Applying Deep Learning for Epilepsy Seizure Detection and Brain Mapping Visualization

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Deep Convolutional Neural Network (CNN) has achieved remarkable results in computer vision tasks for end-to-end learning. We evaluate here the power of a deep CNN to learn robust features from raw Electroencephalogram (EEG) data to detect seizures. Seizures are hard to detect, as they vary both inter- and intra-patient. In this article, we use a deep CNN model for seizure detection task on an open-access EEG epilepsy dataset collected at the Boston Children's Hospital. Our deep learning model is able to extract spectral, temporal features from EEG epilepsy data and use them to learn the general structure of a seizure that is less sensitive to variations. For cross-patient EEG data, our method produced an overall sensitivity of 90.00%, specificity of 91.65%, and overall accuracy of 98.05% for the whole dataset of 23 patients. The system can detect seizures with an accuracy of 99.46%. Thus, it can be used as an excellent cross-patient seizure classifier. The results show that our model performs better than the previous state-of-the-art models for patient-specific and cross-patient seizure detection task. The method gave an overall accuracy of 99.65% for patient-specific data. The system can also visualize the special orientation of band power features. We use correlation maps to relate spectral amplitude features to the output in the form of images. By using the results from our deep learning model, this visualization method can be used as an effective multimedia tool for producing quick and relevant brain mapping images that can be used by medical experts for further investigation.

CCS Concepts: • **Social and professional topics** → *Medical technologies*; • **Computing methodologies** → *Image representations*; *Machine learning*;

Additional Key Words and Phrases: Deep learning, epileptic seizure detection, electroencephalogram

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1 INTRODUCTION

Epilepsy is a neurological disorder that might result in a loss of consciousness, jerking of some body parts, and, in some severe cases, prolonged whole-body convulsions can also be seen. Epilepsy affects people of all ages. It can severely affect the patient's quality of life and can have other social and economic impacts; epilepsy can also result in premature death [1]. Studies show that more than 50 million people around the world are affected by epileptic seizures [1]; out of this, about 70% of patients can be successfully treated with the help of anti-epileptic drugs, while approximately 7% to 8% of the cases require surgical intervention [2]. If detected early, it is possible to suppress the seizure using electrical stimulation [3] or through drugs.

EEG is an efficient and relatively inexpensive technique to analyze and study brain electrical activities by placing electrodes on the skull surface (scalp EEG recording) or from inside the skull (intra-cranial EEG recording) [4]. The scalp EEG is recorded by a non-invasive technique using multiple electrodes, and it has high temporal resolution, making it a more feasible technique for analysis and the monitoring of the changes in brain electrical activity. This data recording is massive and contains synchronous activities of neurons in different areas of the human brain. The scalp EEG is also the commonly used technique for the onset detection and diagnosis of epileptic seizures. These EEG recordings may contain characteristic patterns for seizures that can be detected by trained neurologists, but this task is tedious and expensive and can take several hours for a single patient [5]. To increase the chances of recording seizure occurrences, several hours and even days of EEG recordings are required, which make manual analysis even more difficult. About 75% of epilepsy patients from poor countries cannot afford medical diagnosis or treatment [3]. Because of these limitations, there are many automated efforts developed for seizure detection and prediction [6–12]. The main characteristics of such automated approaches is the extraction of features that best describe the seizures or the period before seizures. These automated approaches have extract features in frequency domain or in the time domain and report several advantages and disadvantages of both. Some automated approaches use both time- and frequency-domain features. However, all these approaches based on domain features have many limitations. Since the EEG patterns in seizure patients are highly variable, these approaches lack robustness and are prone to failure even in slight variations of seizure patterns. In addition, the EEG seizure pattern data are highly dynamic in nature: the properties change across different subjects and over time even for the same patient. Hence, these automated approaches cannot deal with this non-stationary EEG pattern. Another major limitation with the automated approaches is due to the fact that EEG data recording is prone to a range of noise and artifacts such as eye-blinks, muscle movements, and environmental noise. Another limiting aspect of such automated techniques is the small size of EEG datasets, which affects their robustness and performance on test data, as the training is not good enough. Most of the publicly available EEG-seizure datasets are recorded from a small number of patients. Thus, techniques trained on such datasets are not suited for clinical applications. A pattern for the onset of seizure may sometimes look like normal EEG recording. In many cases, the normal EEG and seizure events overlap, which is why it is very difficult to build a generic technique that works for every epilepsy patient with high sensitivity [13]. Seizure detection algorithms try to find pre-ictal (before-seizure) and ictal (seizure) occurrences in the recordings.

To address these limitations, we propose an intelligent method for seizure classification using EEG. EEG signals have low signal-to-noise ratio and show considerable sensitivity towards noise. Besides, artifacts like muscular activity and blinking of eye can cause many issues in EEG recording and feature extraction; therefore we propose a CNN based deep learning method. Deep CNN is able to enhance performance by extracting relevant patient-specific EEG features. The major contribution of the proposed method is the CNN architecture for seizure detection. Epileptic seizures are hard to detect, as EEG seizure patterns vary significantly among patients. We try to extract spectral, temporal features from EEG epilepsy data and use them to learn the general structure of a seizure that is less sensitive to variations, thereby building a cross-patient seizure classifier. Our model reaches state-of-the-art performance on patient-specific detectors and achieves significant improvement in cross-patient detection. While we achieved good accuracy for cross-patient data, the sensitivity is also very high for almost all patients. Also, we use cropped training strategy to increase the size of the dataset, as deep learning requires a lot of data. By using this training strategy, deep learning models can be applied for even small datasets. Another contribution is that, by using the visualization technique, we can understand the features used by CNN to give accurate results. The visualization method uses correlation maps, which show the features related to band-power features that help us to achieve the correct output. We investigate whether domain-specific knowledge and class-discriminative features are being used by CNN to achieve high performance. We can compute combined feature value for all the receptive fields and then we can calculate how a feature value affects the output of each CNN layer. Hence, by calculating the correlation between feature values and layer outputs, we can come to know what features are being used by CNN. Our system can be quite useful to improve the diagnosis, monitoring, and treatment of epilepsy patients. It can be very useful in developing countries where access to a neurologist is limited. Manual inspection and diagnosis of seizure patients is a time-consuming and tiresome procedure; however, our system can give a quick and accurate view of where the seizures are actually located inside the brain, thus reducing the diagnosis time, reducing cost. The method can be used as a fast brain-mapping technique to show only important and relevant features for seizure detection. Overall, this research makes the following contributions:

