Detection of Epilepsy Seizures Based on Deep Learning with Attention Mechanism

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Abstract. Epilepsy cannot be underestimated as it can negatively impact every one of all ages and reduce the quality of life. Epilepsy can lead to sudden tumble and loss of awareness or consciousness, disturbances of movements. Fortunately, epilepsy seizures can be controlled if epilepsy is detected and treated properly. One of the widely used methods for detecting and diagnosing epilepsy is monitoring and analyzing electroencephalogram (EEG) signals. However, the traditional methods of monitoring and analyzing EEG have some challenges such as high costs, requirements of experienced medical experts, non-scalability, or non-support real-time and long-term monitoring. Therefore, in this paper, we present an advanced deep learning neural network approach for the automatic detection of epilepsy seizures. The proposed approach with a customized attention mechanism can be used for a single EEG channel. We evaluate the approach with the Bonn dataset and the CHB-MIT dataset and achieved higher than 98% accuracy, 99% sensitivity, and 98% specificity for a single EEG channel in most of the cases. The results show that the proposed approach is a potential candidate for enhancing automatic epileptic seizure detection systems.

Keywords: Epilepsy · Seizure · Deep learning · Attention mechanism · EEG

1 Introduction

Epilepsy which is a non-communicable neurological disease, is a central nervous system disorder. The brain activity of a person with epilepsy can become abnormal, causing seizures or uncommon physical behaviours [1]. Epilepsy can occur and affect anyone regardless of ages, genders, and human races [1,2]. Although epilepsy is not a contagious disease, epilepsy cannot be underestimated [2,3]. Epilepsy can lead to sudden tumble and loss of awareness or consciousness, disturbances of movements [3]. People with epilepsy have a three-time higher risk of premature death than normal healthy people [3]. For instance, an epilepsy seizure occurring at a certain time can lead to serious consequences such as sudden falling, drowning, and car accidents [1].

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Epilepsy can be categorized into sudden and long-term recurrent epilepsy. Sudden epilepsy means that a patient will have seizures unexpectedly in a random interval whilst seizures of recurrent epilepsy occur repeatedly. Therefore, it is more difficult to deal with or diagnose sudden epilepsy than long-term recurrent epilepsy. Both epilepsy types can negatively impact a patient's quality of life. In clinical, epileptic seizures can be categorized into three types including focal onset, generalized onset, and unknown onset depending on the location where the epileptic seizures are activated. Particularly, focal seizures occur on a certain location of a brain and mainly affect one cerebral hemisphere whilst generalized seizures begin in both halves (hemispheres) of the brain at the same time [4]. The unknown onset seizures are the special type in which the beginning of a seizure is unknown. The unknown onset seizures often occur at night and later might be diagnosed as a focal or generalized seizure [5].

Fortunately, epilepsy seizures can be controlled if epilepsy is detected, diagnosed, and treated properly. For instance, it is estimated that more than 70% of the people having epilepsy could avoid seizures if they have used anti-seizure medicines [3]. Currently, the two most common predictors of seizures recurrence are a documented etiology of the seizure and an abnormal electroencephalography [3]. A documented etiology of seizure mainly relies on the medical history collections that have many drawbacks including unreported and missed cases. The method of using Electroencephalogram (EEG) signals seems to be more appropriate as it can overcome the existing limitations of the documented etiology.

Many approaches have been proposed for the automatic detection of epileptic seizures. Among these approaches, systems based on machine learning are widely used as these systems can help achieve a high accuracy level of seizure detection. [6–10]. However, it is still required to have more advanced approaches that can help improve the accuracy of automatic detection of epileptic seizures. Therefore, to achieve the target, this paper proposes an effective and versatile neural network approach based on a customized attention mechanism. The approach uses a single-channel EEG for detecting epilepsy seizures and is evaluated with the Bonn dataset [11] and the CHB-MIT dataset [12] that are open-source and widely used datasets.

