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SCIENTIFIC PAPER

Deep learning based smart health monitoring for automated prediction of epileptic seizures using spectral analysis of scalp EEG

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Abstract

Being one of the most prevalent neurological disorders, epilepsy affects the lives of patients through the infrequent occurrence of spontaneous seizures. These seizures can result in serious injuries or unexpected deaths in individuals due to accidents. So, there exists a crucial need for an automatic prediction of epileptic seizures to alert the patients well before the onset of seizures, enabling them to have a healthier quality of life. In this era, the Internet of Things (IoT) technologies are being used in a cloud-fog integrated environment to address such healthcare challenges using deep learning approaches. The present paper also proposes a smart health monitoring approach for automated prediction of epileptic seizures using deep learning-based spectral analysis of EEG signals. This approach processes EEG signals using filtering, segmentation into short duration segments and spectral-domain transformation. These signals are then analysed spectrally by separating them into several spectral bands, such as delta, theta, alpha, beta, and sub-bands of gamma. Furthermore, the mean spectral amplitude and spectral power features are retrieved from each spectral band to characterize various seizure states, which are fed to the proposed LSTM and CNN models. The results of the proposed CNN model show a maximum accuracy of 98.3% and 97.4% to obtain a binary classification of preictal and interictal seizure states for two different spectral band combinations respectively. Thus, the proposed CNN architecture accompanied by spectral analysis of EEG signals provides a viable method for reliable and real-time prediction of epileptic seizures.

Keywords Deep learning · Epilepsy · Healthcare · Internet of Things · Scalp EEG · Spectral analysis

Introduction

Epilepsy is one of the most prevalent fatal nervous disorders, which affects its patients through the occurrence of infrequent seizures [1]. This disorder influences the lives of more than 50 million population of the world, out of which 80% people are the residents of developing and underdeveloped countries [2]. The consequences of these seizure activities give rise to vital medical symptoms in epileptic patients, including aberrant behaviour, muscle contractions, unusual sensations and reduced consciousness etc. [1, 3]. It could further lead to serious injuries or sudden unexpected deaths of its patients due to suffocation, brain damage or accidents [4].

Although these irregular seizures occur less frequently and the patients remain unaffected during 99.95% of total time, they are vulnerable to live under the panic of seizure occurrence and cannot perform normal activities at home, work or while travelling [5]. Consequently, epileptic patients experience worse quality of life with increasing socioeconomic strain on their family or caregivers. Hence, there exists a critical need for a mechanism to automatically predict the occurrence of seizures in epileptic patients. This mechanism could save their lives from sudden mishappenings. It could also enable the doctors or neurologists to make use of various seizure managing remedies effectively for ensuring an improved quality of life for the patients during seizure-free interval [6].

For monitoring of neuronal activities in epileptic patients' brains, electroencephalogram (EEG) is a widely used technique [7]. Basically, the prediction of epileptic seizures

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depends upon the detection of preictal state of seizures (EEG state just before the actual seizure occurrence) among seizure-free interictal states. Traditionally, this task of examining EEG signals is performed by the neurologists, which is a laborious job [8]. So, this process needs to be automated using modern state-of-the-art technologies. Due to non-stationary and non-linear nature of EEG signals, the interictal and preictal seizure morphologies involve high variations for inter-patient and patient-specific analysis [9, 10]. The drastic changes in these seizure morphologies from patient to patient make inter-patient seizure prediction a challenging task [11]. So, most of these approaches, as reported in recent literature, are subjected to patient-specific techniques only [8].

In this modern era of the Internet of Things (IoT) technologies, seizure prediction could be achieved using smart patient monitoring approach based on machine learning-based analysis of sensed EEG signals. To achieve real-time and accurate prediction of seizures activities, deep learning techniques have also gained huge popularity among researchers due to their ability of precisely analysing big data of EEG signals within a short period [12–14].

