JOURNAL OF ENGINEERING AND APPLIED SCIENCE, VOL. 67, NO. 4, AUG. 2020, PP. 925-944
FACULTY OF ENGINEERING, CAIRO UNIVERSITY

A DEEP LEARNING IDENTIFICATION SYSTEM FOR DIFFERENT EPILEPTIC SEIZURE DISEASE STAGES

R. H. GABR[1], A. I. SHAHIN[2], A. A. SHARAWI[3] AND M. A. AOUF[2]

ABSTRACT

Epilepsy is a neurological disorder caused by abnormal discharge in the brain. The electroencephalogram plays an important role in monitoring brain activity in epilepsy diagnostic tasks. The EEG recording of epileptic patients shows abnormal activities including inter-ictal, pre-ictal, and ictal activity. Automatic detection of these abnormal activities aids the neurologists rather than using visual scanning. The selection of discriminative features from different EEG activities is the basis of the seizure detection method. Deep learning is introduced as an efficient approach in computer-aided medical diagnosis systems; it learns features automatically. In this paper, a convolutional neural network (CNN) is employed to classify different epileptic seizure stages. We investigate CNN performance with different signal forms. Firstly, we use a time-domain signal input to a 1-D CNN. Next, we use the time-frequency domain in form of spectrogram and scalogram images as input to an 2-D CNN (Alexnet). The experiments are performed on CHB-MIT dataset which contains long time epilepsy recordings for different patients. Experimental results suggest that the scalogram of the EEG signal increased the CNN classification accuracy to 97%. However, the spectrogram images achieved an accuracy of 73%, while the time domain signals achieved the lowest performance with an accuracy of 64%.

KEYWORDS: Deep learning, CNN, EEG, spectrogram, scalogram, Epilepsy

1. INTRODUCTION

Epilepsy is one of the most common neurological disorders that affect approximately fifty million people all over the world. It is characterized by sudden recurrent and transient disturbance of brain-behavior termed "epileptic seizures". It

[1] Ph.D. Candidate, Systems and Biomedical Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt.
[2] Assistant Professor, Higher Technological Institute, 10th Ramadan City, Egypt.
[3] Associate Professor, Systems and Biomedical Engineering Department, Faculty of Engineering, Cairo University, Egypt, engr.reeham.gabr1@gmail.com

results from abnormal burst of electrical discharge in the brain causing strange sensation, behavior, muscle spasm, or sometimes convulsions and loss of consciousness. It reduces the world population productivity and imposes restrictions and risks on the epileptic patient's daily life. Detection of epileptic seizure plays a significant role in improving the quality of epileptic patient's life. The Electroencephalogram (EEG) is utilized to asses and detect abnormalities of the brain and is widely used for the detection and diagnosis of epilepsy. It studies the brain-behavior from different regions by recording the electrical activity of the brain using scalp or invasive electrodes [1-4]. EEG recordings of patients suffering from epilepsy show different categories of abnormal activity: ictal, whereby the activity recorded during an epileptic seizure, it is of varying length, its symptoms are very brief and marked precisely by EEG experts; pre-ictal, whereby the activity is observed prior to the seizure, it is further the transition from the interictal to ictal state and its symptoms duration and time of appearance is unknown; inter-ictal, whereby the abnormal signal activity is recorded between epileptic seizures and precedes the preictal state; the post-ictal, whereby the activity follows the seizure offset as the patients are recovering from seizure. These activities are shown in Fig. 1 [5, 6].

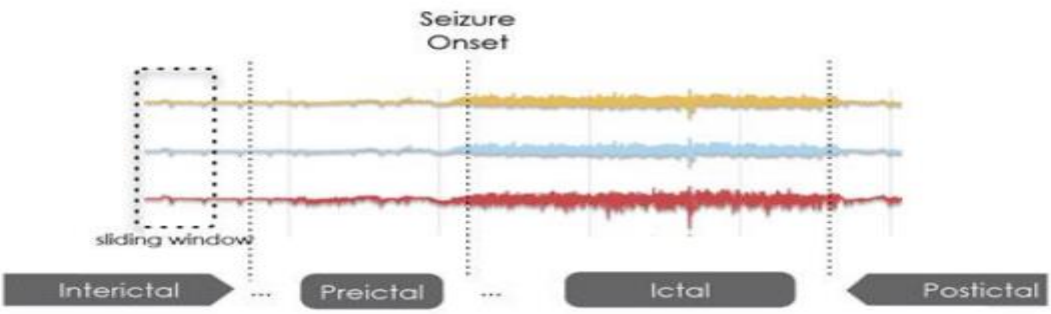

Fig. 1. Abnormal EEG activities of epilepsy disorder [6].

The visual scanning of EEG recording for these activities by an experienced neurophysiologist can be used for detection of epilepsy, however visual review of vast amount of EEG data is inefficient and is very time consuming especially in case of long-term recording [1, 7, 8]. Also, the EEG patterns characterizing the epileptic seizure are similar to artifacts such as eye blink, eye movements, muscle activity, electrocardiogram and electrical interference [1, 9]. Further, the variations of the amplitude and frequency of rhythmical activity which is representative of certain neurological disorders couldn't be interpreted visually [10]. For these reasons, automated detection systems can serve as valuable clinical tools for seizure detection. In these systems, the features that detect distinctiveness of EEG signal before, during and after a seizure has to be determined and evaluated from different domains [11]. Extracting features accurately is of great importance for automatic seizure detection systems performance. Once the features selected then they classified using different types of classifiers to recognize different EEG signals. These traditional techniques based on prior extraction of particular features from different domains encounter many challenges in a real-life situation. First, The EEG is non-stationary signal and its statistical features change across different subjects and for the same subject over time. Second, the EEG data acquisition system susceptible to various range of artifacts that negatively affect the performance accuracy of seizure detection systems [8]. To address these limitations; the Deep learning approach (DL), a new trend and specialized form of machine learning, has been introduced. It does not need prior extraction of such hand-made features; it can learn features from raw data automatically [12]. It has been a successful tool and achieved state-of-art accuracy exceeding human-level performance on many interesting tasks and there is little progress of it in neuroscience research to analyze signals recorded with EEG [8, 13-15].

In this study; Convolutional neural network (CNN), the most successful and widely used deep learning approach, is used to learn automatically the discriminative EEG features of epileptic seizure's different stages. Raw time-domain EEG signal and time-frequency domain images are inputted to the CNN then its performance accuracy were compared using these different formats of EEG signal.