The rest of the paper is organized as follows: Sect. 2 reviews the related work. Section 3 introduces the methodology applied in the proposed approach. Section 4 discusses the experimental results and performance evaluation. Section 5 concludes this work and discusses the future work.

2 Related Work

Different approaches are proposed for the automatic detection of epileptic seizures. Many of them have applied traditional machine learning algorithms. For instance, Bajaj *et al.* [13] proposed a EEG classification method based on empirical mode decomposition. The method utilized Hilbert-Huang transform and least squares support vector machine for the seizure classification and its results reach an accuracy of 97.82%. Xie *et al.* [14] introduced a method using a sparse functional linear model based on wavelet to extract EEG features. Then, the authors applied a simple neural network model for classification. Samiee *et al.* [15] proposed a EEG feature extraction method. The collected EEG segments were mapped into an image that was used as an input of a gray level co-occurrence matrix to extract multi-variate features. The results showed that the method achieved sensitivity and specificity of 70.19%, and 97.94%, respectively. Parvez *et al.* [16] used a phase correlation algorithm to detect local features and a relative correlation between adjacent EEG waves. The EEG signals were divided into epochs and arranged in the form of a 2-dimensional matrix. Then, the signals were applied transformation and decomposition methods for extracting features that were finally classified with least squares support vector machines. The results showed that the proposed method could achieve up to 97.32% sensitivity, and 96.68% specificity. Jaiswal *et al.* [17] proposed two feature extraction techniques for classifying EEG signals. The results showed that the proposed techniques with ANN classifier could reach an accuracy of 99% for both cases of normal and epileptic EEG signals. Tzimourta *et al.* [18] introduced a multicenter method based on discrete wavelet transform for automatically detecting seizure. The authors applied decomposition of 5 levels and extracted 5 features. The classification results showed that the presented method could reach 95% accuracy. Mahmoodian *et al.* [19] introduced an approach for epileptic seizure detection using cross-bispectrum of EEG signals. The approach could achieve an accuracy of 96.8% specificity of 96.7%, and sensitivity of 95.6%.

In addition to the above-mentioned approaches, deep learning becomes widely used in EEG analyses, especially self-feature extraction. Ullah *et al.* [20] presented an automated system for epilepsy detection using EEG signals. The system was based on one-dimensional convolutional neural network (P-1D-CNN) models. The system was tested with the University of Bonn dataset and achieve a high level of accuracy of 99% in many test cases. The authors claimed that the system can be customized for other applications detecting other similar disorders. Wang [21] introduced an approach based on deep learning for classifying different classes of EEG involving seizures. The authors applied one-dimensional CNN consisting of three convolution layers and three fully connected layers. The proposed model was tested with the University of Bonn dataset. The results' accuracy was 97.63%–99.52% in the two-class classification, 96.73%–98.06% in the three-class classification and 93.55% in five-class classification. Türk *et al.* [22] applied continuous wavelet transform to achieve two-dimensional frequency-time scalograms which were then fed for a CNN model to learn the properties of the scalograms. The accuracy results were 98.5%–99.5% in the two-class classification, 97.0%–99.0% in the three-class classification and 93.6% in the five-class classification. Acharya *et al.* [23] proposed an approach base on deep convolution neural networks for automated detection and diagnosis of seizure. A 13-layer deep convolution neural network algorithm could achieve 88.67% accuracy, 90% specificity, and 95% sensitivity. Lu *et al.* [24] presented an approach based on a convolution neural network with residual connections for epileptic EEG classification and automated seizure detection. The results showed that their approach could achieve up to 91.8% accuracy when experimenting with the Bern-Barcelona dataset. Asif *et al.* [25] proposed a framework based on multi-spectral deep feature learning for seizure type classification.The framework has experimented with Temple University Hospital (TUH) EEG dataset and achieved a weighted F1 score of 0.98 for seizure type classification.

