODOLOGY

4.1 Pre-processing

In biomedical signal processing, there are different methods applied for pre-processing and filtering of non-stationary signals, that are contaminated by artifacts during acquisition such as EEG that it can reduce the quality of these signals. Most of these methods are widely used encompass Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT) and Discret Wavelet Transform (DWT) in time and frequency domains.

4.1.1 Short Time Fourier Transform (STFT)

Short Time Fourier Transform (STFT) convert the signal from the time domain to the time-frequency domain. It uses a sliding window function that is multiplied with the signal x(t), and Fast Fourier Transform (FFT) is applied to find the spectrogram which contain characteristics in both time and frequency. It can be defined mathematically by Eq. (1):

$$STFT(v,u) = \int_{-\infty}^{\infty} x(t)w(t-u)e^{-jvt}dt \tag{1}$$

where, x is the signal, w: is the window function, and t is the time period. By using STFT, the spectrogram (S) of signal is the energy around the time-frequency (v, u), and can be obtained by Eq. (2) [17, 23, 31].

$$S = |STFT(v,u)|^2 \tag{2}$$

4.1.2 Continuous Wavelet Transform (CWT)

The most popular method for signal processing is the wavelet transform (WT) contains large amount of information, that characterizes the EEG signals. The continuous wavelet transform (CWT) is defined by using mother wavelet which provides a list of scales of signal that can be analyzed [31]. It can surmount the problem of redundancy of STFT, and it has high temporal resolution than Fourier Transform. Other advantages of CWT are detailed by Mao et al. [17]. The results of the CWT are presented with scalograms and the mother wavelet (φ) can form a basis set of CWT denoted by Eq. (3) [23].

$$\left\{\varphi_{s,u}(t) = \frac{1}{\sqrt{s}}\varphi\left(\frac{t-u}{s}\right)\right\}|_{u\in R, s\in R^+} \tag{3}$$

where, s is the scale parameter, u is the translation parameter that represents the position of the wavelet along the time axis. The CWT of signal $x(t)$ described by Eq. (4) [17, 28, 32, 33].

$$CWT(s,u) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\varphi^*\left(\frac{t-u)}{s}\right)dt \tag{4}$$

4.1.3 Discret Wavelet Transform (DWT)

CWT has some limitations related to the problem of redundancy, because it uses continues implementation of coefficients that the reconstruction of the original signal is expensive [34]. However, the Discret Wavelet Transform (DWT) characterized by non-redundancy that it uses two successive filters high and low pass filters. DWT decomposes the signal $x(t)$ into sub-bands called approximation coefficients $A_i(k)$ and detail coefficients $D_i(k)$ at i^{th} level of decomposition (Figure 3), they are calculated mathematically by Eq. (5) and Eq. (6), respectively [22, 24].

$$A_i(k) = \left\{\frac{1}{\sqrt{N}}\sum_x f(x).\varphi_{j,k}(x)\right\} \tag{5}$$

$$D_i(k) = \left\{\frac{1}{\sqrt{N}}\sum_x f(x).\psi_{j,k}(x)\right\} \tag{6}$$

where, $A_i(k)$: approximation coefficients; $D_i(k)$: details coefficients; N: length of signal x; φ: mother wavelet function; ψ: scaling function. The high-pass filter (g) used the wavelet function $\varphi_{j,k}(x)$, and the low-pass filter (h) used scaling function $\psi_{j,k}(x)$ denoted by Eq. (7) and Eq. (8), respectively [24].

$$\varphi_{j,k}(x) = 2^{j/2}g((2^jx-k) \tag{7}$$

$$\psi_{j,k}(x) = 2^{j/2}h((2^jx-k) \tag{8}$$

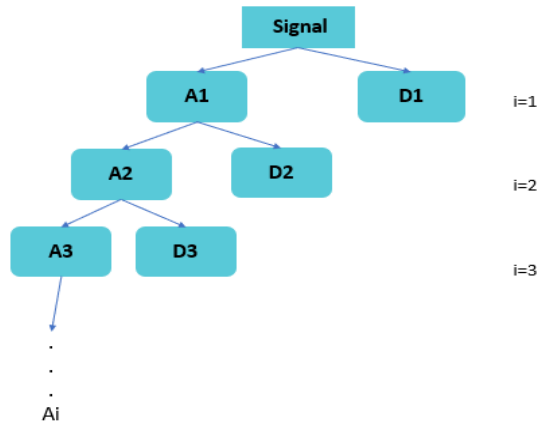

Figure 3. DWT decomposition at three levels

4.2 Feature extraction

This step is crucial for features extraction from different sub-bands after decomposition with DWT in time, frequency and time-frequency domains [35], and nonlinear analysis [36, 37], for using in the classification approach [38]. These statistical features including mean, variance, coefficient of variation [39], standard deviation, Skewness, Kurtosis [40], max and min [36], root mean square and Renyi entropy [41, 42]. They are determined by equations from Eq. (9) to Eq. (18). where, N is the length of signal x(t).

