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Predicting Epileptic Seizures from EEG Spectral Band Features Using Convolutional Neural Network

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Abstract

Epilepsy, a globally growing chronic nervous disorder, affects the lives of millions of patients annually through the abrupt occurrence of recurrent seizures. It could result in serious injuries or the death of patients in various accidents. Thus, the automatic prediction of epileptic seizures is essential for alerting the patients well before its actual onset, thereby increasing their chances of being safe. In the present times, internet of things assisted technologies have started exploring the potential of cloud as well as fog computing services for providing solutions to such nervous disorders using deep learning. The present paper also proposes a convolutional neural network-based automatic seizure prediction model in a cloud-fog integrated scenario. This model utilizes EEG segments of shorter time durations, which are characterized by discrete spectral features, such as spectral power and mean amplitude spectrum. These features are extracted from five spectral sub-bands of 23-channel EEG signal recordings, including delta, theta, alpha, beta and gamma sub-bands. The performance evaluation through various simulations reveals the efficiency of the proposed model for seizure prediction using EEG segment duration of 30 s. In conclusion, the analysis of simulation results, as well as performance comparison with other contemporary methods evidently disclose that the proposed EEG spectral band features based convolutional neural network approach is a competent method for accurate epileptic seizure prediction in real-time with an average accuracy of 97.4%, average sensitivity of 98%, average specificity of 96.6% and average false discovery rate of 2.7% only.

Keywords Epilepsy · Healthcare · Convolutional neural network · Internet of things · Cloud computing · Fog computing

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1 Introduction

Epilepsy is a severe nervous disorder, caused by the manifestation of recurrent and abrupt seizures [1], which distresses the lives of approximately 50 million people worldwide [2]. The consequences of these seizures in epileptic patients lead to the rise of vigorous clinical symptoms like anomalous behaviour, weird ambiences, muscle contractions and loss of consciousness etc. [1, 3]. Due to such symptoms, a patient could face brain damage, other major injuries or even death in traffic accidents or in unsafe work atmospheres. Epilepsy is not an entirely curable disorder. But its seizures can be managed and controlled to some level by practising regular meditation activities and taking anti-epileptic drugs. When these therapies fail to control seizures in case of drug-resistant patients, epilepsy surgery is another way of reducing seizure occurrences. But all these solutions are not able to provide any everlasting cure to this disorder. Generally, these uncontrolled seizures occur less frequently with a seizure-free time of 99.95% [4]. Thus, epileptic patients may have the opportunity to follow normal daily routines comfortably during these seizure-free long intervals, thereby easing the socioeconomic burden on caretakers. Only an automatic epileptic seizure prediction system, which can inform patients, their relatives, and doctors in adjacent hospitals before the actual commencement of seizures, may make this happen. In this way, the lives of the patients can be saved by taking preventative measures to avoid serious mishaps.

The electrical disturbances caused in a patient's brain due to epileptic seizures can be monitored using the electroencephalogram (EEG) technique [5]. Generally, the neurologists perform the laborious and time-consuming task of examining these EEG recordings [6]. Based upon their analysis, EEG signals obtained from epileptic patients can be grouped into four states - interictal, preictal, ictal and postictal [7]. The interictal state specifies seizure-free intervals, while the preictal state indicates a period just before the actual occurrence of seizures. On the other hand, ictal state represents ongoing seizure activities, and a time interval after the occurrence of seizures is considered as a postictal state. Thus, the automatic epileptic seizure prediction system can alert the patients after the detection of preictal state of EEG signals only [8].

In this age of technological advances, the internet of things (IoT) has begun to provide numerous solutions in the healthcare industry by employing machine learning and cloud-based services [9, 10]. These solutions include remote healthcare practices [11], workout programs [12], family care units for children and old age people [13, 14], diagnostic solutions for lethal diseases like epilepsy, Alzheimer, stress, schizophrenia etc. [15–18]. In continuance of developing accurate and real-time frameworks for healthcare services, deep learning techniques [19] are also gaining tremendous response from the research community over traditional machine learning techniques due to its ability to handle a large volume of data, termed as 'big data', generated by wearable IoT sensing devices [20]. In many recent publications, the researchers have presented their ideas for the prediction of epileptic seizures by analysing multichannel EEG signals with traditional machine learning as well as deep learning algorithms. The present paper focuses on seizure prediction models presented in recent publications, which utilizes CHB-MIT database [21] of long-term EEG recordings.

In reference to discussing the techniques of automatic epileptic seizure prediction presented in recent literature, a traditional machine learning technique presented by Ouyang et al. 2019 [22] has been found, which makes use of SVM classifier using various features, including positive zero-crossing based interval length series related features and statistical analysis based time-domain features. This classification model gives seizure classification results with an accuracy of 86.50%, sensitivity of 92.75% and specificity of 69.77% for accurate prediction of seizures. In addition to this approach, another SVM based model presented in [23] performs prediction of seizures effectively by considering graph theory-based features along with time and frequency domain features. This model provides classification results of preictal and interictal states of EEG signals of epileptic patients with a sensitivity of 87.75% and specificity of 87.75%. A similar approach provided by Usman et al. [24] utilizes SVM algorithm and empirical mode decomposition (EMD) based feature extraction technique. This approach provides seizure prediction results having a sensitivity of 92.23%.