3 Methodology for Epileptic Seizure Detection Using a Single EEG Channel

In this paper, an approach for epileptic seizures detection using a single EEG channel is proposed. The approach consists of three main stages: feature extraction, classifier training, and classifier evaluation. For feature extraction, a neural network structure based on an attention mechanism is designed. The neural network structure is shown in Fig. 1.

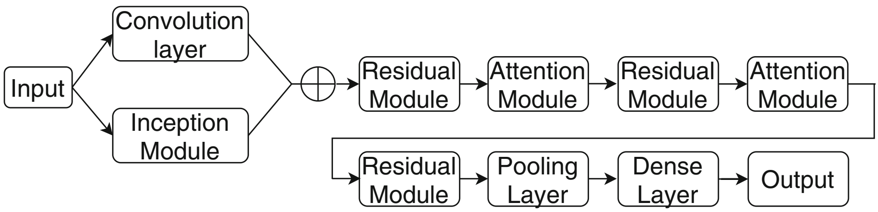

Fig. 1. The proposed neural network structure for a single EEG channel

Before being fed to the structure, raw EEG signals are pre-processed. The pre-processing stage includes data normalization, data fitting, and data re-sampling. In data normalization, raw EEG data having different measurement scales is normalized to have the same scale. We used the standard score method ($Y = \frac{X-\mu}{\sigma}$) which is suitable for distributed data like EEG. In the equation, X and Y are input and output while μ and σ are the mean value and standard deviation, respectively.

It is noticed that raw EEG data from different EEG measurement systems or datasets can be collected by different sampling frequencies. However, the input size should be uniformed. Therefore, data fitting and re-sampling are necessary. First, the B-spline representation [26] of the normalized input is found. Then, the fitted model is re-sampled by a particular frequency. As known that the energy distribution of EEG is mainly between 0.3 Hz and 80 Hz where the frequency components are α wave (8 Hz–13 Hz), β wave (13 Hz–30 Hz), δ wave (0.5 Hz–3.5 Hz), θ wave (4 Hz–8 Hz), γ wave (30 Hz–80 Hz). The effective frequency of EEG signals is not the same but it varies within 0.5 Hz–50 Hz [27]. It would be perfect if the EEG sampling rate is higher than 160 Hz then anti-alias can be achieved without any effort. However, when the neural network structure is too large or deep, the computational time for dealing with the large number of input samples could be very large. In our cases, we would like to develop automatic epileptic seizure detection edge and fog based systems that have limited resources (i.e., computation and memory) comparing to Cloud servers' resources. Therefore, we could not use the original sampling rate of the Bonn EEG dataset (i.e., 173.6 Hz corresponding to 4096 data points in 23.6 s). We had to find out the suitable EEG sampling rate which can achieve reasonable computational time while maintaining a high level of accuracy, sensitivity, and specificity. We tried different sampling rates ranging from 43 Hz to 173.6 Hz from the Bonn EEG dataset by applying moving average filers. Thanks to the cleanness of the EEG signals in the dataset as noises causes by external environments were already removed by experts, results of seizure detection from the applied EEG sampling rates are almost similar in terms of accuracy, sensitivity, and specificity. However, due to our large network, the computational time is dramatically different (e.g., about 4–8 times) between 43 Hz sampling rate and 86 Hz sampling rate. Hence, to reduce computational time and cover most of the characteristic waves (i.e.,α, β, δ, and θ waves) of epilepsy, we decided to apply 43 Hz sampling frequency which corresponds to 1024 points during 23.6 s from the dataset. This selection will be a premise for our future work where some parts of data processing and feature extraction will be run at edge and fog devices. Nevertheless, it is recommended to apply the higher EEG sampling frequency such as 173.6 Hz, or even much higher when Cloud-based systems having powerful computational resources are used. Due to the scope of the paper, edge and fog computing is not discussed in this paper. The detailed information of edge and fog-based systems for health monitoring including requirements and specifications are discussed in detail in [28–30].