The paper starts with the literature review on the different methods of automatic detection using both classical machine learning and deep learning approaches. This is followed by the material and methods section, it consists of EEG datasets used in this study followed by the methods that explain the construction of different forms of EEG and the proposed Deep learning network architecture. Finally, the experimental results with discussion and conclusion are introduced.

2. LITERATURE REVIEW

For automatic detection using classical machine learning, several features extraction, selection, and classification techniques have been reported in the literature; most of them use hand-wrought features in different domains. It is concluded that the time-frequency domain analysis of the EEG can add valuable information by providing an image of spectral contents of EEG that varied with time [10]. Several methods of time-frequency analysis of signal as Short-time Fourier transform (STFT) and other several distributions were studied and compared to classify the EEG segments to epileptic and non-epileptic seizures. The obtained results indicated their high classification ability in epileptic seizure detection [16]. The Continuous Wavelet Transform (CWT) was used as an alternative time-frequency domain method for feature extraction to discriminate between normal and ictal EEG. The CWT provided an optimal representation of the signal that can be used for automatic decision support tools [17, 18]. The spectrogram produced by STFT and the scalogram produced by CWT are valuable methods in analyzing the frequency contents of EEG. By comparing them; the scalogram is preferred with its frequency-varying resolution, it offeres a more detailed view of the low-frequency region [10].

Classification of EEG signals to various epilepsy states; inter-ictal, pre-ictal, ictal and post-ictal is of great concern in the literature. For automated classification of EEG into normal, inter-ictal and ictal classes; the Discrete wavelet transform was used in [19] to decompose the EEG signal into different frequency sub-bands then features selected using independent component analysis and finally classified using six classifiers. The support vector machine classifier with a radial basis function achieved the highest performance. For automatic detection of normal, pre-ictal, and ictal conditions from EEG signals; four different entropy features extracted in [20] from the collected EEG signals and then fed to seven different classifiers. The fuzzy classifier was able to differentiate the three classes with high accuracy. To classify the brain state into one of four possible epileptic behaviors: inter-ictal, pre-ictal, ictal and post-ictal; fourteen features extracted from EEG signal in [21] and six types of neural network architecture are compared. Their experiment evaluated using single patient and multiple patients. The results showed that it is possible to find a good classifier to four brain states based on neural networks; however, the classifier of one patient cannot be used for another patient [21].

All the above studies used traditional machine learning approaches that start~~s~~ with features being manually extracted from the EEG signal and then classified using different classifiers. Although a few studies based on these methods achieved good accuracy and sensitivity; most of them are patient-specific systems. They did not obtain satisfactory results for independent patient seizure detection because epileptic seizures have a non-stationary activity and its pattern varies significantly across patients. Also the accuracy of these methods is affected negatively with EEG artifacts. Recently, the Deep learning approach has been used for EEG analysis, it is considered as an excellent tool to discover hidden patterns and abnormalities in medical data automatically even in the presence of noise [22].

There are different approaches for the deep learning (DL) network; A Long Short- Term Memory network (LSTM), one of DL approaches, was used for the detection of epileptic seizures using the time series EEG data. Compared to the state of art methods; the approach can effectively discriminate between the normal and seizure EEG in presence of common EEG artifacts [2]. CNN is another DL approach; it is used in [14] to extract features from the wavelet transformation of EEG signal that can be used to differentiate between different states, inter-ictal, pre-ictal and ictal to predict seizures. The prediction results are promising with a sensitivity of 87.8%. Also for seizure prediction, another study attempted to distinguish between pre-ictal and inter-ictal periods. The DL network trained by labeled data as pre-ictal defined as 15 min before seizure and inter-ictal as anything neither pre-ictal nor ictal. The data segments were transformed into spectrograms. The classifier performance was examined on intracranial EEG signals from ten patients. The prediction system achieved a mean sensitivity of 69% and mean time of warning 27% [22]. An automatic seizure detection system was proposed in a mobile multimedia framework in [22]. The system used the CNN to extract the features from the band-limited signals (theta, alpha, beta, and gamma), then used the SVM for classification. The temporal relation in the EEG signal was captured by the one dimensional (1-D) convolution, and whereas the spatial relation was encoded by the two dimensional (2-D) convolutions. This temporal-spatial combination made the system robust to seizure detection and achieved better accuracy compared with other related systems in literature.

3. MATERIALS AND METHODS

In this section; the dataset is introduced, then the proposed method will be presented to identify different epilepsy seizure stages based on deep learning.

3.1 Dataset

The CHB-MIT EEG dataset used in this study is publically available at Physionet.org. It contains EEG recordings from subjects with intractable seizures after withdrawal of antiepileptic drugs. Recordings are grouped into 24 cases collected from 23 subjects as Case 1 and 21 is the same subject where case 21 is a recording 1.5 years after case 1. It contains male and female patients of different ages. For each case; there are multiple EEG recording files. All EEG signals were sampled at 256 samples per second with a 16-bit resolution. The International 10-20 system of EEG electrode positions was used for these recordings. Signals were recorded simultaneously through twenty-three different bipolar channels via 19 electrodes and a ground attached to the surface of the scalp [23]. In this study, only the EEG signal from frontal-parietal bipolar channel FP1-F7 is used as it could differentiate between states of epilepsy [24].

To implement our proposed method; the pre-ictal, inter-ictal, and ictal files are selected to train CNN as follows: the pre-ictal activity, the periods before seizure onset by five and ten minutes based on literature [14], the inter-ictal activity is selected randomly provided that the period between each two seizures is four hours or more as in [25], and the seizure itself is labeled as ictal activity. The start and end of each seizure was already determined by CHB-MIT experts. Based on these assumptions the number of ictal files used in this study are 146 with different lengths, 108 inter-ictal files and 124 pre-ictal files with five min periods and ten minutes periods. All patients of the CHB-MIT dataset are included as one dataset.

3.2 Methodology

In this study, the CNN is used to learn the EEG features that discriminate between the epilepsy states (pre-ictal, ictal and inter-ictal) via convolution theory. The CNN is 2-D network used to learn image features. In our study, the CNN is adopted as 1-D CNN to learn features of EEG signal in time domain and used as it 2-D CNN to learn features from time-frequency domain images (spectrogram and scalogram). The 2-D CNN used in our study is the Alexnet. The proposed methods are introduced as follows: CNN input layer, CNN features extraction layer, CNN classification layer, and CNN training.

