2020 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES)

Adopting Artificial Intelligence Powered ConvNet To Detect Epileptic Seizures

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***Abstract*—Neural networks and deep learning has gained much attention in the recent years in the medical field. Recent improvements in deep learning has led to computer-aided analysis of medical data, thereby contributing to automated disease diagnosis and detection. Seizures, commonly referred to as epilepsy, is normally detected by neurologists using the traditional approach of visual inspection of EEG waveforms that contain information about the electrical activity of the brain. However, since this is a laborious and time-consuming process, automated and accurate identification of epileptic seizures can improve efficiency and patient's quality of life. In this study, One-dimensional Convolutional Neural network (1D CNN) is used for automated detection of epileptic seizures based on the electroencephalogram (EEG) signal data. Our main objective in this work is to represent a methodology for automatic seizure detection through a 1D CNN model. The proposed model is a binary classification model that can detect whether a person is healthy or epileptic with an accuracy of 99 percent.**

***Keywords*—— seizure, epilepsy, convolutional neural network, deep learning, electroencephalography, artificial intelligence.**

I. Introduction

Epilepsy is a disease that is present in the top 5 neurological disorders in terms of DALY (Disability-adjusted life years) rates globally as in [1]. According to WHO (World Health Organization), about 50 million people word wide suffer from epilepsy [2]. It is non- communicable and affects people of all ages. It is characterized by recurrent seizures, which are sudden, uncontrolled electrical disturbances in the brain. These seizures may or may not be accompanied by convulsions. Patients with epilepsy are at a higher risk to develop psychological conditions such as anxiety and depression, as well as physical disabilities like fractures due to injury during convulsions. It is estimated that 70% of the people living with epilepsy can lead a better life and live seizure-free if properly diagnosed and adequately treated (WHO). Thus, it becomes imperative to develop a diagnostic technique of high accuracy and specificity in order to reduce the disability due to epilepsy.

Currently, one of the methods of diagnosis of epilepsy is by measuring the spikes or changes in the brain's electrical activity during seizure episodes using EEG or Electro-encephalograph [3][4]. Electrodes (or channels) are placed in different locations of the scalp to record these electrical signals. It helps to establish a diagnosis and categorize the case into one of the different forms of the disease, which in turn helps provide adequate treatment. Presently, the reading of these graphs is done manually by neurologists. However, this is a laborious and time-consuming process, requires a lot of effort from neurologists and is also prone to human error, thereby reducing its efficiency. Moreover, the diagnostic reports provided by experts with different level of experience may sometimes provide varying opinions which could be a challenge [4]. This urges the need to develop a computer based automated system for detection of epileptic seizures.

Deep learning has demonstrated promising outcomes in audio and image recognition [5][6]. For epileptic seizure detection researchers have built models using mainly time-frequency domain analysis[7][8]. Several research studies have proposed using artificial intelligence-based classification algorithms to detect epilepsy[9][10]. Results are somewhat compromised due to challenges of filtering noise levels in the EEG signals, and proper selection of features [11]. Data pre-processing and feature extraction is a key step in classifying outputs, and Deep Learning (DL) which is lately developed has shown considerable results in this area.

A literature review focusing on using the different deep learning-based methods for computer-aided seizure detection is presented in [12]. Acharya et al. in [13] first adopted deep learning approach for epileptic seizure detection using CNN. In [14], Akyol proposed DNN and SEA-based model for better prediction of epileptic seizures. In [15], authors summarized feature descriptors and their interpretation to review classification performance metrics. In order to determine significance of distinct features, different experiments were carried out such as non-parametric probability distribution and Bayesian error. Mao et al. [16] combined CNN and continuous wavelet transform (CWT) for classification of epileptic seizures. In [17], authors applied 1-D CNN and multichannel EEG wavelet power spectra on CHB-MIT scalp EEG dataset and achieved 97.25 % accuracy. In [18], authors used CNN architecture to build cross patient seizure detection technique and achieved 96.04 % average accuracy. Jiang et al. in [19], adopted semi-supervised, transfer learning and TSK fuzzy model to enhance model interpretability. In [20], authors used time frequency domain features which are concatenated to build image like features. These image like features are fed to CNN and achieved 97.74 % accuracy.