(1) Mean (μ)

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{9}$$

(2) Variance (σ^2)

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2 \tag{10}$$

(3) Coefficient of variation

$$\mathrm{CV}=\frac{\sigma^2}{\mu^2} \tag{11}$$

(4) Standard deviation (σ)

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \tag{12}$$

(5) Skewness (sk)

$$sk = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^3 \tag{13}$$

(6) Kurtosis (kr)

$$kr = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4 \tag{14}$$

(7) Max and min

$$max = \max\,[x_N] \tag{15}$$

$$min = \min[x_N] \tag{16}$$

(8) Root mean square (*RMS*)

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \tag{17}$$

(9) Renyi entropy (*REn*)

$$REn = \frac{1}{1-q}\ln\left(\sum_{i=1}^{N} p_i^q\right) \tag{18}$$

where,

$$\begin{cases} 0 < q < \infty \\ q \neq 1 \end{cases}$$

4.3 Classification approach

4.3.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised ML classifier used for classification and regression tasks [43, 44]. It based on learning of data then classified them into different classes [45, 46]. Initially, it was introduced by Vapnik and Cortes in 1995 for binary classification, that it consists to separate data into two classes by planes or called support vectors which can be described by Eq. (19) and Eq. (20)

$$W^T x + b = 1 \tag{19}$$

$$W^T x + b = -1 \tag{20}$$

where, *W*: positions of the hyperplane, *x*: data points and *b* take value of +1, -1 [47, 48].

The hyperplane is separated with the same distance between support vectors, that it requires to increase the margin width to obtain the optimal hyperplane [44] (Figure 4), for minimizing errors of misclassification. The optimal hyperplane can be described by Eq. (21) [46, 49, 50].

$$W^T x + b = 0 \tag{21}$$

The margin is the minimum distance from support vectors separating each class to the hyperplane presented in Eq. (22) [51].

$$M = \frac{2}{||w||} \tag{22}$$

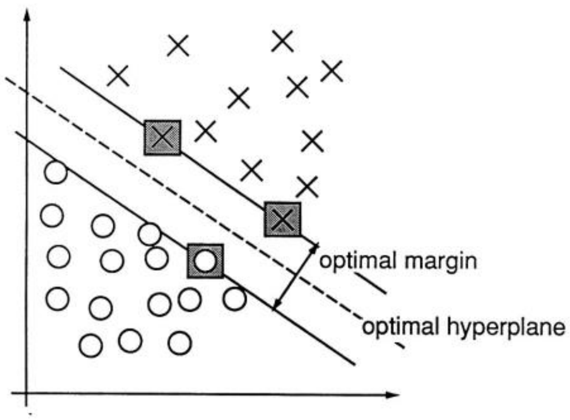

Figure 4. Linear SVM [45]

After that, the SVM was developed for multiclass and nonlinear data [35, 42]. Nonlinear SVM tricks to transform data into higher dimensional feature space based on mapping function (Φ) using kernel functions (*Kf*) [48, 49] defined in Eq. (23). Kernel functions are radial basis kernel function [43, 52], linear kernel function, polynomial and sigmoid kernel function [53], that used to find the hyperplane to separate data [54].

$$Kf(x_i, x_j) = \Phi(x_i)^T \Phi(x_j) \tag{23}$$

4.3.2 Convolutional neural network (CNN)

Convolutional neural network (CNN) is very used in signal and image analysis which is constructed of multiple and successive layers [1, 14]. Its structure consists of several convolution layers with Rectified Linear Unit (ReLU) to extract features, pooling layers which is widely used for dimensionality reduction and avoid the problem of redundancy in feature extraction [31, 55], thus fully connected layer, Softmax and output layer [56, 57].

• Input layer

In this paper, the input layer corresponds to the input images that used after selection of MID which are spectrograms and scalograms images.

• Convolutional layer

The convolution layer is used to extract features from the input images, it convolves the input data or from the previous layer by shifting a filter to produce the feature map. The feature map h^k is determined by convolving input image (I) with weight filter W^k and adding the bias b^k as described by Eq. (24):

$$h_{ij}^k = f((W^k * I)_{\mathrm{ij}} + b_k) \tag{24}$$

where, *h*: is the output of the convolution layer, *f* is the activation function, *W* is the weights, and *b* is the bias. The size of the feature map depends on three parameters: depth, stride, and padding [56, 58].

• Batch normalization

Batch normalization is applied to each layer to make the mean zero and normalize the variance [57].

• Rectified Linear Unit (ReLU) Layer

Rectified Linear Unit (ReLU) is a non-linear function that defined by Eq. (25) that it substitutes all negative pixel values in the feature map by zero with the purpose of introducing non-linearity in the network [57].

$$f(x) = max\,(0, \mathrm{x}) \tag{25}$$

• Pooling layer

The pooling layer is used to reduce data dimensionality and controls the overfitting. Different types of pooling operation are widely used including max-pooling and average-pooling [1]. In this work, the maxpooling layer is applied where the maximum value in each window is determined [57, 58].

• Flatten layer

The Flatten layer is used before fully connected layer to convert a multidimensional tensor into a one-dimensional tensor to facilitate its processing [58].

• Fully connected layer

The fully connected layer is used after the convolutional layer and max-pooling layer. The purpose of the fully-connected layer is to use these features for classifying the input image into various classes based on the training dataset [56, 57].

• Output layer

The output layer used to show the classification results that it predicts different classes based on the features obtained from the fully-connected layer [8]. The two of the most widely used activation functions for classification are Softmax and sigmoid functions. In this study, Softmax which is used as an activation function [56], that the range values of Softmax is between (0,1). The mathematical equation of Softmax is defined by Eq. (26) [59].

$$Softmax(x_i)\,\frac{e^{x_i}}{\sum_{k=1}^{K} e^{x_k}} \tag{26}$$

where, x input and i=1, …, k.

Softmax provides more effective results for binary and multiclass classification. Each class presented by probabilities as outputs and the highest probability value can be considered as the output that each class gives the best prediction [7].

4.4 Proposed framework

The objective of this work is to develop and build an accurate, robust and reliable framework for epileptic disease detection using deep learning in EEG signals. Thus, it will be compared with machine learning technique including two types of SVM classifiers.