The overview of a generalized health monitoring framework for automated prediction of seizure activities in epileptic patients is shown in Fig. 1. This framework could sense multichannel EEG signals from the scalp of an epileptic patient using an EEG headset, which could be transmitted to any nearby edge-layer device continuously using Bluetooth or Wi-Fi technologies. The received raw EEG signals could be pre-processed at edge devices and be further transferred to cloud servers for classification using trained deep learning algorithms. The deep learning algorithms deployed at cloud servers can be trained using previously stored pre-processed EEG features related to different seizure states. After the detection of preictal state of EEG, the process of alert generation would start at the

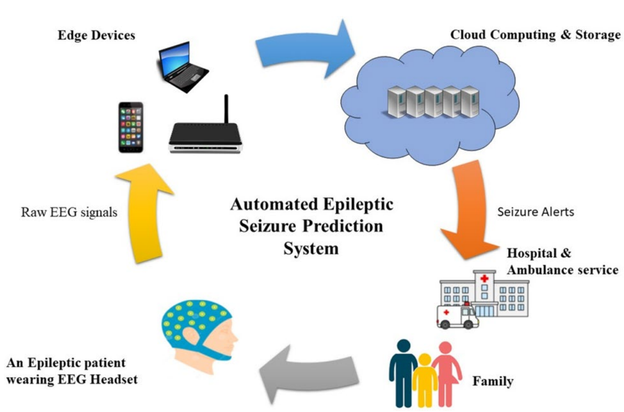

Fig. 1 A generalized overview of smart health monitoring framework for automated prediction of epileptic seizures: a futuristic trend

cloud. It could deliver alert messages to nearby hospitals, ambulance services, the patients as well as their family members to save their lives from sudden unpredicted deaths or major injuries.

Keeping in view of these futuristic frameworks, the present work also proposes a patient-specific smart health monitoring framework for automated prediction of epileptic seizures using deep learning-based spectral analysis of multichannel EEG signals. In this work, EEG signals are filtered and segmented to short duration EEG segments to remove artefacts or noises and to deal with their non-stationary character respectively. Afterwards, these segments are transformed into frequency domain using Fast Fourier transform and are subjected to division into multiple frequency bands including delta, theta, alpha, beta and gamma. Moreover, the gamma band has been further split into two and four sub-bands to use its capability of distinguishing between interictal and preictal states using various spectral features for seizure prediction [15, 16]. Then, spectral-domain features, such as spectral power and mean spectral amplitude, are extracted from each of these bands, which are fed to the proposed architectures of long short-term memory (LSTM) network [17] and convolutional neural network (CNN) [18] deep learning classifiers. The in-depth study of the proposed framework after the analysis of simulation results and comparison with other recently published techniques firmly reveal its effectiveness using CNN algorithm for accurate prediction of epileptic seizures from spectral band features of scalp EEG signals in real-time.

The proposed CNN and LSTM models in this work have been optimized using 'rmsprop' optimization technique to take advantages of its robust nature, fast convergence property and ability to effectively deal with stochastic processes [19]. The other effective optimization techniques, which could be employed for improving the performance of these frameworks in a cloud-fog integrated environment, are arithmetic optimization [20], improved Adam optimizer [21], Aquila optimizer [22], Grasshopper optimizer [23], group search optimizer [24] and hybrid antlion optimizer [25] etc. Thus, a comprehensive examination of simulation results illustrates the efficient utilization of the proposed CNN algorithm empowered with optimized training and hyper-parameter tuning for the desired task of seizure prediction. For this task, the specific contributions of the present work are summarized as follows:

- This work studies the behaviour of multichannel EEG signals using short-duration segmentation to make them pseudo-stationary in nature.
- It analyses the impact of neuronal activities arising in different spectral bands due to seizure onset for its prediction via their spectral features with a special focus on gamma band.

– It proposes spectral bands specific CNN and LSTM deep learning models for the desired task and examines their performance to obtain a real-time solution for seizure prediction.
– Finally, it concludes the appropriateness of the proposed CNN model with different spectral band features for accurate and prompt prediction of seizure activities.

This paper has been organized into various sections. "Introduction" section describes the problem of epilepsy, its solution using modern state-of-art technologies and proposed automated framework of seizure prediction. "Method" section presents various steps involved in the methodology adopted for implementing the proposed approach. Moreover, the results of simulations obtained from this approach are presented in "Results" section, which are carefully analysed and discussed in "Discussion" section. In the end, the last section "Conclusion" discusses the conclusions drawn from the major outcomes of this work briefly.