In the same concern, an extreme learning machine (ELM) based seizure prediction model has been discussed by Cui et al. [25]. This model makes use of bag-of-wave features to predict seizures efficiently with a sensitivity of 88.24%. Similarly, a self-organising map (SOM) based unsupervised learning technique [26] is also taken into consideration for the task of seizure prediction, which incorporates a polling-based decision system with EEG signals. This technique has achieved seizure prediction results having classification accuracy of 91%, sensitivity of 98% and specificity of 88%. Moreover, Zhang et al. [27] takes into account a partial directed coherence method to extract features describing epileptic seizures from changes in functional brain networks. These features are supplied to ELM classifier for classification of interictal and preictal classes, which yields a sensitivity of 89.2%.

Nowadays, researchers are shifting towards deep learning techniques to obtain an accurate prediction of epileptic seizures from big data of multichannel EEG signals of long-term durations. In this regard, a hybrid of convolutional neural network (CNN) and SVM based epileptic seizure prediction approach [28] has been employed, in which CNN extracts features from mean amplitude spectrum of 19 spectral bands for 15-channel EEG signals and SVM algorithm is used for classification of seizure states having a sensitivity of 86.25%. In addition, a Bi-directional long short-term memory network (LSTM) based approach [29] for seizure prediction tasks uses spatial feature extraction using a 2D stacked autoencoder. This technique gives classification results having a sensitivity of 94.6%. Similarly, Duan et al. [30] uses CNN based features extracted from correlation coefficients of eight spectral sub-bands. These features are classified using a bidirectional gated recurrent unit (Bi-GRU) classifier to obtain accuracy, sensitivity and specificity values of 94.8%, 91.7% and 97.7% respectively.

Furthermore, another deep learning approach presented by Truong et al. [31] makes use of CNN for the prediction of epileptic seizures in a generalized manner from pre-processed EEG signals using a short-time Fourier transform. This approach has achieved this prediction with sensitivity value of 81.2%. They have also used a deep neural network consisting of a generative adversarial network (GAN) for extracting features and two fully-connected layers for classification to predict seizures with an area under the curve (AUC) of 77.68% [32]. Similarly, Zhang et al. [33] have also provided a CNN approach for predicting epileptic seizures from EEG synchronization measurements and have obtained an accuracy of 89.98%. Likewise, Usman et al. [34] uses EMD approach on short-duration EEG segments to extract features using CNN and their classification using LSTM. This approach provides seizure prediction results with sensitivity and specificity values of 93% and 92.5%. Similarly, they also [35] makes use of CNN, LSTM and SVM based ensembled classification approach and provides seizure state classification with a sensitivity of 96.28% and specificity of 95.65%. In addition, Gao et al. [36] employs multiscale CNN with dilated convolutions to achieve accurate seizure prediction with a sensitivity of 93.3%.

The overall examination of the above-mentioned literature reveals that the deep learning-based approaches are more accurate than that of traditional machine learning-based approaches for precise prediction of epileptic seizures. But these approaches are dependent on the usage of either raw EEG signals or complex features extracted from them. It leads to a high value of processing and prediction times of these classifiers, making them less suited for real-time classification. However, the frequency domain analysis of EEG signals with computationally-efficient statistical features and classification using deep learning algorithms such as CNN could achieve better results for accurate and real-time seizure prediction in patients with epilepsy.

Therefore, the present work proposes spectral-band features based convolutional neural network technique for automatic prediction of epileptic seizures using long-term CHB-MIT EEG database [21]. This database consists of EEG recordings from 24 cases of epilepsy, collected at Children's Hospital, Boston. These raw EEG signals having 23-channels each, have been pre-processed and filtered for denoising. Then, these signals are segmented into shorter duration segments having durations of 5 s, 10 s, 15 s, 20 s, 25 s and 30 s. The next operation of transformation of these short duration segments into frequency domain has been carried out using fast Fourier transform, which separates them into distinct frequency bands for accurate interpretation of the impact of seizure activities on EEG patterns to describe different seizure states. This work involves five frequency bands, consisting of delta (0.1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz) and gamma bands (> 30 Hz) [37]. These spectral bands further undergo a feature extraction process to obtain two distinct features as descriptors of seizure states, viz. spectral power and mean amplitude spectrum. Finally, a suitable architecture of CNN algorithm has been defined for the purpose of seizure prediction. The results of various simulations and performance comparisons with techniques mentioned in recent literature reveal the suitability of the proposed CNN architecture for the real-time and accurate prediction of epileptic seizures. This paper also uses a 5-minutes intervention period, which starts before the EEG's ictal state in patients with epilepsy [38]. It could be employed to produce and convey the warning messages to patients, their families and doctors in nearby hospitals, so to save patients from major injury or death.