3.2.1. CNN input layer

In this layer, the EEG data is inputted into the network for processing. Three different input formats used in this study; EEG signal in time domain, Spectrogram of EEG signal in time-frequency domain, and Scalogram of EEG signal in time-frequency domain.

a) EEG signal in time domain**:** The EEG signal is a time-domain signal so the signals from all epilepsy stages are inputted to the CNN's input layer as a raw signal without any preprocessing just partitioned to the segements with same length to match the 1-D CNN input layer. All files are partitioned to the minimum ictal length of 1000 sample so the input layer size is [1 1000].
b) Spectrogram of EEG in time-frequency domain: It is a visual representation of signals, it contains more unknown features of the EEG signal in time domain. In order to produce a spectrogram image from the EEG signal, the STFT method is used. The STFT general equation of signal S is given by:

$$\mathrm{S}(\mathrm{m},\mathrm{k})=\sum_{\mathrm{n}=0}^{\mathrm{N-1}}\mathrm{S}(\mathrm{n}+\mathrm{mN'})\mathrm{w}(\mathrm{n})\,e^{-j\frac{2\pi}{N}nk} \qquad (1)$$

Where, S(m,k) indicate the m-index time-frequency frame spectrogram, is the k[th] Fourier coefficient in range [0:k] where *K= N/2*, it is the frequency index corresponding to Nyquist frequency, *N* is the window segment length, *N′* is the shifting step of the time window, *W(n)* is the window function applied to N-point sequence. The spectrogram is defined as the magnitude of *S(m,k)*, it is represented in Eq. (2) [26]:

$$A(m,k) = \frac{1}{N}\left|s(m,k)\right|^2 \tag{2}$$

The window function in STFT method has a constant length, so the STFT has a compromise between time and frequency resolution, long window provides a better frequency resolution but poor time resolution and vice versa.

c) Scalogram of EEG in time-frequency domain: It observes more closely differences between epileptic activities through using a wavelet-based colored map produced using CWT. The analysis window (wavelet) is not only translated as in STFT but dilated and contracted depending on the scale of activity under study. The wavelet dilation increases the CWT's sensitivity to long time-scale events and wavelet contraction increases its sensitivity to short time-scale events. Continuous wavelet transform (CWT) is defined by:

$$cwt_{(a,b)} = \int_{-\infty}^{\infty} x(t)\psi^{*}_{a,b}(t)dt \tag{3}$$

Where x(t) represent the analyzed signal, '*a'* represents the scaling factor and '*b'* represents translation along the time axis, and the superscript asterisk denotes the complex conjugation. $\Psi_{a,b}$ (.) is obtained by scaling the wavelet at time 'b' and scale 'a' where Ψ (t) represents the wavelet [27].

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\frac{t-b}{a} \tag{4}$$

In this study, spectrogram and scalogram images produced using matlab were resized to 227×227 pixels to match Alexnet input layer [227 227 3].

3.2.2. CNN feature-extraction layer

It consists of repeating pattern of this sequence; convolution layer (CL), activation function layer (Relu), and pooling layer. Convolution layer is considered the core building blocks of CNN architectures. It takes input then applies a convolution kernel. The kernel is slid across the input data to produce the convoluted feature (output) data. Pooling layers are commonly inserted between two successive convolutional layers to perform the down sampling process. Tables 1 and 2 present the feature-extraction layer architecture and its hyper-parameters (kernel and stride) of two CNN approaches proposed in this study:

a) 1-D CNN architecture description: The architecture of 1-D CNN and its hyperparameters shown in Table 1.

Table 1. 1-D CNN layers and the hyper-parameters.

# Layer	Layer type	Activation	# kernel	size	Stride
1	1-D convolution (CL)	Relu	3	[1 102]	1
2	Max pooling			[1 2]	2
3	1-D convolution (CL)	Relu	10	[1 24]	
4	Max Pooling			[1 2]	2
5	Convolutions	Relu	10	[1 11]	1
6	Max Pooling			[1 2]	2
7	Convolutions	Relu	10	[1 9]	10
8	Max Pooling			[1 2]	2

b) 2-D CNN architecture description**:** There are many CNN architectures; AlexNet is used in this study with a spectrogram and scalogram image. We Load pre-trained Alexnet network after installing the Alexnet network support package in deep learning toolbox. The layers of Alexnet and the hyper parameters are shown in Table 2. After learning features in convolution layers, the architecture of CNN shifts to the classification layer.

Table 2. Alexnet feature extraction layer and the hyper-parameters.

# Layer	Layer type	Activation	# kernels	Size	Stride	Padding
1	Convolutions	Relu	96	11x11	[4 4]	[0 0 0 0]
2	Max pooling			3x3	[2 2]	[0 0 0 0]
3	Convolution	Relu	256	5x5	[1 1]	[2 2 2 2]
4	Max Pooling			3x3	[2 2]	[0 0 0 0]

Table 2. Alexnet feature extraction layer and the hyper-parameters, (Cont.).

# Layer	Layer type	Activation	# kernels	Size	Stride	Padding
5	Convolutions	Relu	384	3x3	[1 1]	[1 1 1 1]
6	Convolutions	Relu	256	3x3	[1 1]	[1 1 1 1]
7	Max pooling			3x3	[2 2]	[0 0 0 0]

3.2.3. CNN classification layer

It consists of a fully connected layer, activation function layer, and classification layer. In this layer, there are one or more fully connected layers to take the higher-order features and produce class probabilities using the softmax activation function. The classification layer computes the cross-entropy loss for multi-class classification. In the case of 1-D CNN, one fully connected layer with softmax activation function and classification layers used. For Alexnet network, two fully connected layers with Relu activation function and the third one with softmax activation function, the third fully connected layer is modified to match our classification problem as 2 in case of classifying two states and 3 for classifying 3 states of epilepsy. The Alexnet classification layer is modified in this study by adding 2 dropout layers after fully connected layers to prevent overfitting that may result because of training the network with small dataset as shown in Table 3.

Table 3. Alexnet classification layer and hyper-parameters

# Layer	Layer type	Activation	Output	Dropout rate
8	Fully Connected	Relu	4096	
9	Drop out			50%
10	Fully Connected	Relu	4096	
11	Drop out			50%
12	Fully Connected	Softmax	2 or 3	
13	classification Layer			

3.2.4. CNN training

The signal in time domain, spectrogram, and scalogram are loaded to image datastore. The image datastore is a Matlab functionality enabling us to store large data and efficiently read batches of images during training of CNN. The selected files of epilepsy states are divided into two groups; one for training (90%) and others for testing (10%). Training the deep convolutional network was done using the stochastic gradient descent with momentum optimizer. The network trained with a maximum number of 20 epochs with minibatch of size 50. HP workstation with Xeon ® CPU E5-1607 (3GHz) and 8G RAM is used. The training is done using a graphical processing unit (NVIDIA GeForce GTX 1050Ti) as it faster than training on CPU. The deep learning framework is Matlab 2018.