Method

This section discusses the proposed approach of seizure prediction using deep learning-based spectral analysis of EEG signals (refer to Fig. 2). As shown in this figure, the task of prediction of seizure occurrence involves different implementation steps, including filtering of raw EEG signals, time-domain segmentation, conversion into frequency domain, separation of spectral segments of EEG into various distinct frequency bands and extraction of features from obtained spectral bands to describe different seizure states. Finally, the spectral band features of raw EEG signals are fed to deep learning algorithms, like convolutional neural network (CNN) and long short-term memory network (LSTM), for classification into various seizure states.

The proposed approach uses CHB-MIT database [7] of long-term EEG signals for the task of predicting epileptic seizures, which is publicly available at 'PhysioNet' online web portal [26]. This database consists of 24 cases of EEG

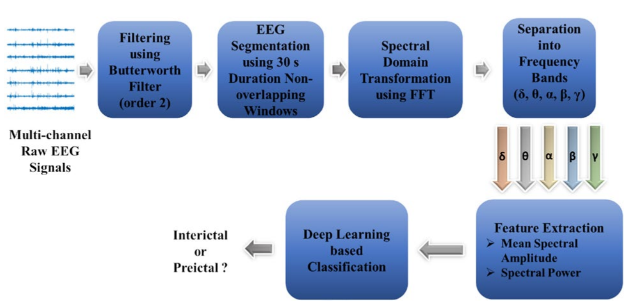

Fig. 2 Proposed seizure prediction approach: methodology

recordings taken from different patients having intractable seizures, which are collected on a time-to-time continuous basis at Children's Hospital, Boston. The epileptic patients under study consist of a total of 22 subjects for 23 cases having 5 males with the age group of 3–22 years and 17 females with an age group of 1.5–19 years. Most of these EEG signals are acquired with 23 channels from epileptic patients' scalps using different electrodes placed with standard 10–20 international system of electrode positioning [27]. The recorded EEG signals are sampled at a rate of 256 Hz and a resolution of 16 bits.

The present work has taken into consideration EEG signals with 23 channels for all cases. In these recorded EEG signals, the ictal states, presenting seizure onsets, are marked by neurologists using specified seizure intervals, which are given in annotation files of this database. The EEG signal states immediately after the end time instant of ictal state are considered as postictal states. This work takes into account an intervention period (IP) of 5 min just before the start time instant of ictal state, which could be utilized for generation and transmission of seizure alerts [28]. The EEG signal states, having an interval of 30 min just before the intervention period, are termed as preictal states. The interictal states are occupied with a temporal separation of at least 4 h either before or after the occurrence of ictal state. The given database, after being labelled with different seizure states in given EEG signals, provides an imbalanced dataset of various seizure state classes, which consists of a small number of ictal and postictal classes and a large number of preictal and interictal classes. Since the task of seizure prediction is primarily dependent upon detection of preictal seizure class among other interictal classes. Therefore, the present work considers a balanced dataset of EEG signal segments associated with the same number of preictal and interictal classes only. The other implementation steps for accomplishing the task of seizure prediction are briefly discussed in the following subsections.

Filtering

During the process of acquisition and transmission of EEG signals, these signals may get affected by different types of artefacts due to body movement or eye movement etc., and may also include various kinds of noises superimposed on them [29]. These artefacts or noise prone EEG signals may lead to the wrong prediction of seizure states during the classification step. Hence, the filtering step has been implemented on given multichannel EEG signals using a second-order Butterworth bandpass filter [30]. This filter has been designed to operate on a frequency range of 0.1 Hz to 128 Hz.

This filter has been employed for the given task due to its passband characteristics of flat and ripple-free spectral response [31]. These characteristics have also been illustrated by the magnitude and phase responses in Figs. 3a and b respectively. These figures clearly demonstrate the perfectly flat frequency response of the filter in its passband within given cut-off frequencies, which drops to zero beyond these frequency limits. Thus, it ensures high precision filtering of EEG signals within specified frequency limits by rejecting unwanted frequency components and having a minimal distortion in output due to slight variation in its phase response. Similarly, Fig. 3d also shows the impact of filtering on the spectral domain representation of an EEG signal amplitude (single channel), which presents reduced artefacts or noise-like spikes as compared to the original unfiltered EEG signal (refer to Fig. 3c).