- The model is able to extract spectral, spatial, and temporal features from EEG epilepsy data and use them to learn the general structure of a seizure that is less sensitive to variations, as the EEG signals have low signal-to-noise ratio and show considerable sensitivity towards noise. Besides, artifacts can cause problems in EEG recording and feature extraction; therefore we propose a CNN based deep learning method.
- The system is tested comprehensively on both cross-patient and within patient EEG recordings. Our system achieves better than state-of-the-art performance on patient-specific detectors and achieves significant improvement in cross-patient detection.
- The system is compared and tested against best-available machine learning and automated and deep learning techniques. The model also outperforms the previous state-of-the-art results on accuracy and sensitivity.
- Most of the public EEG seizure datasets are small, having few subjects and samples. We use a cropped training strategy that is helpful in making the deep learning models to train on comparatively small datasets.
- The visualization technique discussed can build accurate and fast brain maps to study and locate EEG seizures. The visualization method shows the spatial distribution of the features learned by the CNN while learning the seizure and non-seizure classes in different frequency bands. The method also shows that the deep CNN learned to extract and use band-power features with specific spatial distributions.

The remaining article is organized as follows: Section 2 gives the literature review, Section 3 presents the experiments, Section 4 gives the results, the conclusion is given in Section 5, and finally we conclude in Section 6 with the discussion.

2 RELATED STUDY

In [13], the researchers proposed a patient-specific system for predicting seizure. They used EEG to find spectral power features and used a non-linear classifier, support vector machine (SVM). They used 80 seizure events to achieve a sensitivity of 97.5%. The rate of seizure prediction showed that it is possible to use linear spectral power features and nonlinear classifiers for patient-specific seizure prediction. They also demonstrated that gamma-frequency bands were most important for the prediction task.

Researchers in [14] found that before the seizure occurs, there are changes in phase synchronization between different brain regions. In [15], authors followed the same method for eight patients to confirm these findings. In [16], researchers used band-pass filtering before phase synchronization analysis of the EEG and found that there are changes in pre-ictal phase synchronization in the beta band. But researchers in [17] found that the changes in the pre-ictal period are not global but restricted to some specific channels.

In [9], they used the neural network and fuzzy function with a combination of principal component analysis (PCA) for seizure detection and claimed to achieve an accuracy of 97.64%. Researchers in [18] used Wavelet Transform with wavelet de-noising to get a sensitivity of 96.72% and specificity of 94.69% on mice EEG data. Some researchers [19] also developed a method to transform EEG signals into images and applied image processing techniques to obtain an accuracy of obtaining a sensitivity of 98.91% and specificity of 94.35%. In [20], authors analyzed high-dimensional phase space by first reducing it using PCA and then feeding them to linear discriminant analysis (LDA) and Naive Bayesian classifiers for patient-specific seizure detection. They achieved 93.21% specificity and 88.27% sensitivity. The authors of [13] unified spectral and spatial characteristics of EEG in the time domain to form a single feature vector; this feature set was then fed to an SVM classifier. They used the CHB-MIT EEG dataset to achieve a seizure detection accuracy of 96% on a set of 163 seizures and an average delay of 4.6 seconds. This CHB-MIT dataset was also chosen by researchers in [21] to transform EEG signals into images by projecting the patient electrodes into 2-D. They used three different frequency bands of the 1s block between 0 and 49Hz. They showed that deep learning with the recurrent convolutional neural network is an effective technique to perform automatic feature extraction and classification. Some feature extraction techniques analyze features in both frequency and time domain. For this, the researchers in [11] used wavelet-based filters for time-frequency-energy analysis.

All of the foregoing works for automatic seizure detection have employed expert hand-crafted features for seizure detection and classification; some of them make use of spectral features [22] while others' information use the temporal features [13]. As discussed before, EEG seizure patterns have nonstationarity property and can vary patient to patient [23].

Recently, deep learning methods like the CNN have been very successful in automatic extraction of relevant features. These deep learning models have been employed in different fields, such as computer vision, speech recognition, and the like [24, 25]. Researchers have started to apply and investigate the potential of various deep learning models for EEG signals analysis [21, 26–28].