The objective of this research is to apply the artificial intelligence based one-dimensional convolutional neural networks for the detection of seizures. Classification is done using a very simple model with only two convolutional and two dense layers. The number of epochs used to train the model are minimum i.e. 10. So, the model can also be efficiently applied for real time detection and wearable devices.

The paper is organized with the following sections: the first section describes the data used followed by the second section which is methodology and model architecture. The third section focusses on test results and analysis followed by conclusion which is the final section

2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES) | 978-1-7281-4245-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/IECBES48179.2021.9398832

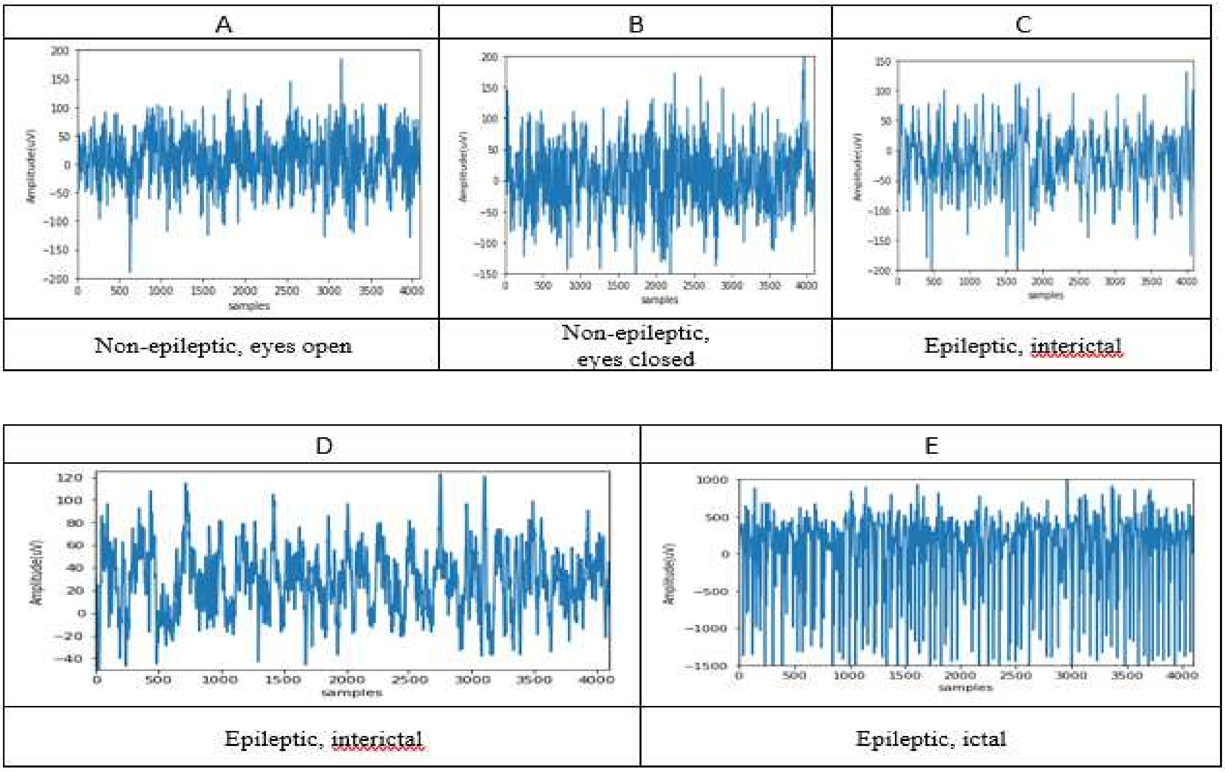

Fig. 1. Sample waveforms from the database

II. METHODOLOGY

A. Data

The dataset used for this study is EEG time series signals compiled by Andrzejak et al. at Bonn University, Germany [21]. The dataset included five segments denoted A-E each containing 100 single channel EEG segments of 23.6 second duration. The signals were recorded with a 128-channel amplifier system after which they were processed through DAQ and filtering techniques with a sampling rate of 173.61 hertz.

All the five segments were used in this research which are as follows:

1) Set A: EEG signals recorded from five healthy volunteers while they were in a relaxed and awake state with eyes opened.

2) Set B: EEG signals recorded from five healthy volunteers while they were in a relaxed and awake state with eyes closed.