4. RESULTS

In the experiments, all selected segments from different patients of CHB-MIT dataset were used to check the ability of deep neural network (CNN) to learn features of epilepsy states generally; most studies in the literature are patient-specific. First, two states are examined: pre-ictal vs inter-ictal, ictal vs pre-ictal, ictal vs inter-ictal using EEG signal in the time domain, spectrogram and scalogram. Second, the three states of epilepsy (pre-ictal, inter-ictal and ictal) are examined together.

The training progress plot is presented below for each trial. The training accuracy is presented in the top subplot which is the classification accuracy on each mini-batch; when this value typically increases toward 100%, the training progresses successfully. In the bottom subplot of training progress; the training loss indicated which is the cross-entropy loss on each mini-batch, this value typically decreases toward zero when training progresses successfully. For classifying different states time domain, we apply the EEG signal to 1-D CNN consists of 2 CL from the architecture described in Table 1. The classification accuracy of differentiating ictal with inter-ictal is 90%, there is clear difference between ictal and interictal activity. During the inter-ictal periods; the EEG recording exhibit occasional abnormalities (transient waveform or spikes). But in ictal periods; the EEG recording is composed of a continuous discharge of theses abnormalities that extends over duration longer than the average duration of these abnormalities in inter-ictal periods [1]. The concern here is to differentiate also between pre-ictal and inter-ictal, pre-ictal and ictal for seizure prediction and detection respectively. The classification accuracy of differentiating pre-ictal with ictal is 89% while inter-ictal with pre-ictal is 53% so the overall accuracy differentiating between different states 50%. Figure 2 shows the classification accuracy of the three classes, the classifier training accuracy oscillates at 50% without trending upward or downward direction which means the training is not converging. In the bottom subplot, the training loss is not decreasing; it is the same from start to the end of training. By adding another 2 convolution layers in CNN architecture, the accuracies become 70% in differentiating between pre-ictal vs. inter-ictal and over all classes the training accuracy becomes 61% as shown in Fig. 3. The elapsed training time was around 17 min. As the selected periods with 10 min before seizure did not give good accuracy, the training was repeated with relabeling the pre-ictal by 5 min before ictal and then classifying different classes with the two network architectures. It is noticed that; by using two CL in CNN architecture, the training accuracy raised to 63 % better than using pre-ictal as 10 min before ictal but it oscillates around 60% which means the training accuracy is not improving and training loss is not decreasing as shown in Fig. 3. The elapsed training time was around 12 min.

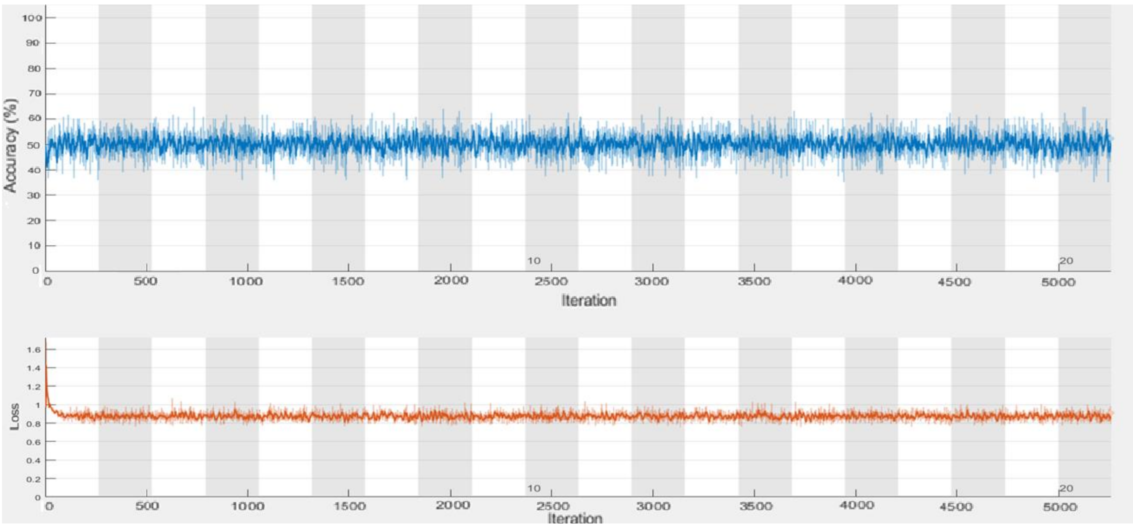

Fig. 2. Training progress for the 3 epilepsy classes using 2 CL of 1-D CNN (Pre-Ictal Labeled as 10 Minutes before Ictal).

The training was repeated by improving the CNN architecture by adding more than two CL, the classifier training accuracy started to oscillate at about 60% and at the end of epoch begin to trend in the upward direction towards 70% and training loss started to decrease. The classification accuracy for pre-ictal and inter-ictal became 76% and the overall accuracy differentiating the three epilepsy states (inter-ictal, pre-ictal, and ictal) became 64% as shown in Fig. 4.

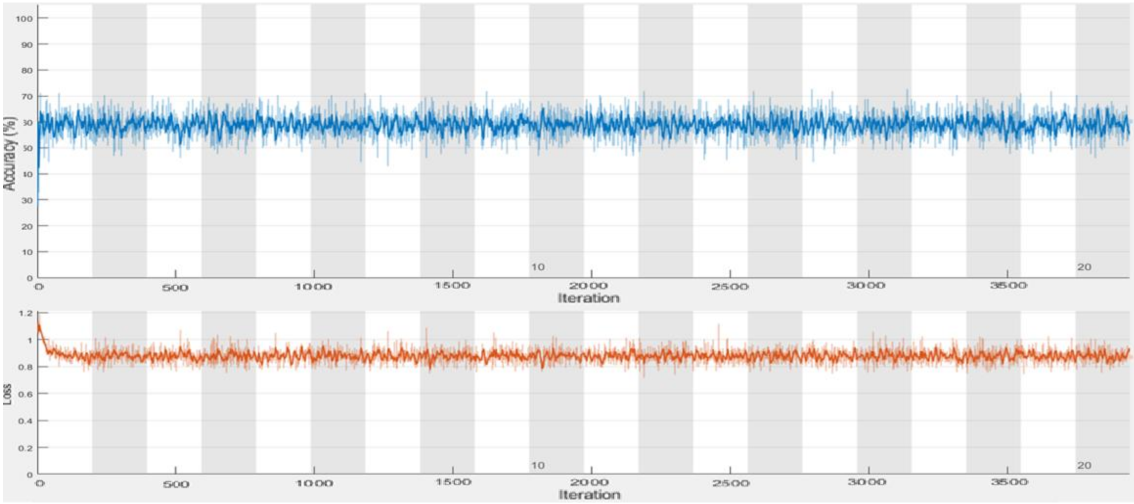

Fig. 3. Training progress for the 3 epilepsy classes using 2 CL of 1-D CNN
(Pre-Ictal Labeled as 5 Minutes before Ictal).