Some researchers have also applied deep learning methodology for detecting epileptic seizures. In [29], they used deep neural networks trained with dropout for patient-specific epileptic seizure detection from EEG data. Some researchers [30] used deep belief networks (DBNs) to detect seizures in multi-channel and high-resolution EEG data. In [31], the researchers showed that DBN can be applied in a semi-supervised learning mechanism for modeling EEG data. This sophisticated technique resulted in fast seizure detection. Some of the works also applied CNN for seizure detection. In [32], CNN was applied automatically to detect spikes in EEG recordings of patients. Researchers in [33] used CNN to extract time-domain feature automatically in intracranial EEG data from epileptic patients. The work in [34] used CNN with stacked autoencoders for analysis and classification of EEG data. There is also a work [35] that uses unsupervised learning to automatically extract features from raw, unlabelled EEG data. This technique used stacked autoencoders and a logistic classifier for patient-specific seizure detection. The work in [36] proposed a robust deep learning model based on stacked autoencoders and a maximum correntropy function that is used for reduction of noise artifacts. The work in [37] uses sparse autoencoder and support vector machine for an EEG signal classification. There is also a work [38] in which the researchers used a semi-supervised stacked autoencoder to give a joint solution for EEG signal analysis and reconstruction.

Most of these deep learning methods are impressive, with some of them yielding good performance; however, the deep learning methods discussed in the foregoing paragraphs are not comparable to the results of the application of same methods based on deep learning, in areas like image and speech processing. Therefore, there is a big void and a need for a lot of enhancement with respect to many aspects of applying deep learning for EEG data analysis for seizure detection.

Deep CNN have also achieved remarkable results in many fields, such as computer vision and speech recognition, surpassing previous state-of-the-art techniques [39, 40]. Deep CNN is variant of deep networks that learn local and spatial features in data by using convolutions. Deep CNN usually has multiple successive convolutional layers [24]. These networks, at the initial layers, learn low level and spatial features, and in the deeper layers it progressively extracts more global, high-level features towards the end. In the initial layers, they learn simple shapes such as edges, boundaries, and learn to recognize complex shapes such as complete objects in the depth of the model. Deep CNN has shown good results for end-to-end learning, which is automatically learning features from raw data; these are especially well suited for large datasets and can extract and use a hierarchical structure in raw signals. However, issues with CNN are difficult to interpret and require a large amount of training data.

Therefore, in this study, we use deep CNN for end-to-end learning and analysis of multi-channel EEG epilepsy data for seizure detection and for meaningful visual interpretation.

In this study, we propose a deep CNN-based architecture to extract robust features from raw EEG data to detect seizures. Since seizures are difficult to detect, because EEG seizure patterns vary significantly among patients, most of the automated approaches discussed in the literature review, which achieve good accuracy, are patient-specific. There can also be overlap between seizure and non-seizure events, which is why it is very difficult to build a generic technique that works for every epilepsy patient with high sensitivity. The previous techniques that achieve somewhat good accuracy for cross-patient seizure detection have low sensitivity. We try to extract spectral, temporal features from EEG epilepsy data and use them to learn the general structure of a seizure that is less sensitive to variations. Thus, our system can be used as an accurate cross-patient classifier. We compare the results to the previous state-of-the-art models for cross-patient seizure-detection task. Deep learning requires huge data to train, but we have limited epilepsy data. To do away with this disadvantage, we use cropped training strategy, which increases the size of the dataset by multiple folds. Since deep learning models are mostly used as black boxes and we do not get access or understand the features they use to give accurate results, we use a method proposed for EEG in [47] to visualize the orientation of band-power features. We calculate correlation maps to relate spectral amplitude features to the output in the form of images, using which we can understand whether the CNN actually uses spectral and band-power features as found by previous studies. Hence, we can visualize the feature learning taking place inside the deep CNN model. The method can be used as a fast brain-mapping technique to show only important and relevant features for seizure detection. The visualization method, if refined, can be used in the future as an effective multimedia tool for producing quick and relevant brain-mapping images utilizable by medical experts.

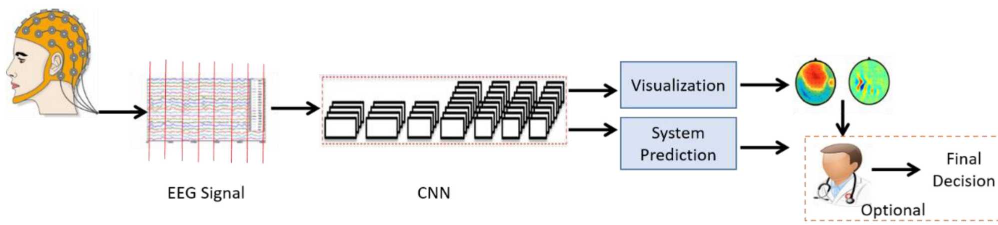

Fig. 1. Block diagram of the proposed seizure detection and brain-mapping visualization system.

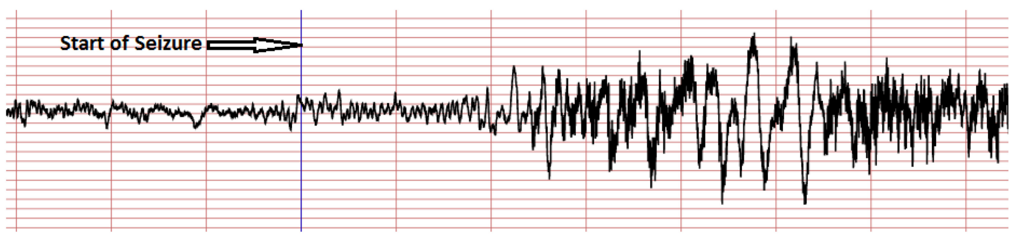

Fig. 2. Annotation showing the start of seizure in a single channel.