4.4.1 Classification with SVM

In the first stage, DWT is applied to decompose EEG signals into different sub-bands. Then, statistical features are extracted in time-frequency domain from these subbands. After that, two models of SVM are applied for classification process including linear SVM (LSVM) and quadratic SVM (QSVM). The bloc the framework is illustrated in Figure 5.

4.4.2 Classification with MID-CNN model

In the second stage, a proposed MID-CNN model of deep learning is examined. Before that, the EEG signals are processed and converted to different spectrogram and scalogram images by using STFT and CWT, respectively defined by multi-input data (MID). After that, the selected images of MID with dimensions of 228x228x3 are input to the MID-CNN network for extraction features and classification. The bloc diagram of the proposed model is shown in Figure 6. The MID-CNN model composed of two layers C1 and C2 with one convolutional layer (Conv1 and Conv2) in each layer, followed by a batch normalization (BN), Rectified Linear Unit (ReLU), and max pooling (MP) layers. The first convolutional layer used 16 filters with kernel dimensions of 5×5, and the second employed 32 filters with kernel dimensions of 3×3. Batch normalization is applied to each layer to make the mean zero and normalize the variance. For the next layer, ReLU have been used as an activation function which it has a faster execution time when compared to the tanh and sigmoid activation function. Then, this is followed by max pooling layers with dimensions of 2 ×2, to mitigate overfitting of the dimension of each feature map and effectively reducing its spatial dimensions that the MP layers down sampling data with a pooling size of 2. Then, a flatten layer (FL), one fully connected (FC) layer, and a Softmax output layer are used. After the flattening process, the fully connected layer comprising 128 units that is used for dimensionality reduction. Different names and types of MID-CNN layers is presented in Table 2, and parameters of the configuration is detailed in Table 3. Subsequently, this model is simple which required only in their architecture two layers compared with other algorithms that they used more layers. Thus, the convolution layers used for this network used minimum number of filters. The CNN component effectively extracts spatial features from the images input data. Moreover, this approach based on MID-CNN network and augmentation of data collecting with MID input images ensures that this model reaches with an optimal performance level.

4.4.3 Training and validation

The most common measure of success in deep learning is the accuracy that the mean purpose is how many of the objects in the data set were correctly classified. The splitting of training and testing in this paper is used by 90% for training and 10% for testing. A more advanced set of validation techniques known as cross-validation is employed and known as k-fold cross-validation. To select a value of k, the advantage of higher values is obvious that retaining more data for training. In this work, 10-fold cross-validation is used. However, the common disadvantage is that higher values of k significantly increase the time required for training, and associated with higher variance of the accuracy estimated [28, 31].

Table 2. Architecture of the proposed MID-CNN

Layers	Type of layers
MID	Input images (228×228×3)
C1	Conv1(5,16)
	BN
	ReLU
	MP (2,2)
C2	Conv1(3,32)
	BN
	ReLU
	MP (2,2)
FL	Flatten
FC	Fully connected
Output	Softmax

Table 3. Parameters of the configuration [22]

Parameters	Number
Optimization function	Adam
Epochs	100
Batch size	6
Learning period	5
Learning rate	0.001

4.5 Performance evaluation

The performance evaluation provides the effectiveness of classification approach by computation of statistical parameters defined by accuracy (ACC), sensitivity or recall (SEN), specificity (SPE), precision (PRE) and F1-score (FSC) which are implemented and defined by Eq. (27), Eq. (28), Eq. (29), Eq. (30) and Eq. (31), respectively [23, 26, 41].

$$ACC = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}\ (\%) \tag{27}$$

$$SEN\ (recall) = \frac{\mathrm{TP}}{\mathrm{TP+FN}}\ (\%) \tag{28}$$

$$SPE = \frac{TN}{TN+FP}\ (\%) \tag{29}$$

$$PRE = \frac{TP}{TP+FP} \times 100 \quad (30)$$

$$FSC = \frac{2*precision*sensitivity}{precision+sensitivity} \quad (31)$$

where, TP: true positive, FN: False negative, TN: True negative, FP: False positive.