3) Set C: EEG signals measured during seizure-free intervals (interictal) from the hippocampal formation of opposite hemisphere of the brain.

4) Set D: EEG signals measured during seizure-free intervals (interictal) from the epileptogenic zone.

5) *Set E:* EEG signals recorded from epileptic patients during seizure.

Figure 1 depicts the types and waveform samples of all the five different segments of data. Each record within each of the five different classes has 4097 samples.

B. Convolutional Neural Network (CNN)

Convolution is a mathematical operation of two functions that produces a third function that expresses how the shape of one is modified by the other. If a signal s(t) passes through a system with impulse response h(t), the output s(T) is the convolution of s(t) with h(t), as shown in Figure 2.

Fig. 2. Defining convolution

CNN is a class of Deep Neural Network (DNN). CNN is similar to Artificial Neural Networks (ANN) which is made up of a layer of neurons with weights and biases. It takes several inputs and the weighted sum is passed through a non-linear activation function. Back propagation algorithm is used for optimization of the network loss function. Unlike ANN, CNN operates on tensors (volumes) and spatial structures.

A CNN typically consists of an input layer and an output layer, along with multiple hidden layers. The CNN model used in this study consists of the following hidden layers (i) 1D convolutional layer (ii) batch normalization layer (iii) pooling layer and (iv) fully connected dense layer. In addition, the activation functions used are ReLU and Softmax.

1) Convolutional Layer: Convolution can be thought of as a specialized linear operation that involves sliding the kernel over the input signal for feature extraction. Image data is a two dimensional grid of pixels which requires 2D convolution while time-series data is one-dimensional. As the input in our study is time-series EEG data, 1D convolution is used. As illustrated in Figure 3, the kernel h with weights 'W' is slid in one dimension along the axis of time of length 'n'. EEG signals are recorded at regular time intervals using electrodes (channels) that are placed on the head of the person. The kernel moves along the axis of time from the beginning of the time series to the end and their values are multiplied by the corresponding time series values. The resulting sum becomes the new value of the univariate time series as shown in Figure 3. The kernel then moves to the next block and repeats the process to the end of the block extracting features for the new series.

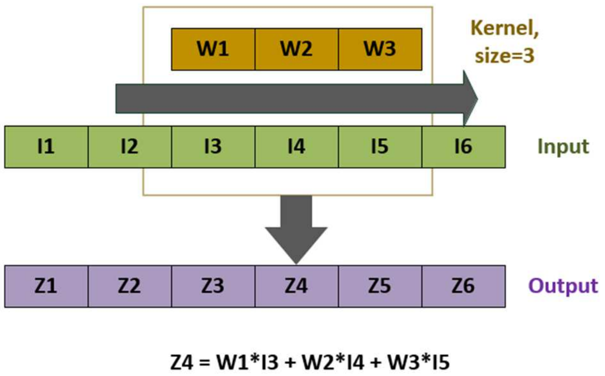

Fig. 3. Illustration of 1D convolution

If the input to the convolutional layer is i of length n and the kernel is w of length k, the convolution can be represented as follows :

$$\text{Output} = z(n) = \sum_{n-0}^{N-1} i_n \, w_{k-n} \quad (1)$$

2) Batch Normalization Layer: The batch normalization technique is used to standardize inputs to the convolutional layer that follows. In our modeling exercise, this layer transformed and standardized the EEG signal inputs with a mean of zero and a standard deviation of one. The internal covariance shift was reduced as defined in thereby improving the overall speed and efficiency of the training process.

3) Pooling Layer: Pooling layer helps get rid of redundant features and is employed after the convolutional layer. The two common methods include average pooling and max pooling. Average pooling involves computing the average value of the neurons while Max pooling picks the maximum value. In this study, Global Average pooling was used as the final pooling layer where the pool size was set to the input size and the average value selected from the entire pool as the output. So the number of features in the feature map was considerably down sampled.

4) Fully-connected dense Layer: Fully connected layers connect every neuron in one layer to every neuron in another layer. It accepts flattened output from the convolutional layers.

5) Activation Functions: In a neural network, the activation function decides whether the incoming signals have reached the threshold and should output signals for the next level. The activation function used in this study are Rectified Linear Activation Unit and Softmax.

a) Rectified Linear Activation Unit (ReLU): The output of the Rectified Linear Activation function or ReLU will be equal to the input if the input is positive, else it will be zero. ReLU is a preferred activation function because of its efficiency.

b) Softmax: When a neural network is used for classification, it can be either a binary classification or a multiclass classification. The Softmax activation function is used in multiclass classification to express inputs as a discrete probability distribution.