3 EXPERIMENTAL AND COMPUTATIONAL DETAILS

Figure 1 shows a block diagram of the proposed seizure detection and brain-mapping visualization system. The input to the system is the EEG signals obtained from the electrodes of the EEG scalp mask. Each electrode in the mask produces an EEG signal. As there are 24 channels in the used mask, we have 24 EEG signals. The signals are divided into overlapping frames and fed into the proposed architecture of the CNN. The system outputs both the predicted class (seizure or non-seizure) and brain-mapping visualization in different frequency bands. A specialized medical doctor can then take the final decision with the aid of the system's output.

3.1 Dataset

In this work, publicly available CHB-MIT EEG epilepsy database is used [41]. It consists of multichannel 686 scalp EEG recordings from pediatric subjects with intractable seizures. A lot of research work has been evaluated using this database, so it is quite helpful for comparison. This dataset contains data recorded from 23 epilepsy patients, including 18 females and 5 males between the ages of 10 and 22 years. The anti-seizure medication was withdrawn from the patients, and EEG was recorded for many days after withdrawal. This dataset was recorded to analyze seizures in patients to assess the need for surgery. The beginning and end of each seizure were annotated in a separate file (Figure 2 shows such an example). The dataset was recorded using the 10–20 international system of an EEG electrode montage scheme. The dataset has 969 hours of scalp EEG recordings, and there are 173 seizures. Almost all the EEGs were recorded for 1 hour, and there are some that were recorded for 2 hours and 4 hours. Different types of seizures are present, adding to the variability in the dataset. The dataset has at most 24 channels, and each of them was recorded at 256Hz with 16-bit resolution.

Each EEG recording is classified either as a seizure, if it contains at least one seizure; or as a non-seizure, if it contains none. One hundred and ninety-eight recordings out of 686 contain seizures. About 80% of the seizure recordings include more than 25 seconds of seizure activity; on average, there are 45 seconds of seizure activity. Therefore, to increase the seizure class and balance the dataset, we used a sliding window to crop the dataset. We divided the dataset by

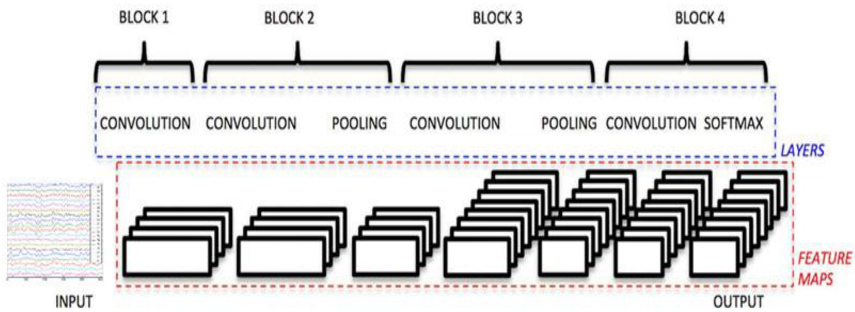

Fig. 3. Deep CNN architecture.

randomly choosing 20 patient records for training and 3 patient records for testing for patient-specific results. For cross-patient computation, we trained and tested the system by having each patient as a test set and the rest as a training set for all 23 patients.

3.2 Input Representation

Some researchers have used electrode voltage over the flattened scalp surface to convert the EEG data into topomap images [27]. However, the evidence shows that the EEG signal has correlation over time-series [42]. Therefore, in our method, the CNN takes raw EEG as input data. We represent the input signal as 2D array having time-steps as its width and EEG electrodes as its height. This method has been used by researchers for input dimensionality reduction.

3.3 Deep CNN Architecture

Deep CNN is good at learning the hierarchical structure of natural signals such as images and audio [39, 40]. CNN uses convolutions to learn spatial, temporal and spectral features automatically from the raw input signal. A typical CNN uses many convolutional and pooling layers together with the non-linearity function to extract good features. Pooling operation helps remove redundancy in extracted features and also helps reduce data dimensionality. Therefore, CNN are best suited for automatic learning of features from raw input data, although CNN usually requires a large amount of training data and is difficult to interpret.

Our deep CNN model (Figure 3) is inspired by the winning architecture [24] in computer vision, and it consists of four blocks of convolution and max-pooling layers, and a dense classification layer at the end. The first convolution operation is broken down into two convolution layers as EEG is multi-channel signal [47]. Our model has the first convolution over time followed by convolution over electrodes as shown in Figure 4. Then, we have the max-pooling layer. This is followed by another normal convolution max-pooling block. After this, we have a convolution followed by a fully connected softmax classifier. The convolution operation can be expressed by Equation (1):

$$y_{i'j'k'} = \sum_{ijk} w_{ijkk'} x_{i+i',j+j',k}, \tag{1}$$

where $x = (x_1, \ldots x_k)$ is the input for the network layer and $w = (w_1, \ldots w_n)$ is the learned weight and k is the number of channels and k' is the number of filters. The max-pooling operation is written in Equation (2):