Due to the scope of the paper, theoretical information of CNN including the convolution layer, pooling layer, activation function, batch normalization layer, and loss function will not be described in this paper. The detailed information of CNN can be found in [31]. The core of the proposed CNN structure is an attention module based on the attention mechanism that is inspired by an attention mechanism used in computer vision [32]. In general, the attention mechanism helps detect a focused point and enhances the representation of an object at that point. Via our experiments, we found that a neural network structure with the attention mechanism can be a good premise for EEG signal processing. Therefore, the attention mechanism is utilized and customized in the proposed approach for processing EEG signal processing.

In the customized attention mechanism, attention modules shown in Fig. 2 have been designed. Each attention module can be split into an attention trunk and a skip connection. In an attention trunk, the output from the previous module (i.e., residual module) is an input of the trunk. The bottom-up and top-down structures described in [33] are applied to achieve the same size attention mask M(x). This structure imitates the feed-forward and feedback attention procedure which is similar to the feature selection process of a feature pyramid network [33].

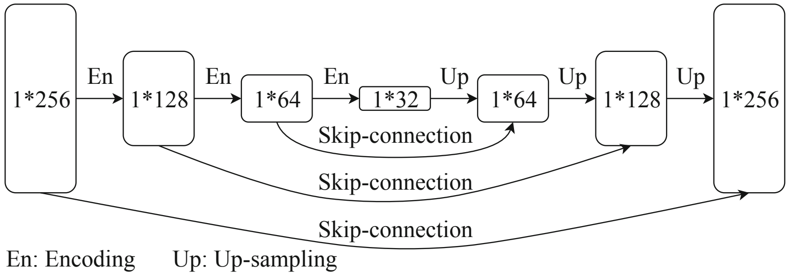

Fig. 2. The proposed attention module for single EEG channel

The output of the attention module is calculated via a formula: $H_{i,c}(X) = M_{i,c}(X) * T_{i,c}(X)$ where i is a range of all the input spatial locations, X is an input vector, $M_{i,c}(X)$ and $T_{i,c}(X)$ are the output of an attention trunk and a skip connection part, respectively. Another important part of the attention mechanism is an attention mask which is used as a feature selector during the feed-forward process and a gradient updater during the backpropagation process.

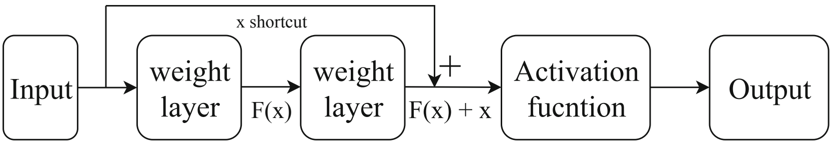

Fig. 3. The basic residual block

The basic residual block of the residual module is shown in Fig. 3 where input and output are vector x and vector y; H(x) and F(x) are the function of the whole residual block and the residual function, respectively. The whole residual block can be represented via the formula: $y = H(x) = F(x) + x$. Since the residual block has two weight layers, the whole residual block can be expressed as by the formula: $y = F(x, M_i) + x$. In our structure, several residual blocks are used to build a residual module which can be seen in Fig. 4.

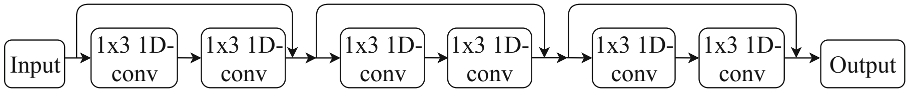

Fig. 4. A three-layer stacked residual module

To extract useful features from EEG, an inception module placing at beginning of the proposed structure was designed based on the inspiration of the design of the inception network [34,35]. In the inception module, several kernels having a size of 1×3, 1×5, and 1×7 are used for the basic convolution layer to avoid patch-alignment issues. Before these kernels are applied, the 1×1 kernel is applied for reducing computation. The result of each convolution is concatenated for forming a multi-dimensional tensor which will be used as an input of other modules. The structure of the inception module is shown Fig. 5.