This paper has been organised into different sections. Section 1 gives the introduction of epilepsy, its seizure states, the usefulness of new technologies for seizure prediction, techniques of seizure prediction presented in recent publications and a brief description of the proposed model. The overview of the proposed seizure prediction model has been elaborated in Sect. 2. Moreover, the methodology adopted and various steps involved in the implementation of the proposed model are discussed in Sect. 3. Section 4 describes various simulation results obtained after the implementation of this framework and also discusses the interpretation of results to find certain conclusions. Finally, Sect. 5 provides the conclusion of the proposed technique for automatic epileptic seizure prediction.

2 Proposed Model of Seizure Prediction

This section describes the proposed model for automatic prediction of epileptic seizures using the cloud-fog hybrid approach and IoT infrastructure (refer to Fig. 1). This model can be represented with the help of layered architecture, consisting of three layers, viz., user layer, fog layer and cloud layer. The user layer consists of patients wearing bluetooth or wi-fi enabled EEG headsets, which are used to sense EEG signals from the patient's scalp. The sensed

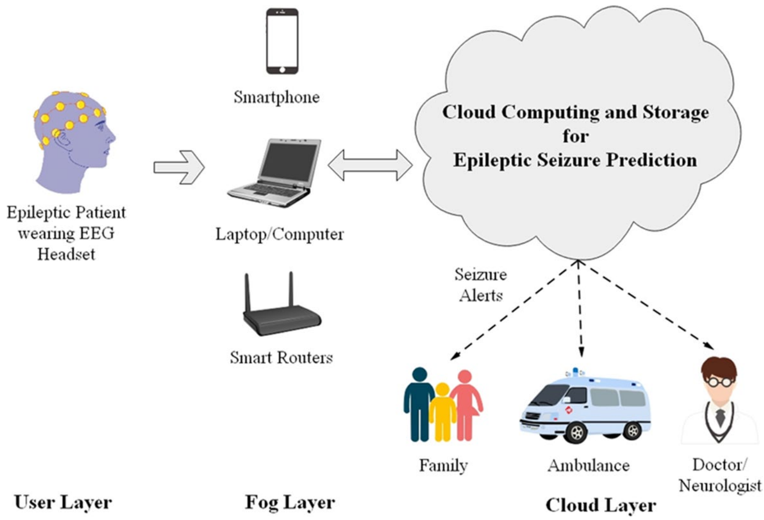

Fig. 1 Overview of proposed seizure prediction model

EEG signals are transferred to edge devices like smartphones, local computers or laptops and smart routers, which forms a fog layer. These fog-layer devices are capable of storing and pre-processing the raw EEG signals before sending them to the cloud layer. The pre-processing step includes the combination of various subtasks, such as filtering, segmentation, frequency domain transformation, frequency bands separation and feature extraction etc. These edge devices at the fog layer can perform their operation for epileptic patients situated in different real-time scenarios, which may include mobile, office, home or hospital scenarios. Finally, the pre-processed EEG signals can be transferred to the cloud layer for the prediction of seizure states as well as storage.

At the cloud server, the received pre-processed EEG signals are fed to a CNN classifier, which has been trained using previously-stored and pre-processed long-term EEG signals labelled by neuroscience experts. Upon detection of preictal state of seizures, the cloud layer performs its duty of generating the alert message and transmitting it to the patient, their family or relatives and doctors in nearby hospitals within a specified intervention period of 5 minutes. Thus, a patient's life can be saved by avoiding major injury or sudden death and he/she could be able to have a better quality of life.

The inclusion of fog layer makes this model a cloud-fog integrated approach, which overcome limitations of cloud-only architecture such as reduced latency in the transmission of sensed EEG signals to the cloud, fewer security constraints for data storage, a lower requirement of transmission bandwidth due to pre-processing on local edge devices, less dependence on central cloud servers and scalability [39]. Thus, this kind of cloud-fog integrated model using CNN based classification and spectral band features is capable of providing accurate and real-time prediction of epileptic seizures efficiently.

3 Implementation of Proposed Model

This section presents the methodology taken into account for implementing the task of epileptic seizure prediction. The implementation of the proposed paradigm has been conducted on a system with Intel CORE i7-8750H processor having a base frequency of 2.21GHz, random access memory of 16GB, a 6GB graphics processing unit of NVIDIA GeForce GTX 1060 having Max-Q design and a base clock of 1.506GHz and operating system of Microsoft windows 10 via Python version 3.8 language. This implementation process includes various steps like filtering, segmentation, frequency domain transformation, spectral bands separation and spectral feature extraction to obtain the classification of preictal and interictal states for seizure prediction. These steps are visible in Fig. 2.