$$y_{ijk} = \max\{y_{i'j'k} \ : i \leq i' < i + p, j < j' < j + p\}, \tag{2}$$

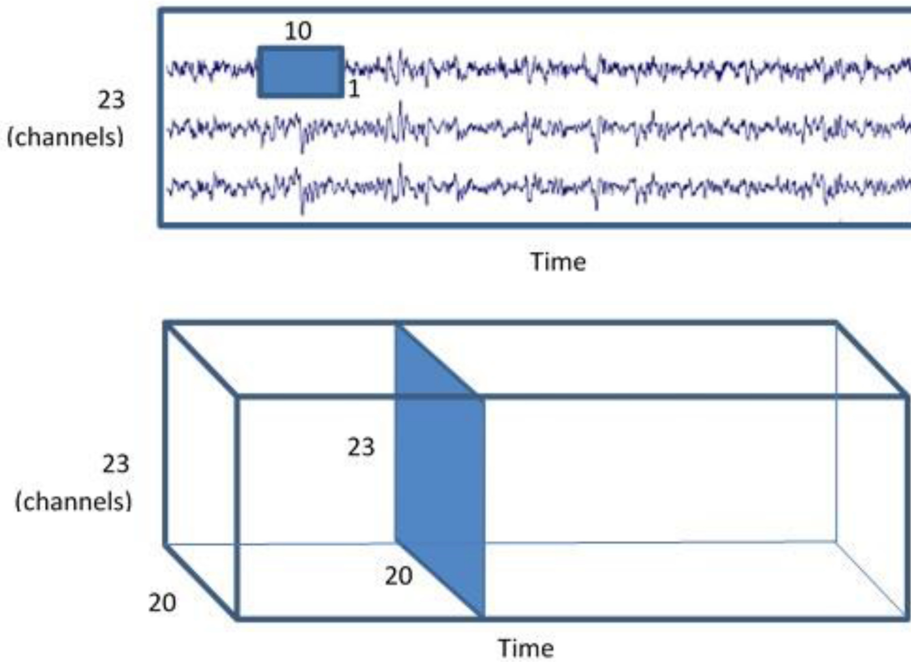

Fig. 4. The first convolution split into two parts (first across time and the second across all electrodes).

where p is called the padding operator. ELU (Exponential linear unit [43]) is used as the activation function, can be expressed by Equation (3):

$$y_{ijk} = x_{ijk} \;\; for\; x_{ijk} > 0 \; and \; y_{ijk} = e^{x_{ijk}} - 1 \; for\; x_{ijk} \leq 0, \tag{3}$$

$$y_{ijk} = \frac{e^{x_{ijk}}}{\sum_{t=1}^{D} e^{x_{ijt}}}, \tag{4}$$

Equation (4) represents the softmax operation or the normalized exponential function, which is used to denote a probability distribution of a D-dimensional vector.

We also make use of best strategies available from recent advances in deep learning and machine-learning research on CNN. We have made use of novel regularization strategy, which is dropout [44] and batch normalization [45]. Exponential linear units [43] have been shown to be fast and more accurate than rectified linear units.

3.4 CNN Training

We divided the dataset such that we randomly chose 20 patient records for training and 3 patient records for testing for patient-specific results. For cross-patient computation, we trained and tested the system by having each patient as a test set and the rest as a training set for all 23 patients. In this way, when the system is tested, it has not seen the patient before and it is a completely new test case for the system. The testing done in this cross-patient manner is very challenging and the results are generalized.

These sets were retained until the complete training and testing phase was over, after which we randomly chose another training set and testing set. Finally, we calculated the results by averaging the values obtained in all phases. The CNN is trained separately for each patient, and the softmax layer produces probability score for the patient-specific EEG data. Finally, we trained the entire

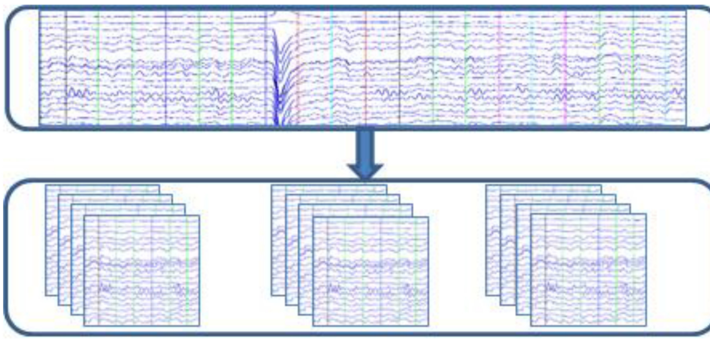

Fig. 5. Using sliding window of 2 seconds to crop the signal.

Table 1. Structure of CNN Layers

Layers	Type
1	Conv (10 × 1, 20 filters)
2	Conv (20 × 23, 20 filters)
3	Max-pool (2 × 1, stride 2)
4	Conv (10 × 20, 40 filters)
5	Max-pool (2 × 1, stride 2)
6	Conv (10 × 40, 80 filters)
7	Softmax, Dense layer (2 classes)

deep CNN model to map the highest probability to the correct labels. We used mini-batch stochastic gradient descent to optimize the parameters for the network by employing a back-propagation algorithm as a supervised learning algorithm [39]. The softmax classification function uses the output from the feature extraction function so that the CNN network can optimize both functions simultaneously.

We used cropped training strategy [46] as we have limited data. The CHB-MIT dataset consists of just 173 seizure data, so the CNN can easily overfit during training. Using cropped training increases the amount of data and enhances the performance of CNN. Figure 5 shows an example of overlapping cropped signals.

For this study, we used 2-second input window crops. We created the largest possible number of window crops, making it one crop for each sample (timestep) in EEG data. This creates new training examples from the original set, thereby increasing the training set. Each window crop will use the same output label that we have for that entire event. Thus, our CNN is using features from all window segments of the event and can learn global features extracted from the entire event. This helps our model to learn general features and not be patient-specific.

The CHB-MIT dataset has 256 Hz sampling frequency. Since each cropped window is of 2 seconds, each window consists of 500 samples. The first convolution operation is performed over the time axis and the second is done for all the electrodes. The filter size and number of filters for convolution and max-pooling operations are shown in Table 1. It took us approximately 5 hours to complete training and testing for 90 epochs on each patient on the cross-patient data. However, for patient-specific training, it took only 2 hours, as the number of iterations is less as compared to the cross-patient approach.