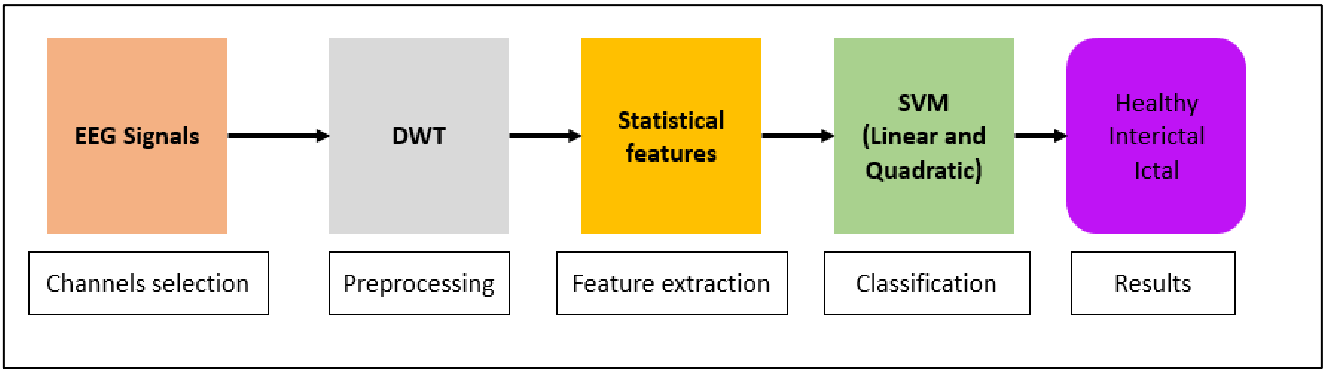

Figure 5. ML learning for EEG classification using SVM

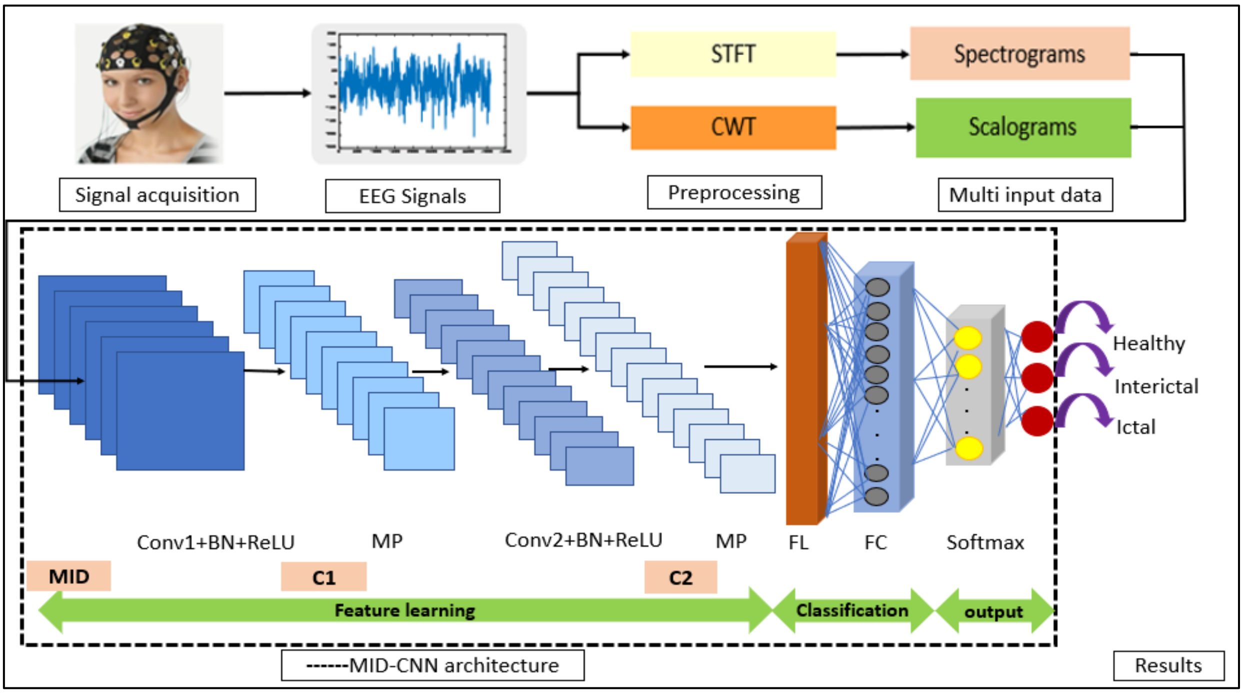

Figure 6. Proposed MID-CNN model

5. RESULTS AND DISCUSION

5.1 Experimental results

In this paper, the dataset of University of Bonn is used to evaluate this work. The first step consists to pre-process the EEG database by using DWT to decompose the EEG signals into subbands using Daubechies 4 (db4) at eight level of decomposition. Then, various features are extracted from the sub bands and classified with LSVM and QSVM. The results of classification process are showed in Table 4 and Table 5. Figure 7 and Figure 8 represent the histograms of the classification results with SVM classifiers.

After that, the STFT and CWT methods are applied to convert EEG data into images defined by MID that contain all characteristics of signals in time and frequency domain. Then, these images will be input in the first convolutional layer collected of 228×228×3 image's dimensions. They will be passed through two convolution layers with two Bach normalization layers, ReLU layers and max-pooling layers. Then, they are followed by a flatten layer, fully connected layer and Softmax of activation function that the output layer makes the final decision of the classification process. However, this work used another type of networks and experiments which are similar, but the number of layers is different that the system is examined with one, two, three and four layers. This procedure is evaluated to demonstrate the efficacity of using two layers which is an optimal value for training of MID. After using STFT and CWT and classification by CNN, the obtained results of these networks are showed in Tables 6-9. Thus, the Figures 9-12 represent the histograms of proposed CNN algorithms compared with different layers, respectively. The classification of signals through extracted features by operator is powerful method in detection of epilepsy such the SVM classifiers. Meanwhile, the application of deep learning by using the proposed algorithm to classify images data spectrograms and scalograms corresponds to MID features yields better results than SVM. Moreover, Table 10 represents the outline of the comparison accuracies by using SVM and different MID-CNN networks. Therefore, Figure 13 represents histogram of accuracy of all classifiers in this study. It demonstrates the effectiveness of application of proposed MID-CNN network presented in this work that it can perform better with high accuracy. Finally, the comparison with other works in the literature review are presented in the Table 11, thus Figure 14 illustrates obtained results compared with other works, which it has higher performance by using new MID-CNN model.

