Artificial Intelligence Evolution
https://ojs.wiserpub.com/index.php/AIE/

Research Article

Automatic Epileptic Seizure Detection Based on EEG Signals Using Deep Learning

Mohammad Karimi Moridani[1*], Seyed Sina Jabbari Behnam[1], Mahdyar Heydar[2]

[1]Department of Biomedical Engineering, Faculty of Health, Tehran Medical Sciences, Islamic Azad University, Tehran, Iran
[2]Department of Electrical Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran
Email: karimi.m@iautmu.ac.ir

Received: 28 August 2021; **Revised:** 22 October 2021; **Accepted:** 27 October 2021

Abstract: About one percent of the world's population suffers from epilepsy. A patient with epilepsy must be diagnosed early and accurately if they are to have any chance of being treated successfully. One method for diagnosing epilepsy is by carefully analyzing the Electroencephalogram (EEG) signal. We propose a method for signal processing EEG signals that detect epilepsy based on time-frequency features extracted from the signal and used as input for a neural network classifier. With the help of a convolutional neural network with deep learning, better and more efficient features were obtained and an accurate diagnosis was provided. It resulted in a significant difference between the two individuals upon analysis of the EEG signal. As compared with the previous method, the proposed technique distinguishes between healthy and epileptic signals with specificity 98 ± 2%, sensitivity 99 ± 0.7%, accuracy 98 ± 0.6%, and F-score 98 ± 0.5%. It is possible to use EEG signal analysis to detect the onset of seizures, especially in infants, as an effective tool to diagnose cases of suspected clinical signs of seizure onset.

***Keywords*:** Electroencephalogram (EEG), epileptic seizure, time and frequency domain features, Convolution Neural Network (CNN), deep learning

1. Introduction

One of the most important problems for people worldwide is the rapid growth of various diseases related to the nervous system. Some of these diseases, like epilepsy and myocardial infarction, are of theoretical significance, which differs from other people of different ages. Epilepsy is a disease of the nervous system that affects millions of people, or one percent of the world's population. The cause of this neurological disease is a defect in brain cells' electrical activity due to the stimulation of nerve cells [1, 2].

Epilepsy is generally divided into two categories based on the type of disease (general) and local epilepsy (partial) and also according to the cause and etiology can be due to genetic, structural, metabolic, or unknown [3].

People with epilepsy are 2 or 3 times more likely to die prematurely than a normal person. Eighty-five percent of cases are in developing countries, and at least half of all cases of epilepsy begin in childhood or adolescence [4]. However, it may occur suddenly in people over 65 years of age [5]. Electroencephalogram (EEG) is a graphical method of recording electrical activity in the brain that measures electrical activity changes in the event of voltage fluctuations in the brain through several electrodes placed on the scalp at different locations in the brain [6]. Studies on the EEG

DOI: https://doi.org/10.37256/aie.2220211123

signal show that the signal's statistical features and dynamic behavior change during a seizure [7].

One of the most common methods for diagnosing epilepsy is the visual diagnosis of a neurologist's electroencephalogram. This method has many drawbacks, including the presence of severe artifacts in the muscle signals, Electromyogram (EMG), Electrooculogram (EOG), and Electrocardiogram (ECG). Also, the doctor's misdiagnosis or the length of the data obtained can make the diagnosis time-consuming and tedious. Recent advances in neuroimaging and analysis have led to research into the brain's functional and structural correlations.

In recent years, due to the importance of this disease, researchers have studied this phenomenon to diagnose as much as possible and use different methods.

This study aimed to increase the accuracy in the diagnosis of epilepsy by utilizing the features of linear and nonlinear domains so that by these parameters, the distinction between the three categories, the patient's normal state, the stage before entering the seizure, and seizure is possible.

Some recent research has used a set of linear and nonlinear features simultaneously to diagnose epilepsy [8]. According to EEG research, the signal's statistical features and dynamic behavior changed completely during a seizure [7].

Numerous studies have been performed to detect seizures by EEG wave analysis, neuronal activity changes, and nonlinear deformation of brain signals that may be present before the onset of the attack [9-10].

Besides, the EEG can be used in many studies, including recognizing emotions [11], measuring alcohol consumption [12], changing brain waves with smoking [13], diagnosing the sleep phase [14], and so on. Each patient's EEG signals have specific characteristics. At the onset of one patient's seizure, the EEG signal may be very similar to another patient's non-seizure EEG pattern. These reciprocal changes of the patient in seizures and activity during non-seizures cause the patient's non-specific classification to be weak or inaccurate at the time of diagnosis.