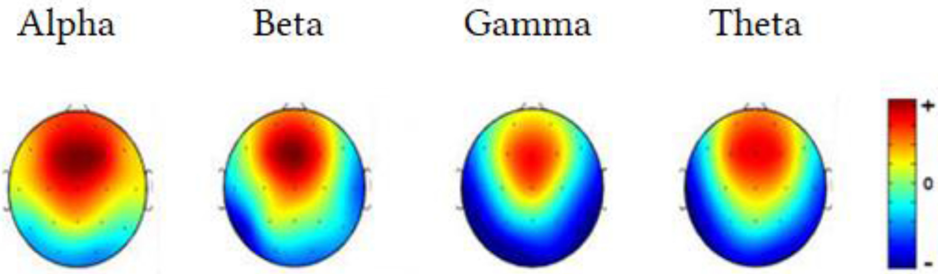

Fig. 6. Correlation maps showing seizure states of a patient.

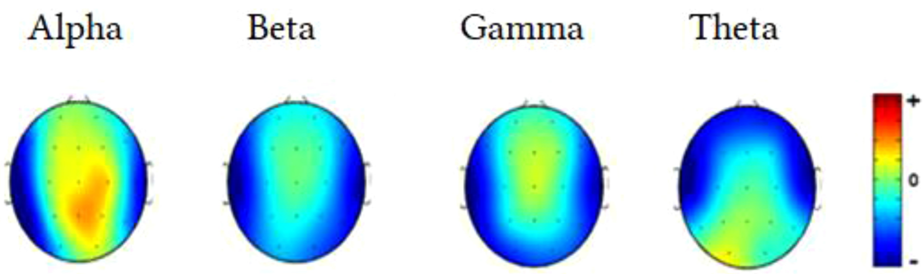

Fig. 7. Correlation maps showing non-seizure states of a patient.

3.5 Visualizing the Learned Representations

As described before, the issue with CNN is that it is difficult to interpret and understand what the network is learning, how it is achieving such outstanding results, and what types of features these models use for classification. Therefore, in this study, we also analyze methods to visualize internal functions and calculations for the CNN. We try to interpret which features the CNN used and from which layers they are extracted. A feature map is calculated for receptive fields in intermediate layers, which can show whether this feature affects the output of those particular layers or not. We want to find out what EEG features the CNN is actually using and in which CNN layers these features are extracted. We know that the features the CNN layers depend upon they perceive through their receptive field. Therefore, to find which features CNN layers are using, we can investigate whether domain-specific knowledge and class-discriminative features are being used by them. We can compute combined feature value for all the receptive fields and then we can calculate how a feature value affects the output of each CNN layer. Thus, by calculating the correlation between feature values and layer outputs, we can come to know what features are being used by CNN.

For this, we use the correlation maps proposed by [47] to analyze and see how CNN learns from spectral amplitude features. We know from the literature that the alpha, beta, and gamma bands provide the discriminative information for classification of motor signals. These amplitudes from alpha, beta, and gamma frequency bands were used to calculate the average values for various frequency bands and used as feature values. Then these mean feature values were correlated inside a receptive field for each layer of the CNN as its total spectral amplitude with the output for each layer. These values are correlated to the output of the corresponding layer. The correlation maps formed are a measure of the total spectral amplitude of a unit (see Figures 6 and 7). These correlation maps were compared to the layer output to see which of the features are used by the CNN. Positive or negative correlations showed that the CNN can learn new information about these features. To crosscheck whether the correlation used the amplitude features, the amplitude was changed to see whether the output of CNN changed. By varying the data artificially, the amplitude and features are also altered, and we can see whether there is a change in the output of the CNN. In this manner, it can be confirmed whether the amplitude features are used by the CNN. If the positive or negative correlations are different from those of untrained CNN, it suggest that the model uses amplitude features more than it did before training. We also make small changes in the amplitude of the inputs to see whether there are changes in output classes. By this correlation method, we can come to know which feature amplitudes cause the CNN to change its outputs.

To make changes in the spectral amplitude, all the input training trials are converted into the frequency domain by using Fourier transform. Then, Gaussian noise is randomly added to make changes in the amplitudes. After the changes, the frequency domain signal is converted back into the time domain. Then the output of CNN is computed for input trials before and after making changes to the amplitude. The output was computed just before the softmax layer. These values are then correlated with the change in the CNN outputs.

The spectral amplitude changes that were studied are related to the different movement classes in the alpha, beta, gamma, and theta frequency bands. These results were used to construct scalp topographies. The scalp correlation maps show correlation between classes and frequency bands. For seizure cases there was a power increase related to seizure class, which is shown in Figure 6 as darker (red) in color. The scalp topography shows that when we changed the amplitude of the corresponding brain regions, they showed positive correlation (red in color), which tell us that these frequency bands and regions were responsible for the class output. In this way, we can make out what channels and frequency the CNN is using to produce the output and which brain regions are involved. As we can see in Figure 6 in the alpha and beta frequency bands, the scalp regions that were more involved in the seizure-class output calculations are visibly darker or red in color. In the same manner for non-seizure classes as shown in Figure 7, the scalp topography shows normal activity, which does not produce any positive correlation when the related amplitudes are changed. Thus, the visualization method shows the spatial distribution of the features learned by the CNN while learning the seizure and non-seizure classes in different frequency bands. The method also shows that the deep CNN learned to extract and use band-power features with specific spatial distributions.