Table 4. Results of the classification approach by linear SVM (LSVM)

Case	ACC (%)	SEN (%)	SPE (%)	PRE (%)	FSC (%)
A/E	99	100	98	100	98.98
A/D	88.5	84.6	93.2	83	87.8
A/D/E	86.7	89.5	81.0	79.4	80.19

Table 5. Results of the classification approach by quadratic SVM (QSVM)

Case	ACC (%)	SEN (%)	SPE (%)	PRE (%)	FSC (%)
A/E	99.5	100	99	100	99.49
A/D	89.5	87.6	91.5	87	89.19
A/D/E	89.7	92.5	84.8	84.9	84.85

Table 6. Results of the classification approach by CNN with 1 layer (MID-CNN -1L)

Case	ACC (%)	SEN (%)	SPE (%)	PRE (%)	FSC (%)
A/E	98.8	100	97.5	97.6	98.84
A/D	94.23	96.9	91.5	92	94.39
A/D/E	95.8	98.33	93.33	93.7	95.96

Table 7. Results of the classification approach with CNN with 2 layers (MID-CNN -2L)

Case	ACC (%)	SEN (%)	SPE (%)	PRE (%)	FSC (%)
A/E	100	100	100	100	100
A/D	95	100	90	90.9	95.23
A/D/E	98.3	95.2	100	100	97.54

Table 8. Results of the classification approach with CNN with 3 layers (MID-CNN -3L)

Case	ACC (%)	SEN (%)	SPE (%)	PRE (%)	FSC (%)
A/E	95	97.5	92.5	92.9	95.14
A/D	92.5	95	90	90.05	92.46
A/D/E	96.7	90.9	100	100	95.23

Table 9. Results of the classification approach with CNN with 4 layers (MID-CNN -4L)

Case	ACC (%)	SEN (%)	SPE (%)	PRE (%)	FSC (%)
A/E	97.5	97.5	97.5	97.5	97.5
A/D	91.25	95	87.5	88.37	91.57
A/D/E	93.3	95	97.5	95	95

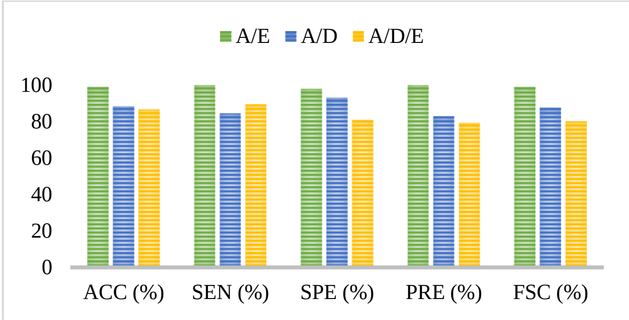

Figure 7. Histograms of the classification results by linear SVM (LSVM)

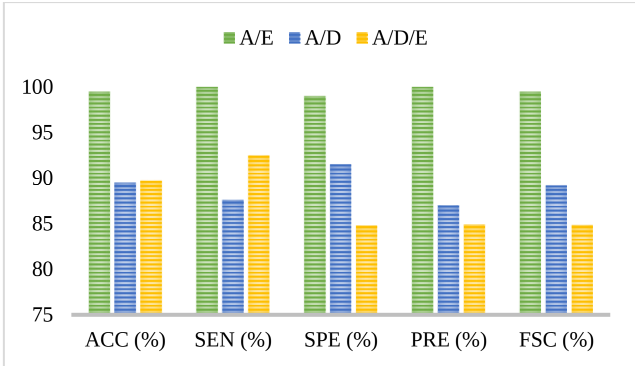

Figure 8. Histogram of the classification results by quadratic SVM (QSVM)

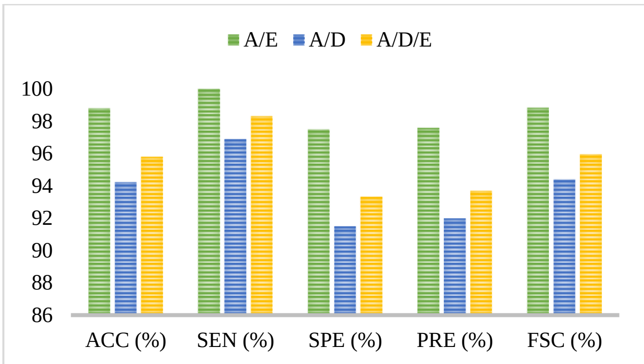

Figure 9. Histogram of the classification results by CNN with one layer (MID -CNN -1L)

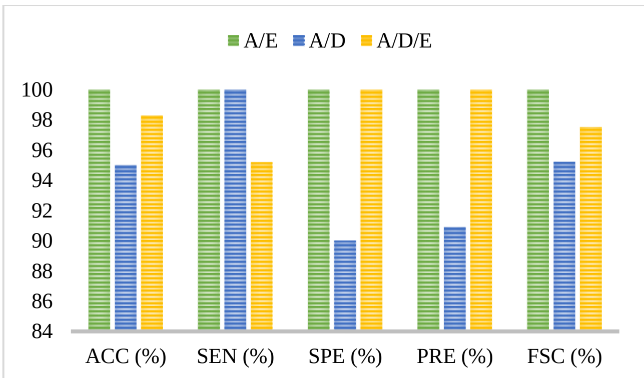

Figure 10. Histogram of the classification results by CNN with two layers (MID-CNN -2L)

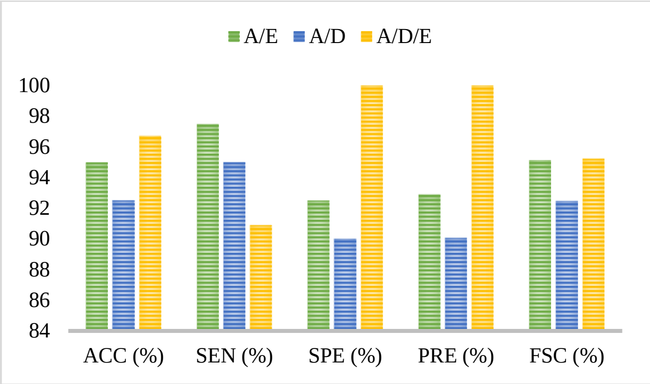

Figure 11. Histogram of the classification results by CNN with three layers (MID-CNN -3L)