C. CNN Architecture

In this study, CNN is used to detect if a person has seizure or not. For this purpose, we considered three different CNN models M1, M2 and M3 in our initial experiment as shown in Table I, and the best model M1 was selected based on its performance and accuracy in classifying healthy and epileptic patients.

The architecture of the proposed CNN based seizure detection system used in this study is shown in Figure 4. Table II depicts the summary of the model implemented. The proposed CNN architecture includes eight layers; two convolutional, one batch normalization, two pooling, one dropout and two fully connected layers. Each convolution block consists of 128 filters with ReLU as the activation function. Max pooling is introduced after the first convolutional layer followed by batch normalization. Global average pooling is employed after the final convolutional layer. The stride is set at 1 for the pooling and convolution operations. Two fully connected layers follow the Global Average Pooling and dropout layers. As CNNs learn quickly, dropout is introduced between the last hidden layer and the fully connected dense layer to slow down the training process and avoid overfitting. The output layer has two output neurons for classification, and Softmax activation function is used in the output layer.

D. Model Implementation

From table II it can be observed that the input EEG signal data comprised of 4097 samples is convolved using conv1d_1 layer with 128 filters with a kernel size of 3 to arrive at a tensor volume of 4095 X 128 neurons. Max Pooling is then applied to every feature map thereby reducing the output volume to 1365 X 128. Batch normalization is employed to standardize the data prior to feeding it into the next convolutional layer, Conv1d_2. The output of Conv1d_2 layer which is 1363 X 128 is further convolved through the process of global average pooling. The flattened output is then fed into the two fully connected layers and a softmax activation function that can predict two classes.

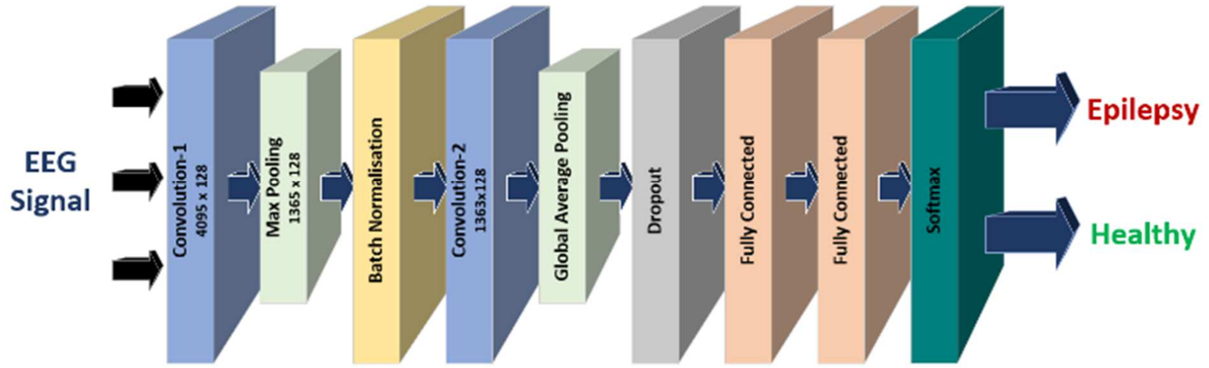

Fig. 4. Illustration of CNN architecture of the proposed model

TABLE I. ARCHITECTURE OF ALL THREE MODELS USED IN THE STUDY

Model	M1	M2	M3
Convolution 1	√	√	√
Batch normalisation			√
Max pooling	√	√	√
Batch normalisation		√	√
Convolution 2	√	√	√
Global average pooling	√	√	√
Dropout	√	√	√
Fully connected dense	√	√	√
Fully connected dense	√	√	√

III. TRAINING AND TESTING

The 1D-CNN model was trained using backpropagation with a batch size of 10 which means 10 signals were employed for each training or gradient update. Since fewer samples were used for each training, the overall training procedure took less time utilizing less memory. The number of epochs or iterations used were 10. A ten-fold cross validation technique was used to evaluate the model where the EEG data set was split into ten groups or folds and the last group was used to test the model performance as shown in the example below.