The elapsed training time was around 20 min. It is noticed that to improve accuracy it is required to increase layers as earlier layers identify common features while the later layers focus on more specific features in order to differentiate different categories but it increases the training time especially in case of a large number of files. Also, the pre-ictal as 5 minutes before ictal produces accuracy higher than pre-ictal as 10 min before ictal.

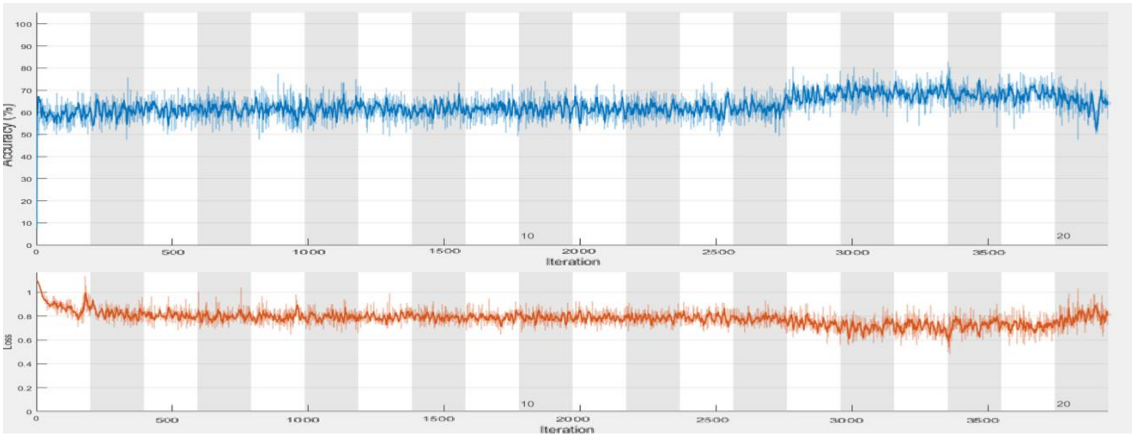

Fig. 4. Training progress for the 3 epilepsy classes using 4 CL of 1-D CNN
(Pre-Ictal Labeled as 5 Minutes before Ictal).

Table 4 shows the classification accuracy between the different stages by labeling the pre-ictal as 5 and 10 min before ictal using two CL of 1-D CNN shown in the first raw and four CL of 1-D CNN shown in the second raw.

Table 4. Classification accuracy using time domain signal and 1-D CNN

	Pre-ictal _10min				Pre-ictal _5min			
Epilepsy States	Pre&Int	Ict&Pre	Ict&Int	All	Pre&Int	Ict&Pre	Ict&Int	All
2CL, 1-D CNN	53%	89%	90%	50%	63%	81%	88%	58%
4CL, 1-D CNN	70%	93%	90%	61%	76%	86%	91%	64%

To Improve the classifier performance; the experiment is repeated using time-frequency images of the EEG signal. The spectrogram and scalogram images are used to train the 2-D CNN (Alexnet). First, using spectrogram images of ictal, pre-ictal and inter-ictal as input to Alexnet improved the classification accuracy than using signal in time domain. As shown in Figs. 5 and 6; the training accuracy in the top subplot increases and does not oscillates at certain accuracy as in time domain also the training loss in the bottom subplot decreases and is not fixed as in time domain. The overall accuracy of classifying different classes by labeling pre-ictal as 10 min and 5 min is 63% and 73% respectively. Table 5 shows the classification accuracy between different stages by labeling the pre-ictal as 5 and 10 min before ictal using spectrogram images. The accuracy of classification using spectrogram images of the EEG signal is better than using a time-domain signal even the number of images is less than the segments of time domain and the elapsed time is decreased to around 2 minutes.

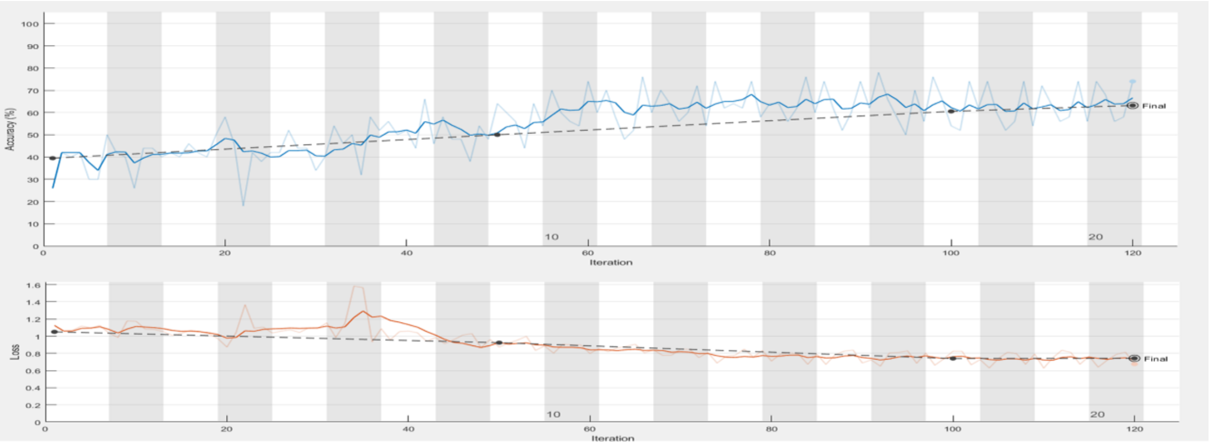

Fig. 5. Training progress for the 3 epilepsy classes using spectrogram images (Pre-Ictal Labeled as 10 Minutes Before Ictal).