This model utilizes CHB-MIT database [21] of long-term EEG recordings for 24 cases of epileptic subjects suffering from intractable seizures, collected at Children's Hospital, Boston. This database is publicly available at PhysioNet web portal [40]. These EEG recordings are acquired from 22 subjects consisting of 5 males having ages of 3-22 years and 17 females having ages of 1.5-19 years for the first 23 cases. These 23 channel EEG signals (24 or 26 channels in some cases) are acquired from the scalp of an epileptic patient by means of electrodes, which are positioned with standard 10-20 electrode placement technique [41]. These signals are sampled with a rate of 256Hz. The present research work takes into account 23 channel EEG signals for all 24 cases. The time-domain representation of acquired multichannel EEG signal with different seizure states is shown in Fig. 3. The ictal states of EEG signals have been identified using annotation files given in the database description, which are marked by specialized neurologists. A period of 5 minutes just before seizure onset in ictal state has been reserved for warning message generation and transmission and is termed as intervention period. The preictal period of 30 minutes has been taken before the intervention period. A gap of at least 4 hours has been considered

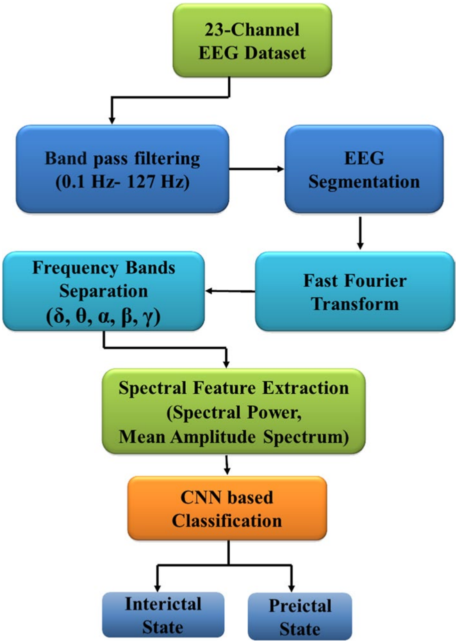

Fig. 2 Implementation steps for proposed seizure prediction model

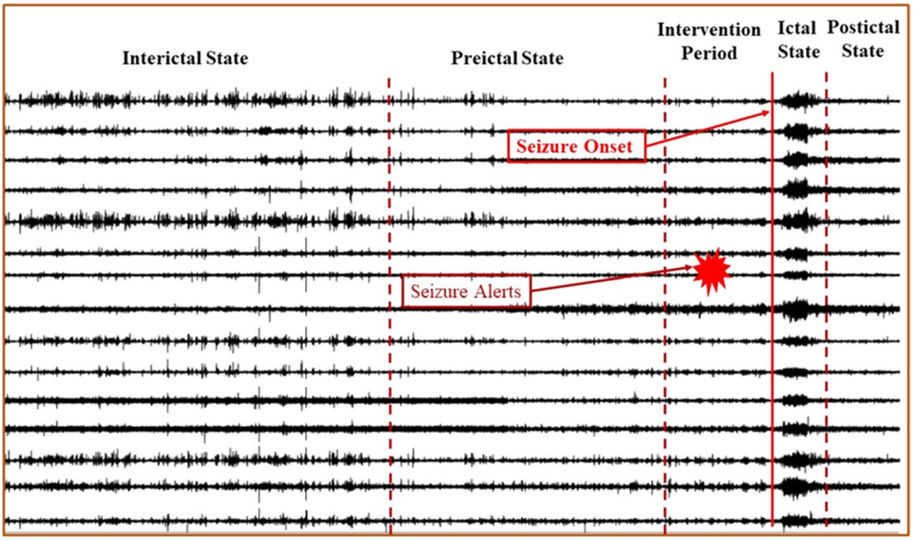

Fig. 3 Multichannel EEG signal presenting various seizure states

from the start and end of ictal period for defining interictal state, representing seizure-free intervals.

After a series of implementation phases, the given dataset produces an unbalanced collection of data samples with various seizure labels. As a result, the current study uses a balanced dataset with an equal number of data samples labelled with solely preictal and interictal states. It is because of the reason that the identification of the presence of preictal states among interictal states of seizure-free intervals is required for seizure prediction. All implementation steps for carrying out epileptic seizure prediction are explained in the following subsections.

3.1 Filtering of EEG Signals

The given EEG signals acquired from scalps of epileptic patients are prone to various kinds of noises and artefacts [42], which need to be removed or minimized for accurate prediction of seizure states. Therefore, these raw EEG segments are initially fed to a Butterworth bandpass filter [43, 44], so that only the desired frequency components would be available at its output. This filter has been designed with specifications of second-order, the lower cut-off frequency of 0.1 Hz and upper cut-off frequency of 127 Hz. Because of its flat and ripple-free spectral response in its passband, this filter has a wide range of applications in biomedical signal processing [45].