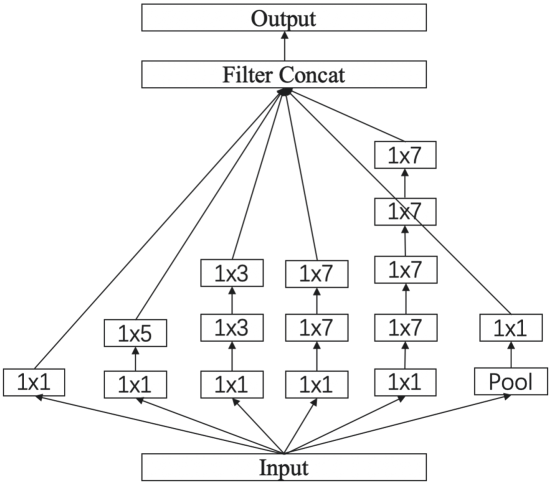

Fig. 5. Inception module structure

4 Experimental Results and Performance Evaluation

We used a cross-validation method and two different datasets such as the Bonn dataset and the Children's Hospital of Boston-Massachusetts Institute of Technology Dataset (the CHB-MIT dataset) to evaluate the proposed neural network structures [11,12]. In the cross-validation method, a small set of data is fed into the structures and the model's performance is estimated when it applies predictions on unseen data. The overall procedure of the cross-validation method with the k-fold described in [36] includes 4 main steps such as (i) randomly shuffling all the data; (ii) randomly selecting data into k categories; (iii) using each category as a testing set to evaluate the model while using all other categories as a training set to train the model, recording the model's performance and iterating the process for k times; (iv) Summing up the performance of all models and concluding the final summary of the proposed neural network structure. In our experiments, the k time value is set to 10, and the accuracy, sensitivity, and specificity are calculated per each test. Then, the average parameters of the final score of each classifier are used on each task. The formulas for calculating accuracy (Acc.), sensitivity (Sen.) and specificity (Spec.) are presented below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} * 100\%$$

$$Sensitivity = \frac{TP}{TP + FN} * 100\%$$

$$Specificity = \frac{TN}{TN + FP} * 100\%$$

where true-positive (TP) is the number of normal signals correctly identified as normal signals and true-negative (TN) is the number of ictal signals correctly detected as ictal signals; false-positive (FP) is the number of normal signals which are incorrectly detected as ictal signals and false-negative (FN) is the number of ictal signals which are incorrectly detected as normal signals. In the experiments, different tasks in the Bonn dataset and the CHB-MIT dataset shown in Table 1 are evaluated.

Table 1. Tasks on the Bonn dataset and the CHB-MIT dataset

Task	Task meaning	Bonn dataset	CHB-MIT dataset
ZO-S	Normal - Ictal	X	X
NF-S	Interictal - Ictal	X	X
Z-S	Normal with closed eye - Ictal	X	
F-S	Interictal on focal area - Ictal	X	
ZONF-S	Nonictal - Ictal	X	X
ZO-NF-S	Normal - Interictal - Ictal	X	X
Z-F-S	Normal with closed eye - Interictal in focal area - Icta	X	
Z-O-N-F-S	All 5 subclass classification	X	

All the experiments with a single EEG channel in this section are achieved from a computer having an Intel XEON X5675 processor and an NVIDIA GeForce GTX1080Ti GPU that have specifications (e.g., memory and computation) similar to edge and fog devices used by typical health monitoring systems. The deep learning framework is PyTorch [37]. The performance results of the proposed network structure for a single EEG channel are compared with the state-of-the-art approaches including deep-learning-based and traditional algorithm-based approaches. The comparison results are shown in Table 2. The results show that the proposed approach can achieve nearly 100% accuracy in many tasks such as ZO-S, NF-S, Z-S, F-S, ZONF-S, Z-F-S except for the case of all 5 subclass s which have 86.4% accuracy. The reason for a high accuracy rate is that normal signal segments, interictal signal segments, and ictal signal segments are clearly distinguished in the Bonn dataset. One of the reasons causing a lower accuracy rate in the case of 5 subclasses is that the data of cases of "eye open" and "eye closed" is not much different. In some data segments, the data of these cases is almost similar. This issue also affects the results of other state-of-the-art approaches [23,24].