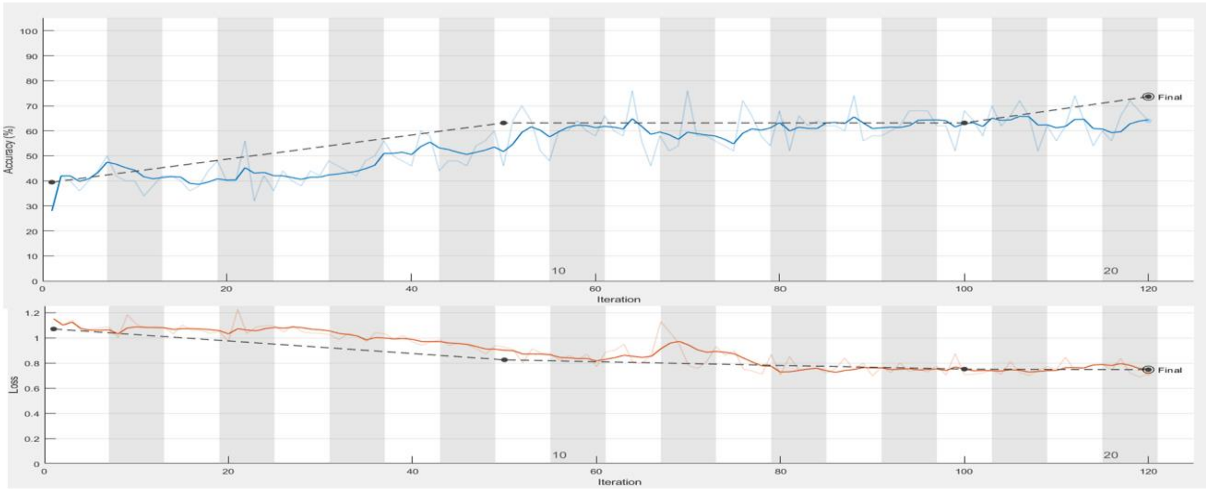

Fig. 6. Training progress for the 3 epilepsy classes using spectrogram images (Pre-Ictal Labeled as 5 Minutes Before Ictal).

Table 5. Classification accuracy using EEG spectrogram and Alexnet.

Pre-ictal _10min				Pre-ictal _5min			
Pre& Int	Ict&Pre	Ict&Int	All	Pre&Int	Ict&Pre	Ict&Int	All
52%	81%	88%	63%	61%	76%	81%	73%

The experiment is repeated but with scalogram images of EEG signal to train Alexnet. The results were very promising as shown in Figs. 7 and 8 below. Figure 7 shows the results obtained using scalogram images with pre-ictal labeled as 10 minutes before ictal. The training accuracy in the top subplot of the increases toward 80% and the training loss in the bottom subplot decreases toward zero. Figure 8 shows the results obtained using the scalogram for training with pre-ictal labeled as 5 minutes before ictal. There is a great improvement in training accuracy which now tends to 100 % and cross-entropy tends towards zero. Table 6 shows the classification accuracy between different states by labeling the pre-ictal as 5 and 10 min before ictal using scalogram images. It is showed that the Alexnet with scalogram of EEG signal with pre-ictal period labeled as 5 min before the ictal can differentiate between epilepsy stages and can be used for epilepsy detection and prediction with minimum training time around 2 min. The time required to classify one scalogram image is 0.025 sec.

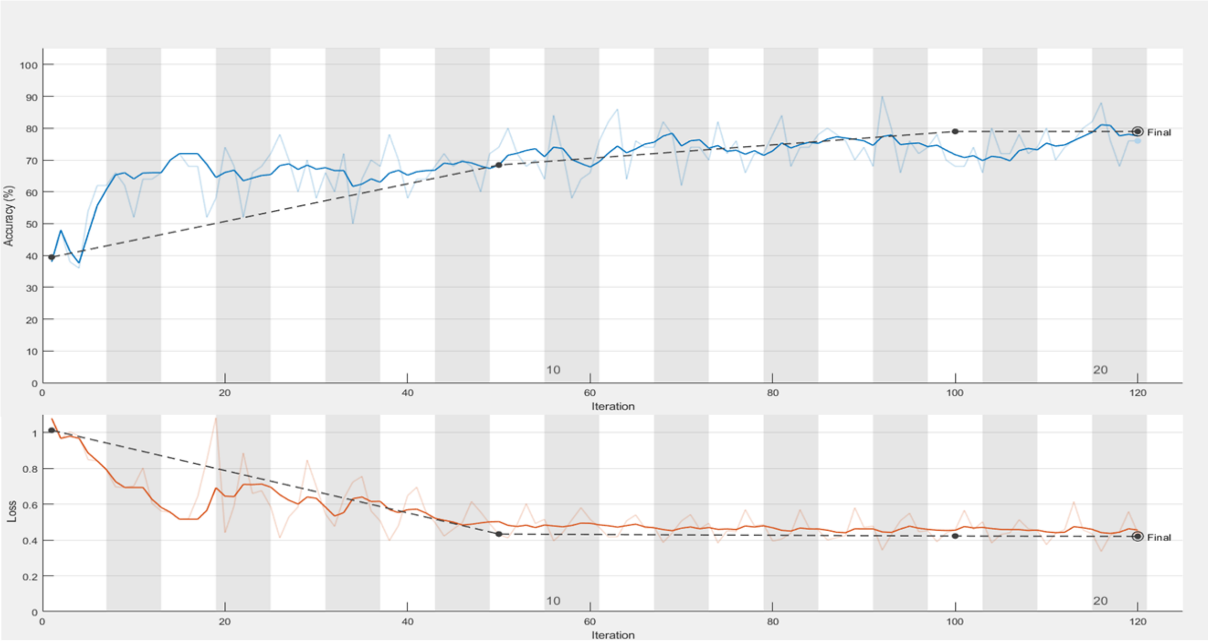

Fig. 7. Training Progress for the 3 epilepsy classes using scalogram images (Pre-Ictal Labeled as 10 Minutes before Ictal).