Katagal et al. showed that the frequency of epileptic seizures increased significantly despite obstructive sleep apnea, and treatment of this disease reduced and controlled epileptic seizures [15]. Nobili et al. presented a study on people with epilepsy. They found that patients with epilepsy who developed sleep-induced sleep disorders were more likely to die suddenly from the disorder and have epileptic seizures [16]. Yambe et al., using Lyapunov power and brainwave behavior and time series, discussed the prediction and control of seizures. In another study, an adaptive method for detecting epilepsy from EEG waves was introduced using adaptive neuro-phase and Lyapunov systems [17]. Subasi et al. showed that the diagnosis of epilepsy is made using wavelet domain tools and neuro-phase systems using minor changes in brain signals [18]. Another study evaluated Quantitative EEG (QEEG) findings and anticonvulsant therapy in children with epilepsy [19]. In 2021, Kukker et al. achieved accuracies of 96.79% and 93.81%, respectively, by EEG and using the Q-Learning ASSISTED and Q-Learning Fuzzy methods [20]. In 2019, in the diagnosis of epileptic seizures, Mayank Kumar Jareda et al. achieved accuracies of 6.89% and 87%, respectively by SVM and KNN algorithms [21].

The rest of this paper is organized as follows:

In the second section, the database is introduced, and the proposed method in this paper is devoted to the processing of EEG signals for feature extraction. The third provides the simulation results obtained from the proposed method, and the next sections present the discussion and conclusion.

2. Materials and methods

2.1 *Database*

The data used in this study was collected from the Physiont Database. This data was recorded by Children's Hospital Boston (CHB) and the Massachusetts Institute of Technology (MIT) and included EEG recordings of children with seizures [22].

Subjects were monitored for several days after discontinuation of anticonvulsant drugs to detect seizures and evaluate their candidacy for surgery. Data were recorded using an electroencephalographic device that included 23 people at the time of epileptic seizure and non-epileptic seizure.

In this study, 69 signals belonging to 23 people were used during epileptic and non-epileptic seizures. Of these, 5 are female, and 5 are male. All signals are sampled at 256 samples per second with a resolution of 16 bits. All signals from the database provider are labeled epileptic and non-epileptic. More details about the patients are given in Table 1. The mean and standard deviation of the patients' age is 9.98 ± 5.68 years. Inclusion criteria were the scheduled clinical EEG observation and female or male aged 5-90. As exclusion criteria, it can be mentioned that data collection may be affected by autism or another developmental disorder.

Table 1. Personal characteristics and number of seizures in patients

Case	Gender	Age (years)	Number of seizures	Total seizure time (s)
Patient 1	F	11	7	70
Patient 2	M	11	3	30
Patient 3	F	14	7	70
Patient 4	M	22	3	30
Patient 5	F	7	5	50
Patient 6	F	1.5	7	70
Patient 7	F	14.5	3	30
Patient 8	M	3.5	5	50
Patient 9	F	10	3	30
Patient 10	M	3	7	70
Patient 11	F	12	3	30
Patient 12	F	2	13	130
Patient 13	F	3	8	80
Patient 14	F	9	7	70
Patient 15	M	16	14	140
Patient 16	F	7	6	60
Patient 17	F	12	3	30
Patient 18	F	18	6	60
Patient 19	F	19	3	30
Patient 20	F	6	6	60
Patient 21	F	13	4	40
Patient 22	F	9	3	30
Patient 23	F	6	3	30
Mean ± std	M: 5 F: 18	9.98 ± 5.68	5.61 ± 3.06	56.09 ± 30.56

Figure 1 shows the EEG signal of a patient during an epileptic seizure. The number of channels recorded by the standard 20-10 is equal to 23.