Table 2. Comparison with state-of-the-art approaches when evaluating on the Bonn dataset

Task	Acharya *et al.* [23]			Lu *et al.* [24]			Tzimourta *et al.* [18]			Our proposed approach		
	Acc.	Sen.	Spec.	Acc.	Sen.	Spec.	Acc.	Sen.	Spec.	Acc.	Sen.	Spec.
ZO-S	0.990	0.970	1.0	0.993	1.0	0.990	-	-	-	**1.0**	**1.0**	**1.0**
NF-S	0.980	0.940	**1.0**	0.979	0.981	0.981	0.981	**0.986**	0.972	**0.986**	0.980	0.99
Z-S	0.990	0.980	1.0	1.0	1.0	1.0	0.999	1.0	0.917	**1.0**	**1.0**	**1.0**
F-S	0.925	0.85	1.0	0.975	0.98	0.97	0.977	0.976	0.979	**0.995**	**0.99**	1.0
ZONF-S	0.992	0.970	0.997	0.993	0.98	**0.997**	0.952	**0.997**	0.974	**0.994**	0.99	0.995
ZO-NF-S	0.887	0.95	0.90	0.976	0.975	**0.979**	0.958	0.960	0.977	**0.978**	**0.978**	0.978
Z-F-S	0.966	0.967	0.969	0.933	0.933	0.941	0.961	0.961	0.980	**0.993**	**0.993**	**0.994**
Z-O-N-F-S	0.418	0.418	NaN	0.795	0.796	0.819	0.822	0.822	**0.950**	**0.864**	**0.864**	0.869

Note: Values in bold text having the best values in their compared category

The comparison results show that the proposed approach is better than other state-of-the-art approaches [18,23,24] in terms of accuracy, sensitivity, and specificity in most of the cases. The difference is around from 1% to 8% depending on the case. Although the proposed approach cannot achieve better results in some cases, the difference is around 0.1%–0.2% except for the case of specificity in a 5 subclass task.

In the second experiment, we evaluated the proposed approach on the CHB-MIT dataset and compared it with other state-of-the-art approaches. Four tasks shown in Table 1 are applied for the experiment and their results are shown in Figs. 6, 7, 8 and 9. The collection time of raw EEG data is between 1 to 4 h, with a sampling rate of 256 Hz. Specifically, the EEG signals of each patient contain 23 channels. In this paper, we use the EEG channels of FP1-F7, F7-T7, F8-T8, T8-P8, and FP2-F8 to build the CHB-MIT scalp EEG Dataset.

For the ZO-S task, our proposed approach and state-of-the-art approaches [23] have quite similar results for accuracy, sensitivity, and specificity, except for the case of sensitivity and specificity of the approach [24]. In particular, the proposed approach's results are around 3% less accurate and 4% more accurate than the approach [23] and the approach [24], respectively. For the NF-S task, our results are 4%–15% better than others in terms of accuracy and sensitivity. In the case of the ZONF-S task, we have 3% better accuracy results than others