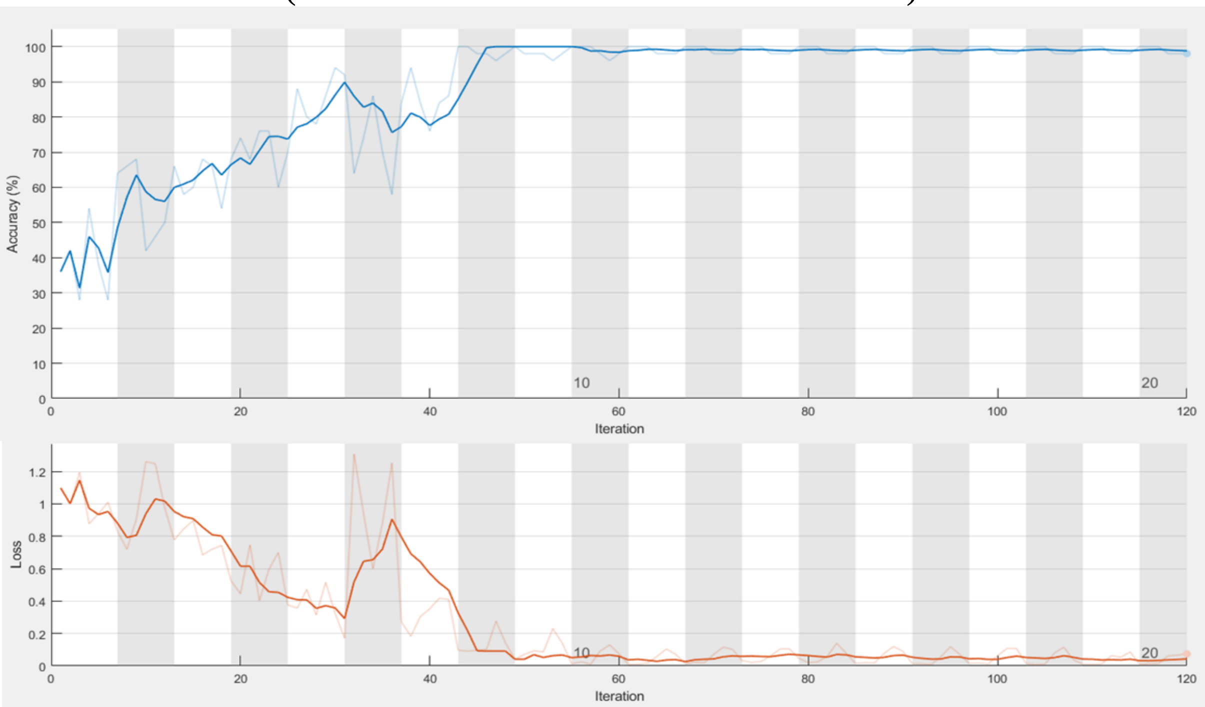

Fig. 8. Training progress for the 3 epilepsy classes using scalogram images (Pre-Ictal Labeled as 5 Minutes before Ictal).

Table 6. Classification accuracy using EEG scalogram and alexnet.

Pre-ictal _10min				Pre-ictal _5min			
Pre&Int	Ict&Pre	Ict&Int	All	Pre&Int	Ict&Pre	Ict&Int	All
60%	100%	100%	79%	100%	96%	100%	97%

The comparison between the accurcies obtained by our proposed method and other methods used in the literature based on deep learning approaches for classifying epilepsy stages is given in table 7.

Table 7. The performance of the proposed method compared to other methods

Author	Time domain	STFT	CWT
[2]	100%	-	-
[22]	-	69%	
[13]	-	-	87%
Proposed method	64%	73%	97%.

As shown in table 7; the previous studies are used only one format of EEG signal to classify the epilepsy states using deep learning (one used time domain signal with LSTM, second used STFT with CNN and the third used CWT with CNN). In our study, we used three different formats of EEG signal (time domain, spectrogram, and scalogram) and trained with CNN. We compared our results using each format with those in literature studies; we found that using LSTM for EEG signal classification in [2] acheived higher accuracy than our proposed 1-D CNN; but this obtained accuracy is for classifying only normal and seizure state without identification to pre-seizure state which taken into consideration in the proposed method, it is more challenging. Also their results are obtained using small dataset cosists of 5 patients only. Furthermore, The LSTM requires more training time than CNN. In future study, the architecture of our 1-D CNN could be improved by increasing the convolution layers to provide better accuricies. In [22], A patient-specific wearable system was developed using CNN to classify iEEG signal. Their system is not good with patients have small number of seizures as the DL requires a lot of samples for training. In our proposed method, the CNN was trained with dataset of patients with different ages and gender to provide a generic system. Also using scalp EEG is easier than using iEEG signal obtained using invasive electrodes. In [13], The CWT was applied to each 22 EEG channels and the wavelet coefficients were used as input to CNN. In our proposed method, scalogram images of FP1-F7 channel only is used and trained with pre-trained Alexnet and they achieved higher accuracy; using single channel will be more applicable in practicing.

5. CONCLUSION

In this paper, CNN is used for the identification of different epileptic seizure stages; inter-ictal, pre-ictal and ictal. The proposed approach has been examined on the CHB-MIT dataset. Different forms of EEG signal in time domain and time-frequency domain are used and different convolution neural network architectures in one dimension and two dimensions analyzed. Comparing the classification accuracy, it is concluded that the time-frequency domain provides better classification accuracy than the time domain signal. It is proved that the method of converting the time-domain signal into images of the time-frequency domain is a good way of applying EEG signal to deep learning classification, it provides higher accuracy and minimum training time. Regarding the time-frequency domain, using scalogram images provided higher accuracy than the spectrogram because of the varying length of its analysis window. The STFT cannot get the best results for signals having large frequency ranges as in epileptic seizures because the dimension of the cell is fixed. The experimental results demonstrate that the scalogram with Alexnet give high accuracy in differentiation between different epilepsy stages even by using raw EEG signal with common EEG artifacts and its performance is very promising. The classification accuracy of differentiating the epilepsy states of inter-ictal, ictal and pre-ictal is 97% by labeling the pre-ictal state as 5 min before the ictal.

DECLARATION OF CONFLICT OF INTERESTS

The authors have declared no conflict of interests.

REFERENCES

1. Tzallas, A. T., Tsipouras, M. G., Tsalikakis, D. G., Karvounis, E. C., Astrakas, L., Konitsiotis S., and Tzaphlidou, M., “Automated Epileptic Seizure Detection Method: A Review Study”, Department of Medical Physics, University of loannina, Greece.
2. Hussein, R., Palangi, H., Ward, R., and Wang, Z. J., “Epileptic Seizure Detection: A Deep Learning Approach”, Electrical Engineering and Systems Science, 2018.
3. Torki, A. A., and Eldeib, A. M., “Driver Drowsiness Detection Using Forehead Brain Signal”, Journal of Engineering and Applied Science, Vol. 63, No. 4, pp. 293-310, 2016.