4 RESULTS

PyTorch deep learning library is used to develop the CNN model. We used GTX 1080 GPU card with 8GB memory to train the models. Figure 8 shows the performance on training, validation, and test data for a subject against training iterations. It took us approximately 5 hours to complete training and testing for 90 epochs on each patienton the cross-patient data. However, for patient-specific training, it took only 2 hours, as the number of iterations is less, compared to the cross-patient approach.

The patient-specific and cross-patient results are listed in Table 2 and Table 3, respectively. Table 4 shows specificity, sensitivity, and accuracy for each patient. We achieved more than 90% values for sensitivity and specificity. The mean accuracy recorded was more than 98%. It can be seen in Table 4 that for some subjects the values for sensitivity was low showing that EEG varies from patient to patient.

The accuracy achieved by our CNN model is better than the existing techniques for EEG seizure detection. The sensitivity and specificity are also better than the state-of-the-art techniques.

Table 5 shows the comparison of our proposed technique with state-of-the-art methods for EEG seizure detection and classification. A patient-specific system for seizure detection is proposed in [41] which achieves 96% accuracy on the CHB-MIT dataset. Recurrent neural networks and

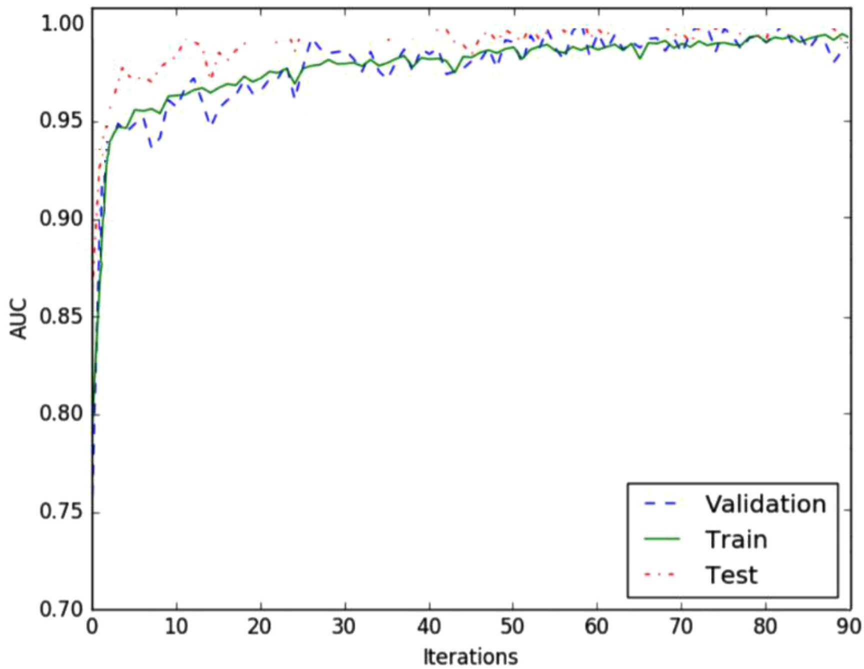

Fig. 8. Performance on training, validation, and test data for one subject against training iterations.

Table 2. Confusion Matrix (%) for Patient-specific Results

Classes	Seizure	No Seizure
Seizure	100	0.00
No Seizure	0.70	99.30

Table 3. Confusion Matrix (%) for Cross-patient Results

Classes	Seizure	No Seizure
Seizure	99.46	0.54
No Seizure	2.76	97.24

CNN have been employed in [21] for cross-patient seizure detection, they report 85% sensitivity. Reveal algorithm is proposed in [48] which uses fuzzy neural networks for cross patient seizure detection and achieve 75% sensitivity. In [49], researchers used k-NN classification technique for cross-patient seizure classification and got 88% sensitivity and 93% accuracy. The results achieved by our CNN model are better than all the above mentioned techniques.

We used methods to visualize the feature learning taking place inside the deep CNN model. Figures 6 and 7 show the correlation map for a patient showing seizure and non-seizure states, respectively, in alpha, beta, gamma, and theta bands. As we can see, the alpha and beta bands show the features in a more explicit manner. This method uses spectral amplitude and band-power features, as discussed before. We used this visualization method because a quick brain-mapping technique shows only important and relevant features for seizure detection.

Table 4. The Cross-patient Results of Segment-based Performance for the Proposed Method

Patient	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	96.88	84.13	98.23
2	99.73	93.50	98.99
3	83.34	96.68	97.51
4	99.49	96.20	97.32
5	59.36	67.57	96.25
6	74.27	99.18	99.99
7	100.00	99.12	99.76
8	68.26	89.36	99.54
9	75.18	94.65	99.59
10	100.00	59.57	89.25
11	100.00	97.75	97.16
12	80.35	97.95	97.49
13	97.20	96.34	98.66
14	88.45	99.39	97.48
15	89.35	98.15	96.45
16	100.00	83.17	99.83
17	92.61	82.35	99.99
18	86.67	98.29	98.55
19	99.90	99.57	98.65
20	98.00	94.24	99.56
21	87.65	99.69	99.57
22	99.67	89.56	96.45
23	93.42	91.49	98.95
Mean	**90.00**	**91.65**	**98.05**

Table 5. The Comparison of State-of-the-Art Techniques with the Proposed Method on the CHB-MIT Dataset