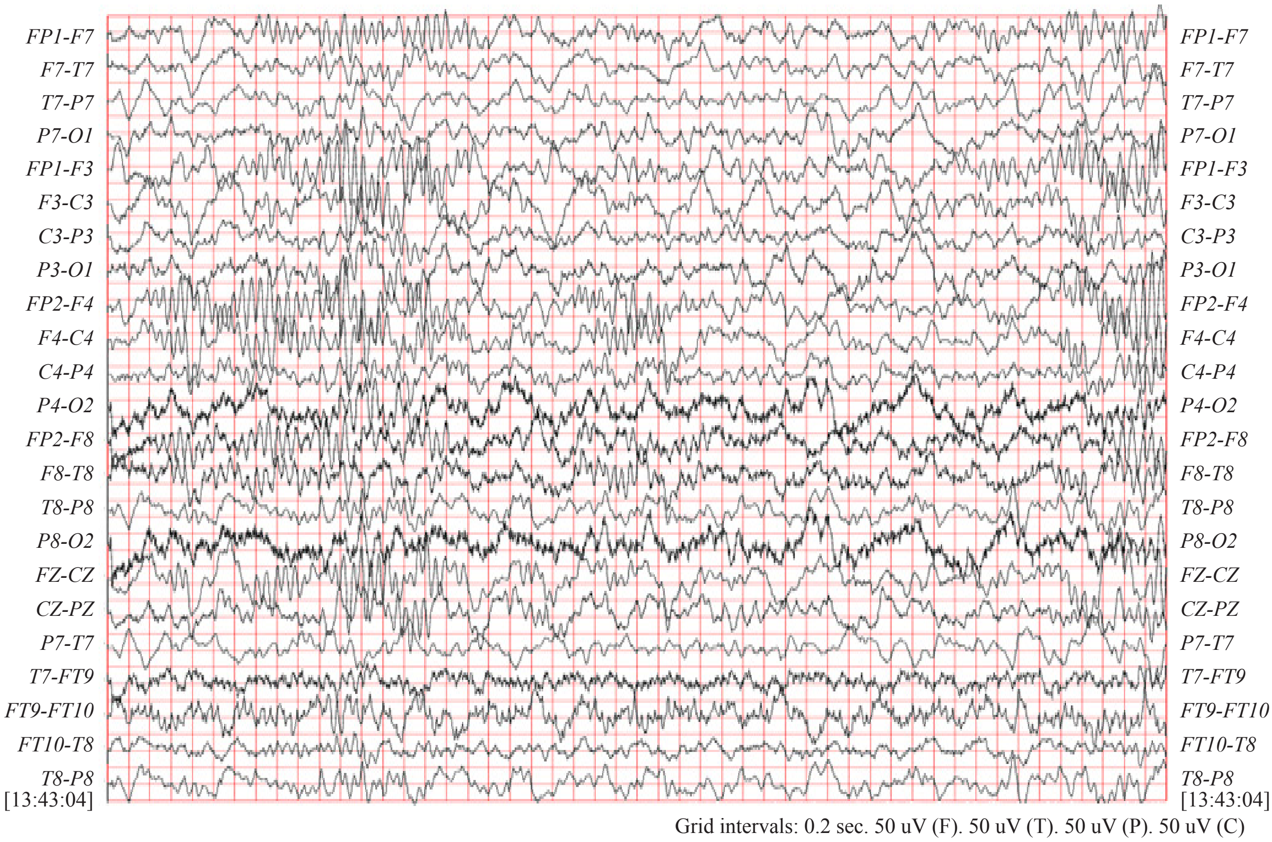

Figure 1. A patient's EEG signal during an epileptic seizure

2.2 *Proposed method*

In this study, considering the effect of epileptic seizures on the brain's electrical activity and its occurrence on brain signals, EEG data were used to diagnose these seizures. The block diagram of the signal processing steps and the generation of the appropriate output can be seen in Figure 2.

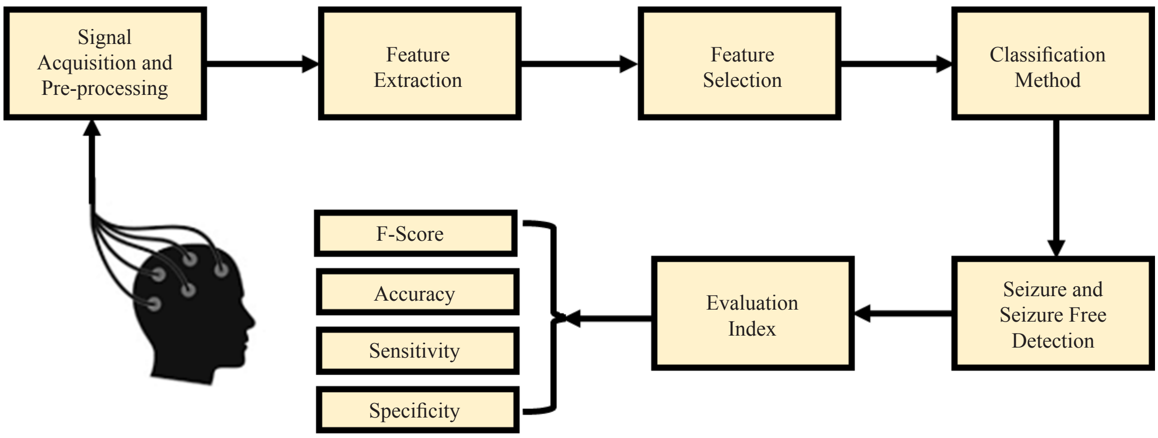

Figure 2. Block diagram of the process of epileptic seizures detection

Then, time-domain and time-frequency domain methods were used to extract the features of the EEG signal. The features used in the time domain are the average amplitude, average power, and energy of the signals during epileptic and non-epileptic seizures. Equations (1) to (3) are related to the features extracted in the time domain [23].

$$Mean(s) = \frac{1}{N}\sum_{k=1}^{N} S_k \tag{1}$$

$$P[k] = \lim_{n\to\infty} \frac{1}{2n+1}\sum_{k=-n}^{n} |S[k]|^2 \tag{2}$$

$$E[k] = \lim_{n\to\infty} \sum_{k=-n}^{n} |S[k]|^2 \tag{3}$$

S is the time-series signal, k is the sample of each signal, and N is the signal samples' sum.