3.2 Time Domain Segmentation

The EEG signals are assumed to be non-stationary due to the existence of continuous disparities in its statistical features over a specified period of time [46, 47]. For accurate seizure prediction, these signals need to be made stationary, so that their statistics can be used for identifying seizure states. As a result, for time-domain EEG signals, a segmentation process should be used to cut long-duration signals into shorter-duration segments. Because of the same statistical properties in the time and frequency domains, these short duration segments are also known as pseudo-stationary segments [48].

The present paper also takes into account time-domain segmentation for dividing EEG signals into shorter duration segments, which include time durations of $5\,s$, $10\,s$, $15\,s$, $20\,s$, $25\,s$ and $30\,s$ without considering overlapping. These shorter signals are very useful in reducing the usage of processor computational power and the bandwidth required for their transmission to the cloud through edge devices. The segmentation process also reduces the requirement of storage of segmented data on the cloud or local devices in the cloud-fog hybrid approach of seizure prediction.

3.3 Transformation into Spectral Domain

In order to obtain accurate and high-speed seizure prediction, the EEG signals are required to be transformed from time domain to spectral domain, because epileptic spikes of these signals are more accentuated in this domain, which makes the prediction task easier [49]. Therefore, this work employs the fast Fourier transform (FFT) technique to convert time-domain EEG signals into their equivalent frequency-domain signals.

3.4 Frequency Bands Separation

The process of frequency bands separation involves dividing spectral-domain EEG signals into different sub-bands, consisting of delta (δ: 0.1–4 Hz), theta (θ: 4–8 Hz), alpha (α: 8–12 Hz), beta (β: 12–30 Hz) and gamma bands (γ: $> 30\,Hz$) [50]. The main aim of separating signals into various sub-bands is significant variations in the characteristics of these bands due to epileptic seizures. Furthermore, these sub-bands variations represent changes in behavioural and functional features of the human brain's structure and may act as markers for describing seizure states [51].

3.5 Spectral Feature Extraction

This step comprises the process of extracting various features from spectral sub-bands of given EEG signals for characterizing different seizure state labels. This process plays a significant role in developing a highly accurate seizure prediction model having high processing and classification speed. For this purpose, the present work suggests two features for each sub-band of EEG signals, viz. spectral power and mean amplitude spectrum [52, 53]. These features for different spectral sub-bands of the single channel of a given EEG signal obtained by taking averages of 23 channels, are shown in Fig. 4, which portrays their variations in case of interictal and preictal states of seizures for epileptic patients.

For a signal $y(n)$ with M data points and its discrete Fourier transform $Y_p(k)$ for a specific spectral sub-band. The spectral power ($\mu V^2/Hz$) for given sub-band can be stated by Eq. 1.

$$P = \frac{1}{M}\sum_{k=0}^{M-1}\left|Y_p(k)Y_p^*(k)\right| \tag{1}$$

where $Y_p^*(k)$ is the complex conjugate of $Y_p(k)$.

In the similar manner, the mean amplitude spectrum, measured in $\mu V\ /Hz$ for a specific spectral sub-band of signal $y(n)$ can be presented by Eq. 2.

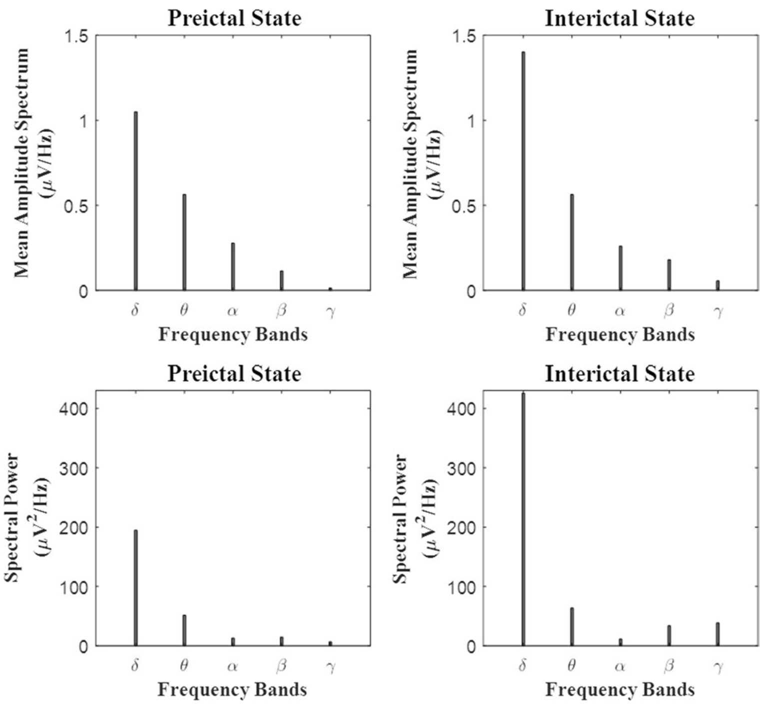

Fig. 4 Spectral power and mean amplitude spectrum for different seizure stages

$$S(k) = \frac{1}{M} \sum_{k=0}^{M-1} \left| Y_p(k) \right| \tag{2}$$

3.6 CNN Based Seizure State Classification

Convolutional neural network (CNN) is a well-known deep learning algorithm [54], which is broadly used for image classification and pattern recognition in computer vision, and natural language processing [55]. These days researchers have also started exploring the potential of CNNs for signal processing, including ECG and EEG signal analysis in biomedical applications [56, 57].