Study	Problem	Design choices	Accuracy	Sensitivity
[41]	Patient-specific	SVM	96%	-
[21]	Cross-patient	CNN + RNN	95%	85%
[48]	Cross-patient	Fuzzy-NN	-	75%
[49]	Cross-patient	k-NN	93%	88%
[50]	Patient-specific	stacked autoencoders	high false positive	100%
[51]	Context-learning-based seizure detection	SVM	88.8%	-
[52]	Patient-specific	DWT	92.30%	-
Proposed	Cross-patient	Deep CNN	98.05%	90%

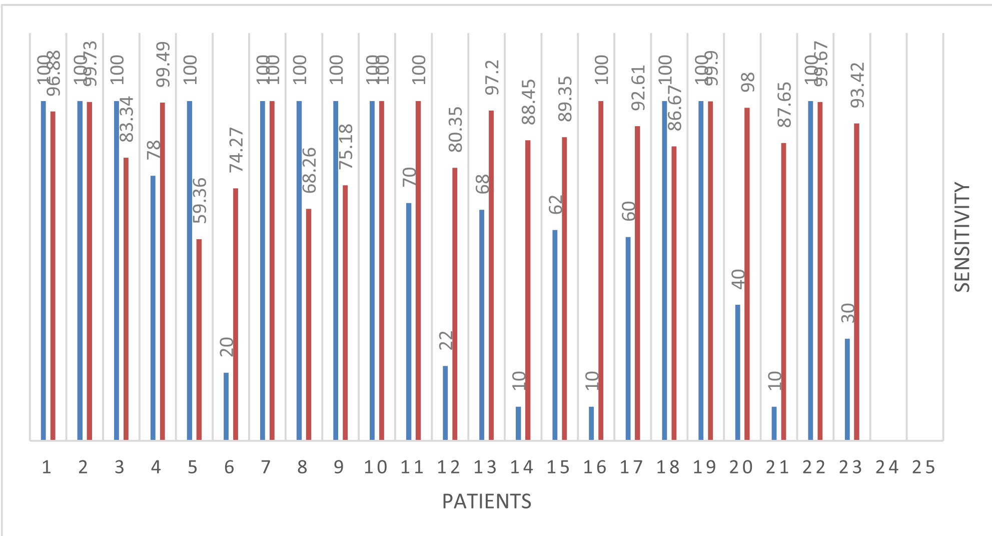

Fig. 9. Sensitivity of the cross-patient algorithm REVEAL [48] (blue) compared to our proposed CNN method (red).

5 DISCUSSION

We presented deep CNN model for EEG seizure detection. Our method was able to learn relevant and robust EEG features automatically. Our deep learning model is excellent for end-to-end learning of EEG data. This study also shows convolutional neural networks can be used as an effective brain-mapping tool.

We use latest advancements and techniques available in the fields of deep learning. Using batch normalization and exponential linear units help us get better accuracies. Therefore, use of the latest advances is essential for achieving good results with the deep learning model.

The size of the dataset is also important for good results when using deep learning models. The EEG dataset that we used was not only small but also unbalanced. Therefore, we used the sliding window for increasing the dataset size, saving the model from memorizing the data.

Many studies [27, 28] have used methods to view the weights and features learned by convolutional neural networks. They have also tried to find which inputs have the most effect on the convolution maps. Here, we use methods to visualize the special orientation of band-power features. Since these methods proved that our deep convolutional neural network actually used the spectral amplitude features for seizure detection, we can use correlation maps to map these features in the form of images. Thus, the method can be used as a fast brain-mapping technique, showing important and relevant features. The method also achieved very high sensitivity for cross-patient data, which means that the system has generalized well. We compared the sensitivity of our method with that of the REVEAL [48] algorithm, which also is a commercial cross-patient seizure-detection algorithm. As we can see in Figure 9, our method outperforms REVEAL for almost all patients. However, we would like to test our system on other public and private EEG epilepsy datasets also.

It took us approximately 5 hours to complete training and testing for 90 epochs on each patient on the cross-patient data. However, for patient-specific training, it took only 2 hours, as the number of iterations is less, compared to the cross-patient approach.

6 CONCLUSIONS

We proposed a generic architecture for EEG epilepsy data classification and analysis using deep CNN. Our method proves that with minor expert knowledge it can be very helpful for medical diagnosis of seizure cases. The study also showed that deep convolutional neural networks can be used as a powerful tool for EEG signals. Our model reaches state-of-the-art performance on patient-specific detectors, able to learn a general representation of a seizure; thus, our system yields significantly improved cross-patient detection results. While we achieved good accuracy for cross-patient data, the sensitivity is also very high almost for all patients.

The architecture proposed in our work consists of a deep convolutional neural network. It is designed to extract spectral, temporal features from EEG epilepsy data while learning general spatially invariant characteristics of a seizure. Our method can be used as a cross-patient classifier as well. We also used methods through which we can visualize what CNN learn; these important features were used to form images depicting brain-mapping. Hence, we can use the output from our deep CNN as input to build an effective multimedia tool for producing quick and relevant brain-mapping images utilizable by medical experts for further investigation of patients. Thus, it can help improve the diagnosis, monitoring, and treatment of epilepsy patients. The system could be particularly useful in cases where immediate access to a neurologist is difficult. Also, the overall time taken by medical practitioners to study seizure cases can be reduced. The system can provide a quick and accurate view of where the seizures are actually located inside the brain, thereby eliminating the need for costly and time-consuming scans.

However, we would still want to see the system's performance on other EEG epilepsy datasets, which have more data. In the future, we also aim to investigate features other than spectral amplitude and band-power features, which play a major role in the success of deep learning methods applied to end-to-end EEG learning and analysis. We would also like to use transfer learning and pre-trained deep learning models in future work to solve issues related to less EEG epilepsy data.

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