Fourier transform and wavelet EEG signal conversion were used in epileptic and non-epileptic attack intervals to calculate the frequency and time-frequency characteristics. In the following, we will examine the mathematical algorithm of these transformations.

Since continuous signals have so many samples that they are challenging to enter into the Wavelet transform formula and require complex calculations to achieve the ability to load and encode the Wavelet transform in MATLAB software, we used the discrete Wavelet transform presented by formula (4) [24].

$$DWT_{(m.k)} = \frac{1}{a}\sum_{n=0}^{N-1} x(n) g\left(\frac{k-b}{a}\right) \tag{4}$$

In this formula, $x(n)$ is the main signal, $a = a_0^m$, $b = b_0^m$, and N is the number of samples in the windowing signal. The function $g(\,)$ is called the mother wavelet. m is an indicator of the level of decomposition. a and b are the translation and scaling parameters. Wavelet analysis at early levels (cD1, cD2) is often accompanied by low-frequency noise information. If these coefficients are ignored, there is very little information lost from the signal. In order to extract features from the above-mentioned cases, Daubechies (db) 6 as DWT subset and wavelet coefficients at four levels (cD5, cD6, cD7, cD8) were used. From these four levels, six features are extracted, including mean, standard deviation, maximum, minimum, median, and power spectrum density.

For neural network input, a matrix consisting of the mentioned features was designed for about 70% of the signals during epileptic and non-epileptic seizures with the same distribution and applied to a Multilayer Perceptron (MLP) neural network Radial Basis Function (RBF). The output of the network was also considered a feature matrix with the dimensions of the input matrix. This matrix has -1 and +1. In this matrix, -1 is assigned to the epileptic seizure and +1 to the non-epileptic seizure period. These two matrices were given to neural networks to be trained. Then, for the network, 30% of the signals belonging to other people who had the same distribution of seizure and non- seizure were applied to evaluate the networks' performance and receive a response to them, and the observed output was calculated.

2.3 *Convolutional neural network*

Convolution Neural Networks (CNNs) are a model of artificial neural networks like the Traditional Neural Network (TNN) that are made up of neurons, layers, and weights. The most important difference CNNs with TNNs, refer to the special ability of CNNs in deep learning. Due to this very important advantage in recent years, the use of CNN's to diagnose diseases in different medical applications has been considered by researchers. Figure 3 shows the steps for detecting an epileptic seizure using CNN.

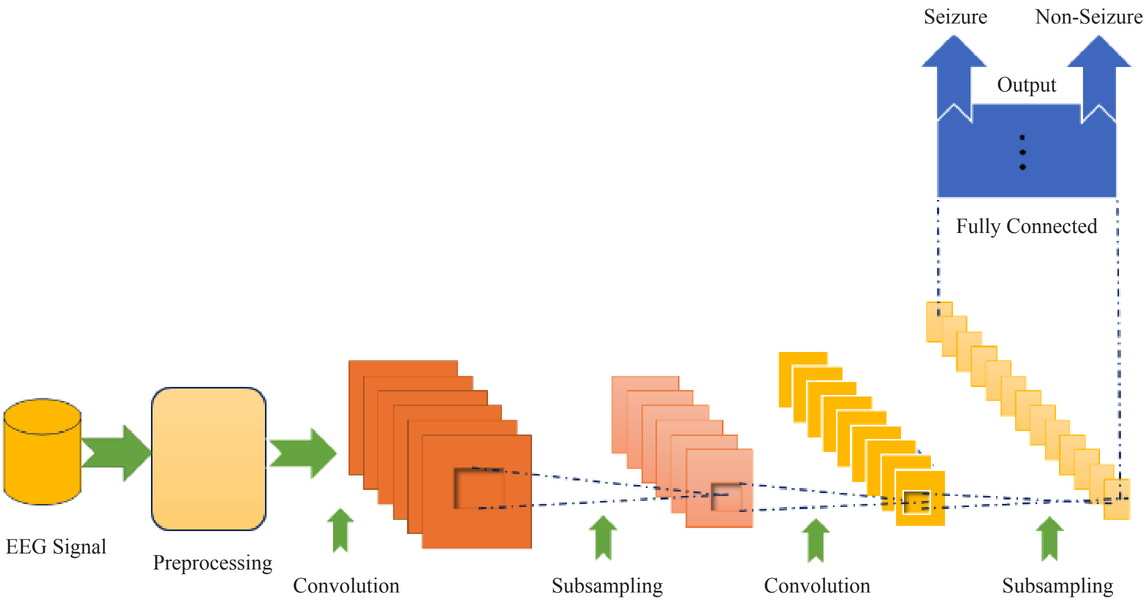

Figure 3. Epileptic seizure detection process with 2-d CNN

3. Simulation results

In the present study, our focus has been on the use of MLP and RBF neural networks and by changing the factors in the structure of the artificial neural network, such as training function, adaptation learning function, performance function, number of the latent layers, and the number of neurons in each layer, transfer function, the performance of proposed algorithm were examined.