The architecture of CNN consists of different layers like convolutional layer, pooling layer, dropout layer, flatten layer, fully connected layers as well as output classification layer with different activation functions [54, 58]. The function of convolutional layer is to perform convolution operations over a set of predetermined number of data points, which are selected by kernels of predefined sizes. The next layer preceded by one or more convolutional layers is pooling layer, which is used to accomplish down-sampling of data points of output sequences of the previous layer to reduce structural complexity for subsequent layers with the help of maximum, minimum or average operations. Furthermore, dropout layer can be added to CNN architecture for eliminating certain redundant inter-neuronal connections to avoid the problem of overfitting and to reduce architectural complexity. The other layer in a row is flatten layer, which performs the task of converting pooled data points of the previous layer into a single column in order to transfer it to a fully connected layer. The purpose of fully connected layers is to build connections in descending order in order to reach the desired number of output class labels. Finally, a particular activation function, usually SoftMax, is used to make a classification layer by embedding all other layers onto this single layer [58].

The present work has defined a CNN architecture for accurate prediction of epileptic seizures, consisting of two convolutional layers with 32 kernels having a size of 3 × 3, and having 'same' padding for each layer; and one max-pooling layer having 32 kernels with a size of 2 × 2. The output of max-pooling layer is fed to dropout layer with a dropping probability of 0.25. Its output is given to flatten layer for converting data points of different dimensions into a single column vector. In order to provide deep appearance to CNN, two fully connected layers are employed using 'Dense' function with output values of 10 and 2 respectively. Finally, the output classification layer has been defined using 'SoftMax' activation function to obtain a binary classification of interictal and preictal states of EEG signals for effectual seizure prediction. The architectural view of defined CNN for seizure prediction task along with output specifications is shown in Fig. 5.

4 Interpretation of Simulation Results

This section describes simulation results and its interpretation for epileptic seizure prediction using the proposed model. It utilizes CHB-MIT database of long-term EEG recordings for implementation of the proposed model. After going through number of pre-processing steps as mentioned in Sect. 3 of this paper, the given dataset has been transformed into large quantity of EEG data samples of dimensions 23 × 10, where each of these segments are expressed using two discrete features, mean amplitude spectrum and spectral power. These features are extracted from five distinctive spectral sub-bands of EEG segments, comprising of δ, θ, α, β and γ bands. This work considers only samples labelled with an equal proportion of preictal and interictal classes in order to create a balanced collection of EEG signals. These datasets for each epileptic subject are divided into two different subsets: training set comprising of 90% samples for training and testing set having 10%

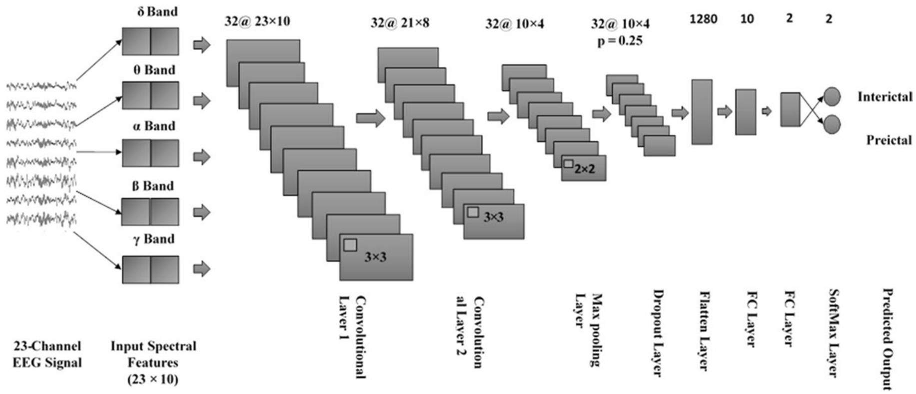

Fig. 5 CNN architecture for epileptic seizure prediction

samples for testing of the proposed model. Furthermore, the training datasets consist of 10% samples, which are reserved for validating the proposed trained model of CNN.

Several simulation experiments have been carried out for EEG segments of five different segment durations using proposed CNN architecture so as to obtain appropriate segment duration to realize an accurate prediction model. The EEG segments include segments of 5 *s*, 10 *s*, 15 *s*, 20 *s*, 25 *s* and 30 *s* durations. The given CNN model employs a batch size of 8 input samples in order to perform training using 'rmsprop' optimizer with learning rate of 0.001 and decay function value of 1×10^{-5} [59] ; and binary cross-entropy loss function [60]. This model has been trained for 100 epochs for obtaining optimum classification accuracy for the task of seizure prediction.