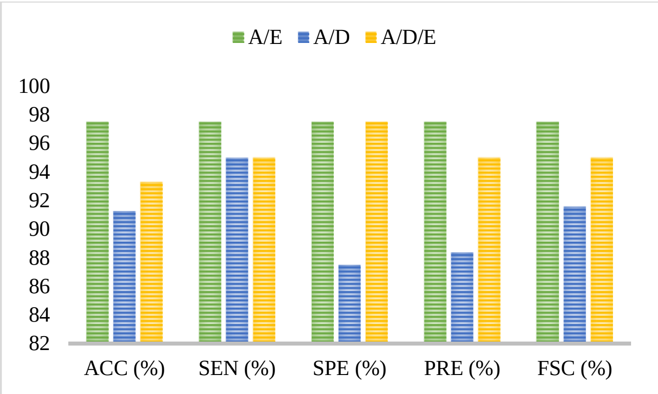

Figure 12. Histogram of the classification results by CNN with four layers (MID-CNN-4L)

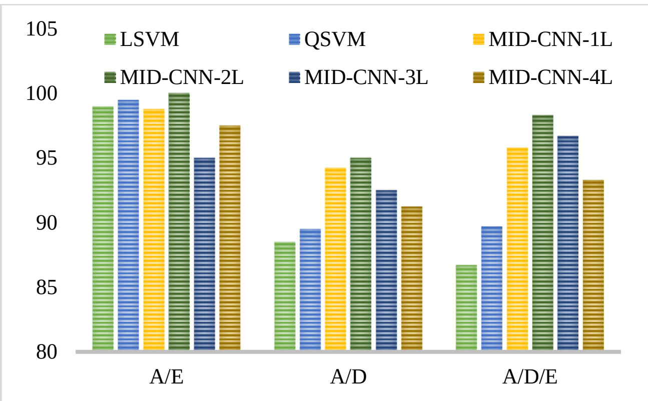

Figure 13. Comparison of the classification accuracy using LSVM, QSVM and different MID-CNN networks

Table 10. Comparison of the classification accuracy by using SVM and different MID-CNN networks

Case	A/E	A/D	A/D/E
LSVM	99	88.5	86.7
QSVM	99.5	89.5	89.7
MID-CNN-1L	98.8	94.23	95.8
MID-CNN-2L	**100**	**95**	**98.3**
MID-CNN-3L	95	92.5	96.7
MID-CNN-4L	97.5	91.25	93.3

5.2 Discussion

This study introduces the automatic epileptic discharges identification that a novel DL algorithm is developed focused on MID and CNN network. It evaluated with Bonn University dataset. Furthermore, it compared with two types SVM classifiers to demonstrate their effectiveness and robustness. According to the results in tables from Table 4 to Table 10, five indicators are implemented by following the mathematics equations presented in section 4 which are the accuracy, sensitivity, specificity, precision and F1-score. On the three tasks, the accuracy of the proposed model is higher by using proposed network with two layers than others. Firstly, DWT utilized to decompose EEG signals and ensures resulting subbands which are undergo to extract statical features in time frequency domains. Then, the extracted features are classified using two types of ML including LSVM and QSVM classifiers which are realized to compare them with the proposed method in order to test the superiority of the proposed model. The second analysis experiment propose new model using MID and CNN to further improve the accuracy of classification and detection of seizures. The training and testing data sets are splitting in 90% for training and 10 % for testing by using 10-fold cross validation.

In the other hand, from the results presented Table 4, the performance using LSVM is 99%, 88.5% and 86.7% for accuracy, in three cases, respectively. The sensitivity is 100%, 84.6% and 89.5% in three cases, respectively. Thus, the specificity reached of 98%, 93.2%, 81% in three cases, respectively. In the other hand, the precision is 100%, 83% and 79.4% in three cases, respectively, and F1-score is 98.98%, 87.8% and 80.19% in three cases, respectively. The accuracy is 99.5%, 89.5% and 89.7% in three cases, respectively by applying QSVM classifier which are presented in Table 5. Then, the sensitivity and the specificity are 100% and 99%, 87.6% and 91.5%, and 92.5% and 84.8% in three cases, respectively. Therefore, higher performance achieved of 100% and 99.49%, 87% and 89.19%, 84.9% and 84.85% respectively for precision and F1-score in three cases.

For MID-CNN-1L network as showing in Table 6, it is found from that the accuracy attained 98.8%, 94.23% and 95.8% in all cases, respectively. Hence, the sensitivity is 100%, 96.9% and 98.33% in three cases, respectively, and the specificity is 97.5%, 91.5% and 93.33%. The precision attained of 97.6%, 92% and 93.7%, thus F1-score are 98.84%, 94.39% and 95.96% in all cases. However, the best results illustrated in Table 7 demonstrate higher performance by using proposed MID-CNN-2L which reached of 100%, 95% and 98.3% for accuracy, in three cases, respectively. Thus, the sensitivity and the specificity are 100% in case of A/E, and in the second and third cases (A/D, A/D/E), they present higher sensitivity of 100% and 90%, and the specificity of 95.2% and 100%, respectively. Moreover, the precision and F1-score are 100% in first case. The results achieved 90.9% and 95.23% for the precision, 100% and 97.54% for F1-score, in the second and third cases (A/D, A/D/E), respectively. From Table 8, the performance by using MID-CNN-3L achieved 95%, 92.5% and 96.7% for accuracy, in three cases, respectively. The sensitivity is 97.5%, 95% and 90.9% in all cases, respectively. In the first case, the specificity, the precision and F1-score are 92.5%, 92.9% and 95.14% respectively. In the second case, they are 90%, 90.05% and 92.46%, respectively. In the third case, the specificity and precision are of 100% for both parameters, and F1-score is 95.23%. Additionally, the obtained results by using MID-CNN-4L which are presented in Table 9, the accuracy, sensitivity and specificity are 97.5%, 97.5% and 97.5%, respectively in the first case. Thus, for the second case, they are 91.25%, 95% and 87.5%, respectively. For, the third case, they are 93.3%, and 95% and 97.5%, respectively. Finally, the precision and F1-score present performance of 97.5% and 97.5%, 88.37% and 91.57%, for the first and the second cases, respectively, then, both parameters are of 95% for the third case.