MATLAB software was used to obtain the simulation results. The simulation results show that the correct choice of inputs to the neural networks is very important because the inputs can increase the network's accuracy and efficiency and significantly reduce the convergence time.

Equations (5) to (8) represent the criteria of sensitivity, specificity, accuracy, and F-score, respectively [25].

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{5}$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{6}$$

$$Accuracy = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}} \tag{7}$$

$$F-score = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} \tag{8}$$

The activation function used in the hidden layer neurons of the MLP neural network for this study, as you can see in Table 2, is a function of the hyperbolic tangent function, which shows the mathematical relationship and the corresponding waveform in Equation (9).

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{9}$$

Table 2 shows the specifications of the MLP neural network's values to achieve the best detection performance results using the neural network.

Table 2. Specifications of adjustable parameters of MLP neural network

Neural network options	Values
Training function	TRAINLM
Adaption learning function	LEARNGDM
Performance function	MSE
Number of layers	4
Number of 1^{st} layer's neurons	10
Number of 2^{nd} layer's neurons	5
Number of 3^{rd} layer's neurons	5
Transfer function	Hyperbolic Tangent

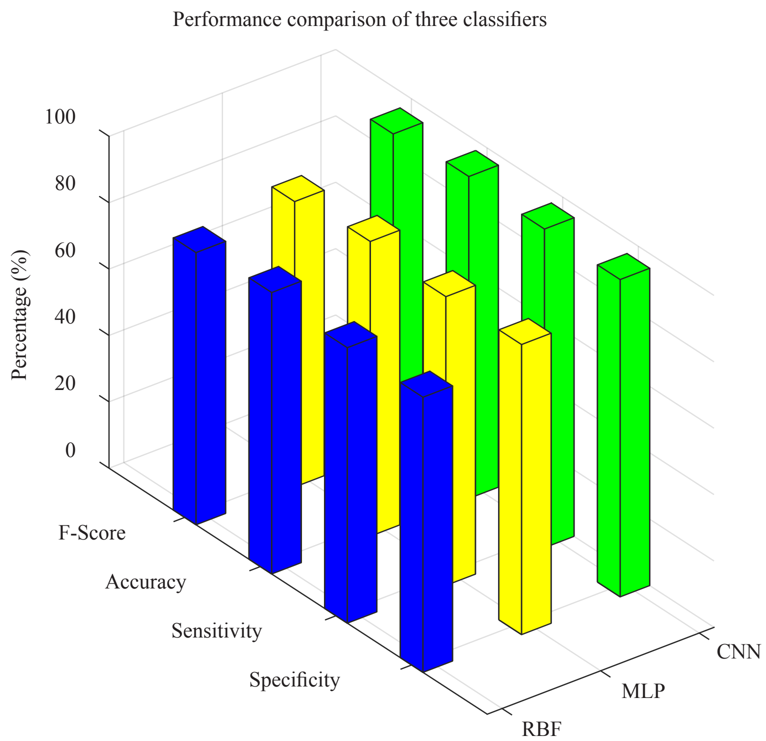

Figure 4. Comparison of the performance for RBF, MLP, and CNN classifier

For RBF neural network to achieve the best response, the values of performance goal and spread constant parameters were set equal to 0.02 and 1, respectively.

Finally, the Mean Squared Error (MSE) criterion was used to compare MLP and RBF artificial neural networks' results. As shown in Equation (10), N is the number of inputs, $Z_{(r)}$ is the actual output value, and $Z_{(p)}$ is the predicted output value.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=0}^{N}\left(Z_{(r)}(i) - Z_{(p)}(i)\right)^2 \tag{10}$$

Figure 4 shows MLP, RBF, and CNN neural networks' performance criteria to detect epileptic seizures. The results were obtained using MLP neural network with the values in Table 2 compared to other evaluated methods. As shown in Figure 4, the criteria for evaluating classifiers in the case of CNN have been used better than different classifiers' methods. This result is because CNN is based on deep neural networks and extracts more efficient and accurate features.

4. Discussion

The use of bio-signals to diagnose and treat diseases has been common for many years. In recent years, with the medical science progress and realization of the importance of neuro- and cognitive sciences, brain signals are used to identify brain functions and to diagnose, control, and treat neurological disorders. Although the EEG plays an important role in monitoring the brain activity of patients with epilepsy and diagnosing epilepsy, a specialist is needed to analyze all EEG recordings to diagnose epileptic activity [26]. But by using artificial neural networks, not only the diagnosis is faster but also individual error is minimized. It is also possible for the doctor to have enough time for preventive actions.