The performance of proposed CNN algorithm has been examined different performance measures like accuracy [61], sensitivity [61, 62], specificity [61, 62] and false discovery rate (FDR) [63, 64]. These performance measures have been obtained from a confusion matrix consisting of different values such as true positive (TP), false positive (FP), true negative (TN) and false negative (FN) and are described using the following equations.

$$Accuracy(\%) = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \tag{3}$$

$$Sensitivity(\%) = \frac{TP}{TP + FN} \times 100 \tag{4}$$

$$Specificity(\%) = \frac{TN}{TN + FP} \times 100 \tag{5}$$

$$FDR(\%) = \frac{FP}{FP + TP} \times 100 \tag{6}$$

Table 1 shows the performance of the proposed CNN architecture for the prediction of epileptic seizures for all 24 subjects of the given dataset considering EEG segment duration of 30 *s*. This table clearly demonstrates that the accuracy of the proposed model lies between 87.1% for subject ID 6 to 100% for thirteen different subjects. In addition to this, sensitivity values lie in the range of 76.47% for subject ID 6 to 100% for seventeen subjects. Similarly, the values of specificity vary from 80% for subject ID 2–100% for seventeen different subjects again. This table also reveals the range of FDR, which should be zero ideally, from a maximum value of 16.67% for subject ID 14 to 0% for seventeen subjects. Moreover, the average values of given performance measures for the proposed CNN architecture utilizing 30 *s* duration EEG segments for seizure prediction show average accuracy of 97.4% ± 4.1%, average sensitivity of 98% ± 5.2%, average specificity of 96.6% ± 6.5% and average FDR of 2.7% ± 5.1%.

As mentioned earlier, the simulation experiments using proposed CNN model are also carried out using EEG segments of 5 *s*, 10 *s*, 15 *s*, 20 *s* and 25 *s* durations along with 30 *s* duration segments. The performance of the given classifier for various input EEG samples of different segment durations is visible in Fig. 6. This figure reveals that the given CNN model provides maximum accuracy of 97.4% and maximum sensitivity of 98% for EEG segments of 30 *s* duration. However, this model provides maximum specificity of 97.5% and a minimum FDR of 2.6% for EEG segments of 15 *s* duration. But for the same CNN architecture, these values of max. specificity and min. FDR for 15 *s* duration segments rise marginally than that of 30 *s* EEG segment duration, which does not

Table 1 Performance analysis of CNN for seizure prediction of 34 epileptic cases

Subject ID	Accuracy (%)	Sensitivity (%)	Specificity (%)	False delivery rate (%)
1	100	100	100	0
2	91.67	100	80	12.5
3	97.96	96.15	100	0
4	100	100	100	0
5	100	100	100	0
6	87.1	76.47	100	0
7	91.67	100	81.25	13.04
8	100	100	100	0
9	97.92	100	96	4.17
10	96.2	97.73	94.29	4.44
11	90	88.89	90.9	11.11
12	100	100	100	0
13	100	100	100	0
14	89.19	97.22	81.58	16.67
15	100	100	100	0
16	100	100	100	0
17	100	100	100	0
18	97.96	100	95.45	3.57
19	100	100	100	0
20	100	100	100	0
21	100	100	100	0
22	100	100	100	0
23	98.31	96.55	100	0
24	99.12	98.31	100	0
Average	97.4	98	96.6	2.7
Std. Dev.	4.1	5.2	6.5	5.1

offer any significant difference in classification performance of the given model. Consequently, it is evident that the proposed CNN architecture provides an efficient prediction of epileptic seizures quite accurately for input EEG segments of 30 s duration.

Apart from the proposed model's simulation analysis, the findings are also compared to other contemporary methods for seizure prediction reported in recent literature, which use both traditional machine learning and deep learning techniques. This comparative study is shown in Table 2, which clearly reveals the usefulness of the proposed CNN model for the prediction of epileptic seizures with better classification performance as compared to other techniques in terms of different performance measures. Thus, the overall interpretation of simulation results and comparative analysis with other techniques mentioned in recent publications evidently reveal that the suggested spectral band features-based CNN model is a suitable method for accurate seizure prediction of epileptic patients in a cloud-fog integrated framework.