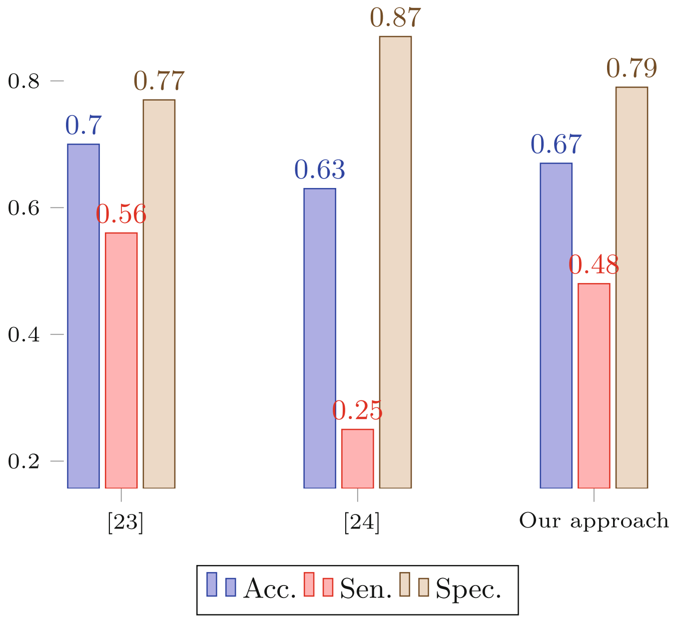

Fig. 6. Results of task ZO-S of CHB-MIT dataset

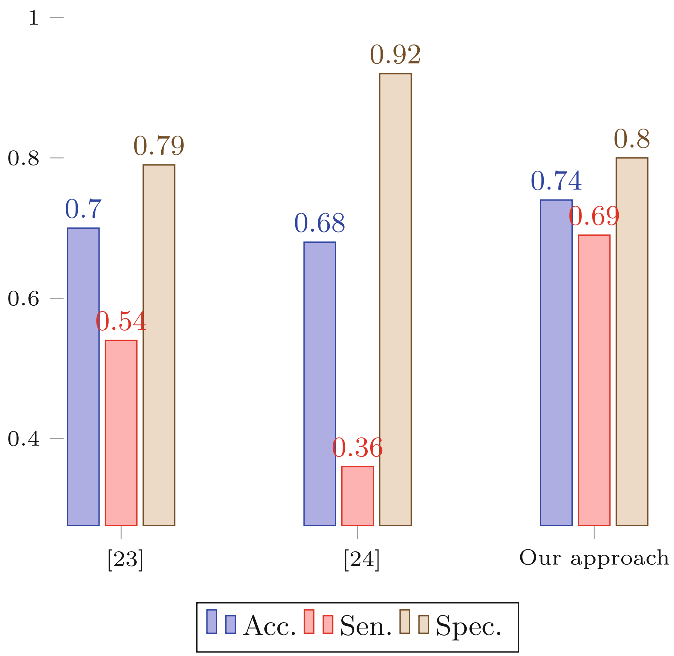

Fig. 7. Results of task NF-S of CHB-MIT dataset

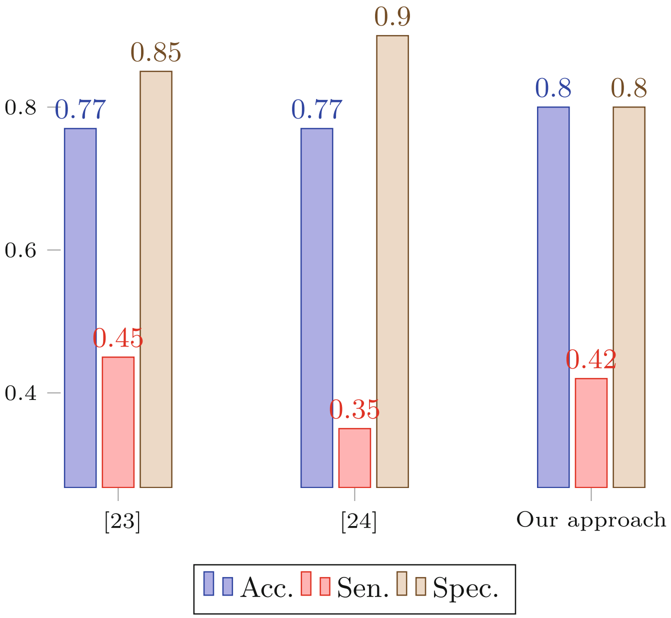

Fig. 8. Results of task ZONF-S of CHB-MIT dataset

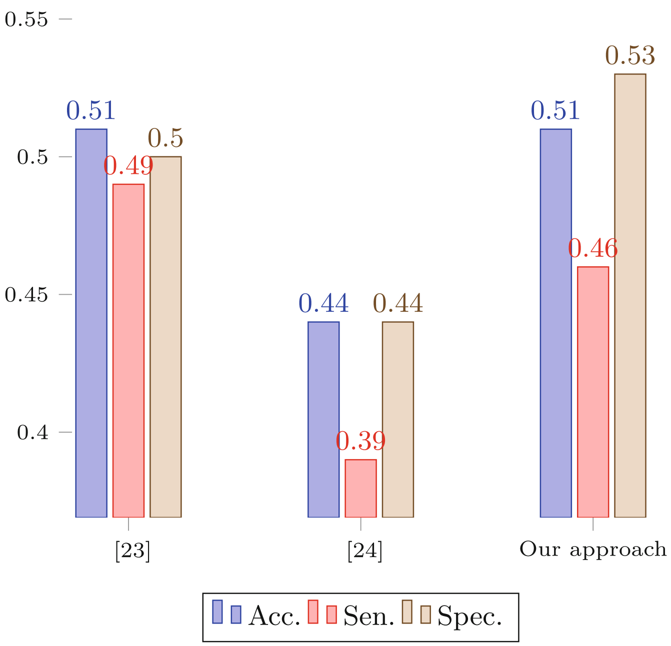

Fig. 9. Results of task ZO-NF-S of CHB-MIT dataset

but our specificity results are around 5%–10% lower than others. For the Z-O-N-F-S task, our results are equal or better than others in terms of accuracy and specificity. For the sensitivity results, our results are 3% lower than the approach [23] but 7% higher than the other approach [24]. Although for the CHB-MIT dataset, none of the compared approaches has the best results in terms of accuracy, sensitivity, and specificity in all tasks, our proposed approach has good results in all compared cases. Particularly, the proposed approach has better accuracy results than others in most cases.

5 Conclusion and Future Work

This paper presented an approach based on advanced deep learning neural networks for automatic detection of epileptic seizures with a single EEG channel. The results of the proposed approach were promising with 98% accuracy, 99% sensitivity and 98% specificity for a single EEG channel for many cases. When comparing with other state-of-the-art approaches, the proposed approach was better in most of the cases. Although the proposed approach achieved good results in terms of accuracy, sensitivity, specificity, the proposed algorithm needs to be more developed and enhanced for suiting to the strict requirements of medical experts. Therefore, in the future, we will customize other models, residual modules and attention modules. The customized modules having skip connections are expected to make the proposed neural networks dynamic to tune the number of layers during training optimally.

In addition, we will use different types of datasets including the one mixed between the Bonn dataset and the CHB-MIT dataset with different percentages of training and test set and dataset having different types of epileptic seizures and other chronic diseases having similar EEG patterns. We will also apply different EEG sampling rates and combine multiple EEG channels from both history and real-time. Furthermore, real-time EEG will be used for evaluating the proposed approach.

In this paper, the latency and usage resources (e.g., memory, central processing unit, and graphics processing unit) for training and testing the proposed deep learning-based approach were not focused and analyzed as the proposed approach is supposed to be run at cloud servers having powerful resources. In fact, the training stage was completed in less than 20 min and the testing stage was done in less than 3 s with the applied computer having resources (i.e., Intel XEON X5675 and GeForce GTX1080Ti GPU). The used computer is similar to edge-based and fog-based devices such as Jetson Xavier NX-based devices. Therefore, there are possibilities to customize the proposed approach for suiting to edge and fog-based systems [28,38–40] to provide fast analysis results at the edge. For example, cloud computing will be utilized to train neural networks whilst edge or fog devices such as smart edge/fog gateways are applied for testing and providing categorized results. This will help overcome the high latency of the existing deep learning and cloud-based systems for EEG analysis.

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