According to the obtained results of accuracy summarized in Table 10, it is demonstrated that the number of two layers is optimal and effective based on MID for seizure identification, and the accuracy of the proposed model reaches 100% in case of A/E that is higher than others. On the other hand, the best accuracy of 95 % and 98.3% achieved by the developed network on the other cases, compared with LSVM and QSVM for different classification tasks to distinguish between healthy, interictal and ictal subjects and the identification of epileptic discharges is verified by using EEG signals.

Table 11. Comparison with other works

Authors	Methods	Classifiers	Number of Layers	Dataset	ACC (%)
Aliyu et al. [6]	DWT	LSTM	1	Bonn	99
Dhar et al. [8]	LBP, EMD, FFT, DWT	MultiSVM CNN-RNN	3	Bonn	67.20 93.30
Sun et al. [11]	Multi-view features	MDFLN	3	CHB-MIT Bonn	98.09 98.4
Boonyakitanont et al. [12]	DWT	ANN CNN	7 6	CHB-MIT	98.62 99.07
Pan et al. [13]	FT, STFT, DWT feature fusion	CNN	4	Bonn	99.08
Hossain et al. [14]	spectral, temporal features	CNN	4	CHB-MIT	99.65
Alharthi et al. [15]	DWT	1D-CNN Bi-LSTM	3	CHB-MIT	96.87
Xu et al. [16]	Normalization	1D CNN-LSTM	4	UCI	99.39
Mao et al. [17]	CWT	CNN	3	UCI	72.49
Ru et al. [18]	AMDA	AM-1D CNN-GRU	13	CHB-MIT	96.06
Khurshid et al. [19]	Data cleaning	DNN	3	KAGGLE	97
Nie et al. [20]	FFT	NLSTM	3	Bonn	99.62
Hassan et al. [21]	Dataset preparation	1D CNN-LSTM	7	Bonn	99.48
Zhang et al. [22]	DWT	CNN-GRU-AM	2	CHB-MIT	99.35
Irwan et al. [23]	STFT	CNN	3	Bonn	100
Malekzadeh et al. [24]	Band-pass filter TQWT	CNN-RNN	3	Bonn Freiburg	99.71 99.13
This Work	**STFT, CWT**	**MID-CNN**	**2**	**Bonn**	**100**