The article presents two methods of diagnosing epileptic seizures. First, time and time-frequency features were used to diagnose the disease. Later, CNN was used to enhance the diagnosis, since it could detect even the smallest changes. In recent years, a lot of research has been done to detect epileptic seizures, and in the following, we will introduce the results of some studies. An article conducted by Goenka et al. in 2018 used data from 44 signals obtained from the ICU and EMU for the diagnosis of epilepsy, and the method was also QEEG. A sensitivity of 73% was reported in the study. But in 2019, Tsipouras Goenka achieved 98.8% classification accuracy using EEG signals and entropy and frequency features. Furthermore, Guha et al. compared the results of MLP and K-NN neural networks in 2020 in a study that involved 500 epileptic patients. They achieved an accuracy of 80% when using the proposed method, compared with 78% and 76% for MLP and K-NN neural networks respectively, as well as 96% for the RBF neural network used by Zhou et al. in 2020. In the same year, Aung et al. Introduced a new method called modified distributive entropy as a feature for diagnosing epileptic seizures and compared the results with fuzzy and distributive entropy. The measurement accuracy of this method was 91%. In 2021, Johnson et al. obtained an average seizure detection sensitivity of 91% across all patients by EEG signal and using a combination of the CNN models and bidirectional long short-term memory (BLSTM) [27]. In 2021, Aayesha Zia et al. carried out research in this field by using the non-linear and non-stationary characteristics of EEG signals with the KNN and FRNN methods [28]. The results of recent studies are shown in Table 3.

5. Conclusion

Epilepsy is a disorder of the human nervous system that can also affect a person's personal life. Numerous studies have been conducted by many researchers on artificial neural networks and the extraction of various features to detect epilepsy. However, the purpose of this paper is to extract features of the EEG signal that can be used to obtain the best input combination to apply to the neural network for better results.

The results showed that the use of CNN has the best performance in epileptic seizure detection. Because the visual diagnosis of epilepsy from an electroencephalogram is so complex, this method greatly helps physicians in their diagnosis. Our focus was on temporal lobe epilepsy in this study, but this method can identify different types of epilepsy to be used.

Due to the complexity and similarity of the EEG characteristics of epileptic patients and the elimination of destructive signal factors such as artifacts and noise, this method is a supplement to help physicians better diagnose and reduce errors.

Table 3. Results of recent research on the detecting of epileptic seizures

Author	Year	Data	No. of Patients/Dataset	Features	Classifier/ Methods	Results
Swami et al. [29]	2016	EEG	University of Bonn	STD, ENT, MEAN, RMS	DTCWT using GRNN	Acc = 95.15%
P. Thodoroff et al. [30]	2016	EEG	CHB-MIT	Image representation of EEG integrating spatial information	Recurrent neural network	Higher Sen, lower FDR
Fujiwara et al. [31]	2017	ECG	14 patients	HRV-based features	Multivariate process control	Se = 91%
Jonatas Pavei et al. [32]	2017	(V-EEG), ECG	Analyzed clinical data from 12 patients (9 female; 3 male; age 34.5 ± 7.5 years), involving 34 seizures and a total of 55.2 h of interictal electrocardiogram (ECG) recordings	HRV parameters: 1-non-linear (SampEn and Lorenzo plot, the cardio-sympathetic index (CSI) and the cardiovagal index (CVI)) 2-Time domain (The standard deviation of all normal RR intervals (SDNN) and the root mean square of the sum of the squared differences of successive normal RR intervals (RMSSD)) 4-frequency domain (low-frequency (LF) High-frequency (HF))	1-SVM 2-leave-one- out cross-vl 3-fast Fourier transform (FFT) 4-power spectral density (PSD)	(<0.5 FP/h) the false positive rate of 0.49 FP/h for ECG recordings from all the interictal periods, with a sensitivity of 94.1% for seizure prediction based on recordings capturing the period 0-5 min before seizure onset.
Sharma et al. [33]	2017			ATFFWT and FD feature	using LSSVM	Acc = 98.67%
Tzimourta et al. [34]	2017		21	Wavelet Transform	Discrete Wavelet Transform (DWT), SVM	Se = 93% Sp = 99%
Ajay Goenka et al. [35]	2018	QEEG	88(44 in the Intensive Care Unit and 44 in the Epilepsy Monitoring Unit)	-	Quantitative EEG Spectrograms	Se = 73 %
Markos G. Tsipouras [36]	2019	EEG		Frequency sub-bands/energy, total energy, fractional energy, entropy	Random forests	Accuracy classification = 98.8%
Naghmeh Mahmoodian et al. [37]	2019	EEG	21 patients	Linear features: three energy-based features, to compute average, maximum,and minimum of the cross-bispectrum respectively (mean, max, min) Nonlinear features: six nonlinear features, two are frequency relation-based features, and two are entropy-based features for computing the degree of disorder in each cross-bispectrum computation	SVM RBF	Se = 95.8% Sp = 96.7% Ac = 96.8%
Guha A. et al. [38]	2020	EEG	500	-	DNN classifier with 5 hidden layer, each layers consists 85 neurons	Se = 80% Acc = 80% Precision = 64% F1 score = 71%
Zhou D. et al. [39]	2020	EEG	500	Linear kernel, non-linear kernel, Fusion kernel	RBF	In fusion kernel: Se = 0.965 ± 0.047 Sp = 0.951 ± 0.021 Acc = 0.963 ± 0.024
Aung S.T. et al. [40]	2020	EEG	500 EEG segments	Fuzzy Entropy, Distribution Entropy, Modified-Distribution Entropy	Modified-Distribution Entropy	Se = 92.5% Sp = 85% Acc = 91% AUC = 96%

Conflicts of interest

The authors declare no competing financial interest.