Trained on Fold 1 + Fold 2 + ... + Fold 9, Tested on Fold 10. Ten models were trained and evaluated with the evaluation score identified.

IV. RESULTS AND DISCUSSION

Three CNN models were built and tested in this study using the Python package Keras. Four data clusters A-E, B-E, C-E and D-E with two segments in each cluster were considered as in table III where a combination of healthy and epileptic patients were considered, and therefore data segment E was common to all clusters. The best model was selected based on its accuracy score for classification of healthy and epileptic patients. Parameters were selected on hit and trial basis. The first model did not employ batch normalization, the second model used one batch normalization and the third model included two batch normalization layers. The second model seemed to perform better when compared to the other two. A ten-fold cross validation was used to evaluate all three models and the tabulated results of the accuracy score of each

TABLE II. DETAILED PARAMETERS OF ALL LAYERS OF THE PROPOSED CNN MODEL M1

Layer #	Layer Type	Layer Name	Output Tensor Size	Kernel Size	Filter Size	Stride, Activation
1	1D Convolution	conv1d_1	4095 X 128	3	128	1, ReLU
2	Max Pooling	MaxPooling 1	1365 X 128	3	128	1
3	Batch Normalization	batch_normalization_1	1365 X 128	---	---	---
4	1D Convolution	conv1d_2	1363 X 128	3	128	1, ReLU
5	Global Average Pooling	global_average_pooling1d_1	1 X 128	--	128	--
6	Dropout	--	--	--	--	--
7	Fully Connected Dense	dense	1 X 100	--	--	--
8	Fully Connected Dense	dense	2			Softmax

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is presented in Table III. The highest accuracy achieved was 99%. The performance was evaluated using the accuracy score which is a reliable performance metrics.

$$Accuracy = (T P + T N) / Total\ Samples$$

where TP (true positive) is the number of epileptic cases predicted as epileptic. TN (true negative) is the number of healthy cases that is predicted as healthy.

TABLE III. PERFORMANCE OF ALL THREE MODELS

Data Cluster	Accuracy (%)		
	Model 1	Model 2	Model 3
A-E	99	99	99
B-E	93	95	96
C-E	96	98	97
D-E	92	95	88

In [22], the authors have achieved maximum accuracy of 98% for A-E and 93% for D-E using Short-time Fourier transform (STFT) only on alpha band while the proposed technique obtained 99% and 95% respectively.

V. CONCLUSION

Epilepsy is normally detected using the traditional approach of visual inspection. Automation of this process presents many advantages, including a faster diagnosis, continuous monitoring, and reduction in the overall cost of medical treatment . Three models were employed in the initial testing phase and the best performing model with high accuracy in predicting the two classes was selected. The proposed model has an 2 convolutional and 2 dense layers CNN architecture that can predict the two classes namely epileptic and healthy with high accuracy. The proposed model has achieved an accuracy of 99%.

Although deep learning algorithms seem to yield promising results when it comes to automated feature extraction, they depend on large volumes of data. Considering this fact, the number of data samples used in this study is not enough to train the proposed 1D CNN model. So, in future this model can be applied to large scale data.

REFERENCES

[1] O. Eeg-olofsson, “Clinical EEG and Neuroscience,” 2012, doi: 10.1177/1550059411433611.

[2] S. Siuly and Y. Zhang, “Medical Big Data: Neurological Diseases Diagnosis Through Medical Data Analysis,” *Data Sci. Eng.*, vol. 1, no. 2, pp. 54–64, 2016, doi: 10.1007/s41019-016-0011-3.

[3] J. E. Le Douget, A. Fouad, M. Maskani Filali, J. Pyrzowski, and M. Le Van Quyen, “Surface and intracranial EEG spike detection based on discrete wavelet decomposition and random forest classification,” in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2017, doi: 10.1109/EMBC.2017.8036865.

[4] K. Fukumori, H. T. Thu Nguyen, N. Yoshida, and T. Tanaka, “Fully Data-driven Convolutional Filters with Deep Learning Models for Epileptic Spike Detection,” in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, 2019, doi: 10.1109/ICASSP.2019.8682196.