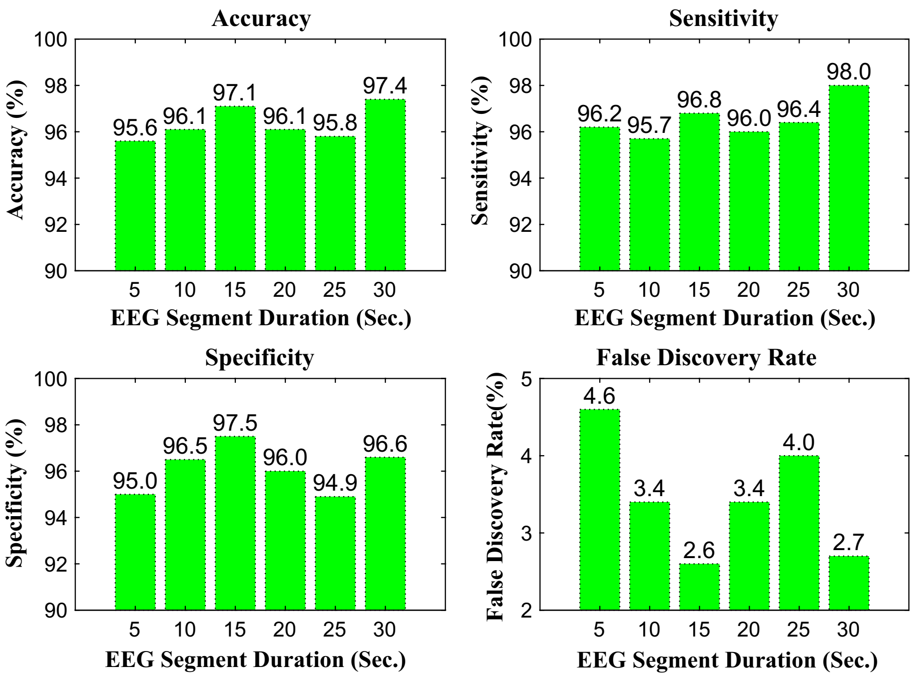

Fig. 6 Performance comparison of proposed CNN architecture for different EEG segment durations

5 Conclusion

Internet of things (IoT) based technologies have emerged as potential solution providers in the healthcare sector with the help of traditional machine learning or deep learning algorithms as well as cloud and fog computing services. The automatic prediction of epileptic seizures is an example of such healthcare solutions, which can predict the pre-ictal state of epileptic patients well before the actual onset of seizures. Thus, the life of a patient can be saved from major injury or sudden death due to the timely reception of warning messages from a cloud-based seizure prediction system.

This paper presents an automatic seizure prediction model in a cloud-fog integrated environment, which uses the proposed CNN architecture for classification of seizure states using EEG segments of different durations. These EEG segments have segment duration of $5\,s$, $10\,s$, $15\,s$, $20\,s$, $25\,s$ and $30\,s$. These are characterized by two discrete spectral features, viz., spectral power and mean amplitude spectrum, taken from five spectral sub-bands of 23-channel EEG recordings, namely delta, theta, alpha, beta and gamma bands. The simulation results obtained after carrying out various experiments for EEG segments of different durations, it has been identified that the proposed CNN architecture performs quite significantly for accurate prediction of seizure activities using EEG segments of $30\,s$ duration. In conclusion, the performance evaluation of this model and its comparative study with other contemporary methods reveal that the proposed CNN model is an accurate and efficient seizure prediction technique, which could be incorporated in real-time seizure prediction applications using a cloud-fog integrated approach. This model could aid patients in remote locations using early warning

Table 2 Comparative analysis of the proposed model with other contemporary methods

Authors	Seizure prediction algorithms	Prediction results
Koutsouris et al. [23]	SVM	Sensitivity =87.75%, Specificity=87.75%
Usman et al. [24]	SVM	Sensitivity = 92.23%
Truong et al. [31]	CNN	Sensitivity=81.2%
Cui et al. [25]	ELM	Sensitivity = 88.24%
Kitano et al. [26]	SOM	Accuracy=91%, Sensitivity=98%, Specificity=88%.
Abdelhameed et al. [29]	Convolutional autoencoder + Bi-LSTM	Sensitivity = 94.6%
Truong et al. [32]	GAN classifier	AUC=77.68%
Ouyang et al. [22]	SVM	Accuracy=86.50%, Sensitivity=92.75%, Specificity=69.77%
Hu et al. [28]	CNN + SVM	Sensitivity = 86.25%
Duan et al. [30]	CNN + Bi-GRU	Accuracy=94.8%, Sensitivity=91.7%, Specificity=97.7%
Zhang et al. [27]	ELM	Sensitivity=89.2%
Zhang et al. [33]	CNN	Accuracy=89.98%
Usman et al. [34]	CNN + LSTM	Sensitivity=93%, Specificity=92.5%
Usman et al. [35]	CNN + LSTM + SVM	Sensitivity=96.28%, Specificity=95.65%
Gao et al. [36]	Multiscale CNN	Sensitivity=93.3%
Proposed model	Proposed spectral-band features based CNN approach for 30 s duration EEG segments	Accuracy=97.4%, Sensitivity=98%, Specificity=96.6%

messages of seizure onset, thereby giving them opportunities to live a better quality of life.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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