References

[1] Litt B, Echauz J. Prediction of epileptic seizures. *Lancet Neurology*. 2002; 1: 22-30. Available from: doi: 10.1016/s1474-4422(02)00003-0.

[2] Subasi A, Ercelebi E. Classification of EEG signals using neural network and logistic regression. *Computer Methods and Programs in Biomedicine*. 2005; 78(2): 87-99.

[3] Berg AT, Berkovic SF, Brodie MJ, Buchhalter J, Cross JH, van Emde Boas W, et al. Revised terminology and concepts for organization of seizures and epilepsies: Report of the ILAE commission on classification and terminology, 2005-2009. *Epilepsia*. 2010; 51(4): 676-685. Available from: doi: 10.1111/j.1528-1167.2010.02522.x.

[4] World Health Organization, epilepsy. Available from: http://www.who.int/mental_health/neurology/epilepsy/en/index.html [Accessed 12th June 2015].

[5] Ramsay RE, Rowan AJ, Pryor AM. Special considerations in treating the elderly patient with epilepsy. *Neurology*. 2004; 62(2): S24-S29.

[6] EEG Signal. The science behind Bo-Tau. Available from: http://www.bo-tau.co.uk/index. php?action=the_science_behind_bo_tau [Accessed 27th August 2012].

[7] Adeli H, Ghosh-Dastidar S, Dadmehr N. Mixed-band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection. *IEEE Transactions on Biomedical Engineering*. 2007; 54(9): 1545-1551. Available from: doi: 10.1109/TBME.2007.891945.

[8] Balli T, Palaniappan R. A combined linear & nonlinear approach for classification of epileptic EEG signals. *Proceeding of 4th international conference of the IEEE EMBS*. 2009. p. 71417.

[9] Adeli H, Zhou ZQ, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transform. *Journal of Neuroscience Methods*. 2003; 123: 69-87.

[10] Adeli H, Ghosh-Dastidar S, Dadmehr N. A wavelet-chaos seizure and epilepsy. *IEEE Transactions on Biomedical Engineering*. 2007; 54.

[11] Soleymani M, Pun T, Pantic M. Multi-modal emotion recognition in response to videos. *IEEE Transactions on Affective Computing*. 2012; 3(2): 211-223.

[12] Wu D, Chen ZH, Feng RF, Li GY, Luan T. Study on human brain after consuming alcohol based on EEG signal. In: *Proceedings of the International Conference on Computer Science and Information Technology (ICCSIT)*. 2010. p. 406-409.

[13] Hanafiah ZM, Yunos KFM, Murat ZH, Taib MN, Lias S. EEG brainwave pattern for smoking behaviour after horizontal rotation treatment. In: *Proceedings of the IEEE Student Conference on Research and Development*. 2009.

[14] Estrada E, Nazeran H, Ebrahimi F, Mikaeili M. EEG signal features for computer-aided sleep stage detection. In: *Proceedings of the IEEE EMBS Conference on Neural Engineering*. 2009. p. 669-672.

[15] Katagal P, Yardi N. The relationship between sleep and epilepsy. *Seminars in Pediatric Neurology*. 2008; 15(2): 42-48.

[16] Nobili L, Proserpio P, Rubboli G, Montano N, Didato G, Tassinari CA. Sudden unexpected death in epilepsy (SUDEP) and sleep. *Sleep Medicine Reviews*. 2011; 15(4): 237-246.

[17] Übeyli ED. Automatic detection of electroencephalographic changes using adaptive neuro-fuzzy inference system. *Expert Systems with Applications*. 2009; 36: 9031-9038.

[18] Subasi A. Application of adaptive neuro-fuzzy inference system for epileptic seizure detection using wavelet feature extraction. *Computers in Biology and Medicine*. 2007; 37: 227-244.

[19] Ouyang CS, Chiang CT, Yang RC, Wu RC, Wu HC, Lin LC. Quantitative EEG findings and response to treatment with antiepileptic medications in children with epilepsy. *Brain & Development*. 2018; 40(1): 26-35. Available from: doi: 10.1016/j.braindev.2017.07.004.