[5] A. Mahajan and S. Chaudhary, “Categorical Image Classification Based on Representational Deep Network (RESNET),” in *Proceedings of the 3rd International Conference on Electronics and Communication and Aerospace Technology, ICECA 2019*, 2019, doi: 10.1109/ICECA.2019.8822133.

[6] T. H. Jaware, K. B. Khanchandani, and A. Zurani, “An Accurate Automated Local Similarity Factor-Based Neural Tree Approach toward Tissue Segmentation of Newborn Brain MRI,” *Am. J. Perinatol.*, 2019, doi: 10.1055/s-0038-1675375.

[7] M. Sameer, A. K. Gupta, D. C. Chakraborty, and D. B. Gupta, “Epileptical Seizure Detection: Performance analysis of gamma band in EEG signal Using Short-Time Fourier Transform,” in *International Symposium on Wireless Personal Multimedia Communications, WPMC*, 2019, doi: 10.1109/WPMC48795.2019.9096119.

[8] A. Subasi, J. Kevric, and M. Abdullah Canbaz, “Epileptic seizure detection using hybrid machine learning methods,” *Neural Comput. Appl.*, 2019, doi: 10.1007/s00521-017-3003-y.

[9] M. Sameer, A. K. Gupta, C. Chakraborty, and B. Gupta, “ROC analysis for detection of epileptical seizures using haralick features of gamma band,” in *26th National Conference on Communications, NCC 2020*, 2020, doi: 10.1109/NCC48643.2020.9056027.

[10] M. Sameer and B. Gupta, “Beta Band as a Biomarker for Classification between Interictal and Ictal States of Epileptical Patients,” in *2020 7th International Conference on Signal Processing and Integrated Networks (SPIN)*, 2020, pp. 567–570.

[11] A. H. Ansari, P. J. Cherian, A. Caicedo, G. Naulaers, M. De Vos, and S. Van Huffel, “Neonatal Seizure Detection Using Deep Convolutional Neural Networks,” *Int. J. Neural Syst.*, vol. 29, no. 4, pp. 1–20, 2019, doi: 10.1142/S0129065718500119.

[12] A. Shoeibi *et al.*, “Epileptic seizure detection using deep learning techniques: A Review,” 2020, [Online]. Available: http://arxiv.org/abs/2007.01276.

[13] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, “Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals,” *Comput. Biol. Med.*, 2018, doi: 10.1016/j.compbiomed.2017.09.017.

[14] K. Akyol, “Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection,” *Expert Syst. Appl.*, vol. 148, 2020, doi: 10.1016/j.eswa.2020.113239.

[15] P. Boonyakitanont, A. Lek-uthai, K. Chomtho, and J. Songsiri, “A review of feature extraction and performance evaluation in epileptic seizure detection using EEG,” *Biomed. Signal Process. Control*, vol. 57, p. 101702, 2020, doi: 10.1016/j.bspc.2019.101702.

[16] W. L. Mao, H. I. K. Fathurrahman, Y. Lee, and T. W. Chang, “EEG dataset classification using CNN

method," *J. Phys. Conf. Ser.*, vol. 1456, no. 1, 2020, doi: 10.1088/1742-6596/1456/1/012017.

[17] R. V. Sharan and S. Berkovsky, "Epileptic Seizure Detection Using Multi-Channel EEG Wavelet Power Spectra and 1-D Convolutional Neural Networks," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2020, doi: 10.1109/EMBC44109.2020.9176243.

[18] F. Pisano *et al.*, "Convolutional Neural Network for Seizure Detection of Nocturnal Frontal Lobe Epilepsy," *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/4825767.

[19] Y. Jiang *et al.*, "Seizure classification from EEG signals using transfer learning, semi-supervised learning and TSK fuzzy system," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 12, pp. 2270–2284, 2017, doi: 10.1109/TNSRE.2017.2748388.

[20] A. Singh, N. Pusarla, S. Sharma, and T. Kumar, "CNN-based Epilepsy detection using image like features of EEG signals," *Int. Conf. Electr. Electron. Eng. ICE3 2020*, pp. 280–284, 2020, doi: 10.1109/ICE348803.2020.9122874.

[21] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top.*, 2001, doi: 10.1103/PhysRevE.64.061907.

[22] M. Sameer and B. Gupta, "Detection of epileptical seizures based on alpha band statistical features," *Wirel. Pers. Commun.*, 2020, doi: 10.1007/s11277-020-07542-5.