4. Abu-Elyazeed, M. F., and Abdel Kader, N. S., "Wavelet Transform as a Preprocessor for Mental Task Classification using EEG Signals", Journal of Engineering and Applied Science, Vol. 50, No. 4, pp. 773-787, 2003.
5. Mula, M., and Monaco, F., "Ictal and Peri-Ictal Psychopathology", Behavioural Neurology, pp. 21-25, 2011.
6. Rashnavadi, T., "EEG Signal Analysis For Epileptic Seizure Prediction: a Review Study", CMBEC37 Conference, 2014.
7. Mishra, R., and Pandey, M., "A Survey on Different Methods for Epilepsy and Seizure Detection By Analyzing EEG", International Journal of Engineering Research and Reviews, Vol. 3, No. 4, pp. 10-15, 2015.
8. Tandle, A., and Jog, N., D'cunha, P., and Chheta, M., "Classification of Artefacts in EEG Signal Recordings and EOG Artefact Removal using EOG Subtraction", Communications on Applied Electronics, Vol. 4, No.1, 2016.
9. Hoey, C. V., Philips, W., and Lemahieu, I., "Time-Frequency Analysis of EEG signals", Circuits, Systems, and Signal Processing Workshop, 1997.
10. Orosco, L., Correa, A. G., and Laciar, E., "Review: A Survey of Performance and Techniques for Automatic Epilepsy Detection", Journal of Medical and Biomedical Engineering, Vol. 33, No. 6, pp. 526-537, 2013.
11. Putten, M., Olbrich, S., and Arns, M., "Predicting Sex From Brain Rhythms with Deep Learning", Scientific Report, 2018.
12. Stober, S., Sternin, A., Owen, A. M., and Grahn, J., "Deep Feature Learning for EEG Recordings", ICLR, Canda, 2016..
13. Khan, H., Marcuse, L., Fields, M., Swann, K., and Yener, B., "Focal Onset Seizure Prediction using Convolutional Networks", IEEE, Vol. 65, No. 9, pp. 2109-2118, 2018.
14. Zhou, M., Tian, C., Cao, R., Wang, B., Niu, Y., Hu, T., Guo, H., and Xiang, J., "Epileptic Seizure Detection Based on EEG Signals and CNN", Frontiers in Neuroinformatics, Vol. 12, No. 95, 2018.
15. Tzallas, A. T., "Epileptic Seizure Detection in EEGs using Time-Frequency Analysis", IEEE, Vol. 13, No. 5, pp. 703-710, 2009.
16. Abibullaev, B., Kim, M. S., and Seo, H. D., "Seizure Detection in Temporal Lobe Epileptic Eeg Using Best Basis Wavelet Functions", Vol. 34, No. 4, pp. 775-765, 2010.
17. Malaver, W. J., "Wavelet Multiresolution Analysis and Dyadic Scalogram for Detection of Epileptiform Paroxysms in Electroencephalographic Signals", Biomedical Engineering, Vol. 33, No. 3, pp. 195-201, 2017.
18. Acharya, U. R., Yanti, R., Swapna, G., Sree, V. S., Martis, R. J., and Suri, J. S., "Automated Diagnosis of Epileptic Electroencephalogram using Independent Component Analysis and Discrete Wavelet Transform", Journal of Engineering in Medicine, Vol. 227, No. 3, pp. 234-244, 2013.
19. Acharya, U. R., Molinari, F., Sree, S. V., Chattopadhyay, S., Hoong, K., and Suri, J. S., "Automated Diagnosis of Epileptic EEG Using Entropies", Biomed Signal Processing and Control, Vol. 7, No. 4, pp. 401-208, 2012.

20. Costa, R. P., Oliveira, P., Prdrigues, G., Leitao, B., and Dourado, A., "Epileptic Seizure Classification using Neural Network with 14 Features", 12th International Conference, Croatia, 2008.
21. Muhammad, G., Masud, M., Amin, S. U., Alrobaba, R., and Alhamid, M. F., "Automatic Seizure Detection in a Mobile Multimedia Framework", IEEE, Vol. 6, pp. 45372-45383, 2018.
22. Kornek, I. k., Roy, S., Nurse, E., Mashford, B., Karoly, P., Carroll, T., Payne, D., Saha, S., Bladassano, S., O'Brien, T., Grayden, D.,Cook, M., Freestone, D., and Harrer, S., "Epileptic Seizure Prediction using Big Data And Deep Learning Toward A Mobile System", BioMedicine,Vol. 27, pp. 103-111, 2018.
23. https://physionet.org/pn6/chbmit/ (Accessed 12/1/2018)
24. Khammari, H., and Anwar, A., "Spectral Based Forecasting Tool of Epileptic Seizures", International Journal of Computer Science, Vol. 9, No. 3, pp. 337-346, 2012.
25. Truong, N. D., Kuhlmann, L., Bonyadi, M. R., and Kavehei, O., "Semi-Supervised Seizure Prediction With Generative Adversarial Network", Frontiers, Vol. 12, No. 95, 2018.
26. Aguilar, R. R., Lopez, A. O., and Pineda, I. O., "Analysis of EEG Signal Processing Techniques Based on Spectrograms", Research in Computing Science, Vol. 145, pp. 151-162, 2017.
27. Ubeyli, E. D., "Combined Neural Network Model Employing Wavelet Coefficients for EEG Signals Classification", Digital Signal Processing, Vol. 19, pp. 297-308, 2009.

نظام تعرف مبنى على التعلم العميق لمراحل نوبات الصرع المرضيه المختلفه

إستخدم البحث نهج التعلم العميق لتصنيف مراحل نوبات الصرع باستخدام اشكال مختلفه لاشارات رسم المخ ، اولا تم ادخال اشارة رسم المخ فى المجال الزمنى الى CNN احادية الاتجاه ثم استخدام صور توضح المجال الزمنى والطيفى لاشارت المخ فى مراحل الصرع المختلفه وادخالها فى شبكة Alex ثنائية الاتجاه .تم اجراء التجارب على حالات من قاعدة بيانات CHB-MIT وحققت التجارب نسبة دقة مرتفعه عند استخدام صور ال scalogram بنسبة كفاءة ٩٧% وباستخدام صور الـ spectrogram نسبة ٧٣% فى حين استخدام اشارات رسم المخ فى المجال الزمنى حققت نسبة ٦٤%.