[20] Kukker A, Sharma R. A genetic algorithm assisted fuzzy Q-learning epileptic seizure classifier. *Computers & Electrical Engineering*. 2021; 92: 107154. Available from: doi: 10.1016/j.compeleceng.2021.107154.

[21] Jareda MK, Sharma R, Kukker A. EEG signal based seizure classification using wavelet transform. *International Conference on Computing, Power and Communication Technologies (GUCON)*. 2019. p. 7-28.

[22] Shoeb AH. *Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment*. PhD Thesis, Massachusetts Institute of Technology. 2009.
[23] Durka PJ. From wavelets to adaptive approximations: Time frequency parameterization of EEG. *BioMedical Engineering Online*. 2003; 2: 1-30. Available from: doi: 10.1186/1475-925X-2-1.
[24] Benovoy M, Cooperstock JR. Biosignals analysis and its application in a performance setting-towards the development of an emotional-imaging generator. *Proceedings of the First International Conference on Biomedical Electronics and Devices, BIOSIGNALS 2008*. Portugal: Funchal, Madeira; 2008.
[25] Moridani MK, Heydar M, Jabbari Behnam SS. A reliable algorithm based on combination of EMG, ECG and EEG signals for sleep apnea detection: A reliable algorithm for sleep apnea detection. *2019 5th Conference on Knowledge Based Engineering and Innovation (KBEI)*. Iran: Tehran; 2019. p. 256-262.
[26] Zhou MN, Tian C, Cao R, Wang B, Niu Y, Hu T, et al. Epileptic seizure detection based on EEG signals and CNN. *Frontiers in Neuroinformatics*. 2018; 12: 95. Available from: doi: 10.3389/fninf.2018.00095.
[27] Craley J, Johnson E, Jouny C, Venkataraman A. Automatedinter-patient seizure detection using multichannel convolutional and recurrent neural networks. *Biomedical Signal Processing and Control*. 2021; 64: 102360. Available from: doi: 10.1016/j.bspc.2020.102360.
[28] Zia A, Qureshi MB, Afzaal M, Qureshi MS, Faya M. Machine learning-based EEG signals classification model for epileptic seizure detection. *Multimedia Tools and Applications*. 2021; 80: 17849-17877.
[29] Swami P, Gandhi TK, Panigrahi BK, Tripathi M, Anand S. A novel robust diagnostic model to detect seizures in electroencephalography. *Expert Systems with Applications*. 2016; 56(1): 116-130.
[30] Thodoroff P, Pineau J, Lim A. Learning robust features using deep learning for automatic seizure detection. *Proceedings of the Machine Learning for Healthcare Conference*. Los angeles; 2016.
[31] Fujiwara K, Miyajima M, Yamakawa T, Abe E, Suzuki Y, Sawada Y, et al. Epileptic seizure prediction based on multivariate statistical process control of heart rate variability features. *IEEE Transactions on Biomedical Engineering*. 2016; 63: 1321-1332.
[32] Pavei J, Heinzen RG, Novakova B, Walz R, Serra RJ, Reuber M, et al. Early seizure detection based on cardiac autonomic regulation dynamics. *Frontiers in Physiology*. 2017. Available from: doi: 10.3389/fphys.2017.00765.
[33] Sharma M, Pachori RB, Acharya UR. A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension. *Pattern Recognition Letters*. 2017; 94: 172-179.
[34] Tzimourta KD, Astrakas LG, Tsipouras MG, Giannakeas N, Tzallas AT, Konitsiotis S. Wavelet based classification of epileptic seizures in EEG signals. *IEEE 30th International Symposium on Computer-Based Medical Systems*. 2017.
[35] Goenka A, Boro A. Quantitative EEG spectrograms: Diagnostic efficacy in Intensive care and Epilepsy Monitoring units and the common seizure mimickers. *Neurology*. 2018; 90(15): P3.266.
[36] Tsipouras MG. Spectral information of EEG signals with respect to epilepsy classification. *EURASIP Journal on Advances in Signal Processing*. 2019; 10.
[37] Mahmoodian N, Boese A, Friebe M, Haddadnia J. Epileptic seizure detection using cross-bispectrum of electroencephalogram signal. *Seizure*. 2019; 66: 4-11. Available from: doi: 10.1016/j.seizure.2019.02.001.
[38] Guha A, Ghosh S, Roy A, Chatterjee S. Epileptic seizure recognition using deep neural network. Emerging Technology in Modelling and Graphics. 2019; 937: 21-28. Available from: doi: 10.1007/978-981-13-7403-6_3.
[39] Zhou DM, Li XM. Epilepsy EEG signal classification algorithm based on improved RBF. *Frontiers in Neuroscience*. 2020; 14: 606. Available from: doi: 10.3389/fnins.2020.00606.
[40] Aung ST, Wongsawat Y. Modified-distribution entropy as the features for the detection of epileptic seizures. *Frontiers in Physiology*. 2020; 11: 607. Available from: doi: 10.3389/fphys.2020.00607.