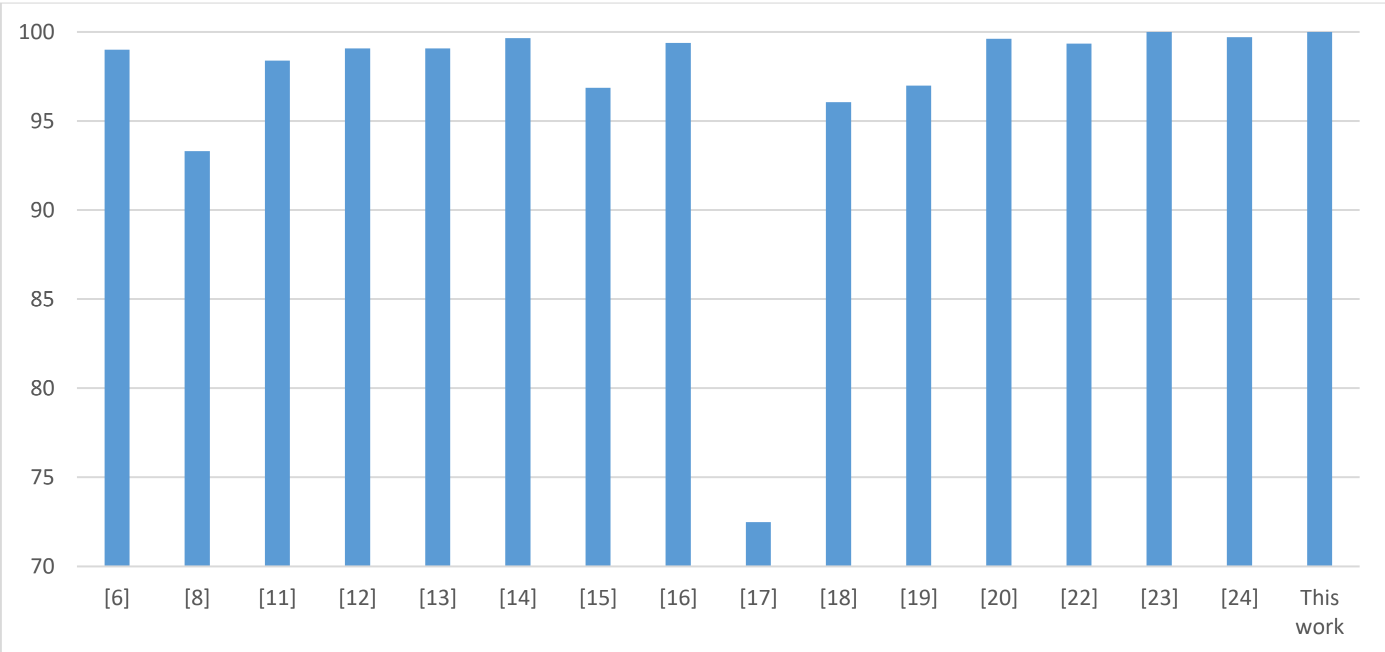

Figure 14. Comparison of the accuracy in this work with others

The obtained results for the proposed model are acceptable, and it is also efficient in the identification of epileptic seizures in EEG signals, since it has been proven that there is an improvement of performance when comparing with existing literature review presented in Table 11. Aliyu and Lim [6] applied DWT and a simple LSTM network in the same dataset of university of Bonn, and they are obtained accuracy of 99%. Moreover, Dhar et al. [8] compared between MultiSVM and CNN-RNN by using LBP, EMD, FFT, and DWT, then they obtained accuracies of 67.20% and 93.30% for multiSVM and proposed CNN-RNN. It is demonstrated that these results are less than obtained by comparison with the proposed network. They used many methods for training here only two methods. Thus, the input data are both of two methods STFT and CWT with CNN and compared with two types SVM classifiers. It has proved the powerful of using the proposed algorithm according to their performance which presents best classification results and accuracy of 100% compared with the previous works.

Boonyakitanont et al. [12] used DWT and comparison between ANN and CNN they are validated their results by applying CHBMIT dataset, the obtained results present higher accuracies for ANN are 98.62% and for CNN is 99.07% of accuracy, but in this work results perform better. Pan et al. [13] used original EEG data, Fourier Transform, STFT and WT with CNN, they obtained an accuracy of 99.08%.

Hossain et al. [14] used spectral, temporal features with CNN in Boston Children's Hospital dataset, however they are used more layers and results are 99.65 % which is less than in this work. In the study by Alharthi et al. [15], a Data integration with DWT and a proposed hybrid 1D-CNN Bi-LSTM is established and evaluated by application of dataset of CHBMIT, they are obtained as results an average accuracy of 96.87%. In other study by Xu et al. [16], a Normalization for processing of EEG datasets and 1D-CNN-LSTM network is proposed for classification. They utilized four layers in their network and that obtained better results 99.39% of accuracy for binary epileptic seizure recognition task by applying UCI dataset. The application of CWT for processing of EEG signals is applied with CNN network which contain 3 layers that it increases implementation of data, and they are obtained accuracy of 72.49% which is less than this work in dataset of UCI [17]. The authors showed the usefulness of using STFT and CNN [23]. The results in this paper achieving accuracy of 100%, however they are used much of layers [21], thus STFT due to the transformation from time to time-frequency domain, may result in information loss. However, in this work, a combination of STFT and CWT can outperform the issue related to the STFT by combining with CWT that encompass EEG patters in time and frequency domains simultaneously and thus augmentation of data with only two layers of CNN which can simplify faster extract features of MID.

Researches on EEG signals classification tends to use complex networks with much of input data that increase learning time However, this work uses two layers of CNN effectively avoid the time-consuming feature extraction process. The CNN can potentially learn features without traditional feature extraction processes compared with ML classifiers. Moreover, the CNN based on MID which prove the strong potential in learning of spatial features. It achieves the highest classification performance and it successfully verified. Finally, the new MID-CNN proposed the It has a promising ability for identification of epileptic discharges and could provide effective performance. It can be used for multi-classification problems can also train effective models instead binary classification problems. In other hand, the proposed network can be used in classification for other dataset to distinguish between different tasks.

6. CONCLUSIONS

In this paper, a new algorithm is developed for automatic detection of epileptic seizures that the main objective is to use deep learning and how it can provide the better results in the classification approach. The proposed convolution neural network (CNN) model with combination of STFT and CWT spectrograms and scalograms defined as MID achieves an improvement of performance previous researches. Thus, here the dataset of University of Bonn is applied to evaluate this work between different tasks such as healthy, interictal and ictal subjects. The results showed higher accuracies of 100% to distinguish between normal and epileptic patients which demonstrates the useful of this algorithm. As conclusion, the classification of EEG signals through extracted features by operator is powerful method with ML in detection of epilepsy, meanwhile, the application of deep learning by using the proposed algorithm MID-CNN to classify images data yields better results than SVM. SVM perform better meanwhile DL increase the performance.

The limitations of this work that the number of layers of convolution and finding the optimal types of filters (kernels) used in CNN are determined by experience for the best results obtained. For future works, to improve the automatic classification approach, this method will used in another dataset and in other pathology detection thus other fields of research studies.

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NOMENCLATURE

2D	Two dimensions
ACC	Accuracy
A_i	Approximation coefficient
ANN	Artificial neural network
BN	Batch normalization
CNN	Convolutional neural network
CWT	Continuous Wavelet Transform
D_i	Detail coefficient
Db4	Daubechies 4
DWT	Discret Wavelet Transform
DL	Deep learning
EEG	Electroencephalography
EMD	Empirical mode decomposition
FFT	Fast Fourier Transform
FN	False negative
FP	False positive
FC	Fully connected layer
FSC	F1-score
FT	Fourier transform
Hz	Hertz (s^{-1})
LBP	Local binary patterns
LSTM	Long short-term memory
MID	Multi input data
MID-CNN	Multi input data- Convolutional neural network
ML	Machine learning
mV	Milli-volts
N	Length of the signal x
PRE	Precision
RNN	Recurrent neural networks
s	Second
SEN	Sensitivity
x	Signal
SPE	Specificity
STFT	Short-time Fourier Transform
t	Time
TN	True negative
TP	True positive

Greek symbols

α	Alpha wave
β	Beta wave
δ	Delta
γ	Gamma
μV	Micro-volt
ψ	Wavelet function
ϕ	Scaling function
Θ	Theta