EEG segmentation

Due to continuous variations in statistical features over a particular time interval, EEG signals become non-stationary, leading to the inaccurate classification of seizure states [32]. To avoid this problem, the long-term EEG signals are required to be divided into smaller duration segments. These segments are considered to be pseudo-stationary due to the existence of similarity between statistical feature values in time and frequency domains [32].

In this concern, the present work applies the process of segmentation of long-term EEG signals into EEG segments of 30 s duration using non-overlapping temporal windows. This value of EEG segment duration has been taken into account after analysing the performance of the proposed models for EEG segments of 500 ms, 1 s, 5 s, 10 s, 15 s, 20 s, 25 s and 30 s duration values. The frequency resolution of EEG segments would be better during spectral analysis with an increase in their segment duration, which results in higher classification accuracy of the proposed model [33, 34]. However, shorter duration segments are needed for keeping EEG signals stationary with an improved temporal resolution at the cost of lower frequency resolution [34, 35]. Therefore, the proposed classification approach aids in choosing an appropriate segment duration to avoid the trade-off between their temporal and frequency resolutions during spectral analysis. These shorter duration segments are also helpful in reducing the computational power requirement of processing units, thereby making low-computational power edge-layer devices able to process these EEG segments easily. Another benefit of the segmentation process is the reduction in transmission bandwidth for sending signals from edge devices to the cloud and reduction in storage requirement on cloud-based databases [36].

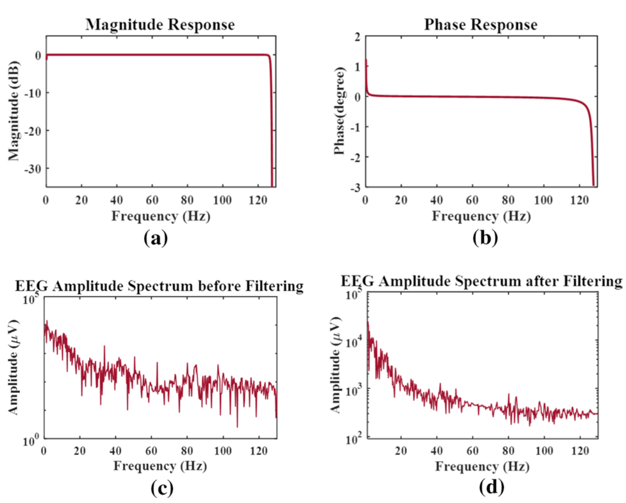

Fig. 3 **a** Magnitude Response, **b** Phase Response of a Second Order Butterworth Bandpass Filter & **c** Spectral Domain representation of EEG signal before filtering, **d** after filtering

Spectral domain transformation

The statistical variations in EEG signals create epileptic spikes, which are predominantly highlighted in frequency domain as compared to that of time domain [37]. These emphasized epileptic spikes in frequency domain act as descriptors for accurate prediction of seizure state classes. Consequently, the given multichannel time-domain EEG signals in this work are also undergone through transformation into the spectral domain using Fast Fourier transform (FFT) technique. Figure 3c presents the frequency domain transformation of an EEG signal using its single-sided FFT based spectral representation. This figure clearly depicts the highlighted epileptic spikes in the frequency domain of EEG signal, which are useful for the accurate classification of seizure states.

Separation into frequency bands

This step deals with the separation of EEG signals into multiple spectral bands in frequency domain, which comprise of delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ) bands [38]. The occurrence of epileptic seizures initiates sudden dynamic disparities in the statistical features of these spectral bands, which further defines fluctuations in functional as well as behavioural physiognomies of the complex structure of the brain. These dynamically varying features also act as descriptors for various seizure state classes [39].

Keeping in view of all these facts, the present work analyses the performance of given deep learning algorithms using two spectral band groups, each containing δ, θ, α, β and sub-bands of γ. This work precisely examines the gamma band along with other spectral bands by dividing it into several sub-bands, because gamma-band oscillations are typically observed during seizures and may also contribute to seizure onset with increasing frequency from preictal state to ictal state [15]. Also, various spectral features obtained from high frequency gamma sub-bands have more descriptive capabilities to distinguish between interictal and preictal states during seizure prediction. Therefore, in this work, gamma band is split into two and four sub-bands in first and second groups of spectral bands respectively. The first spectral band group '6' consists of six distinct bands, including δ (0.1 Hz–4 Hz), θ (4 Hz–8 Hz), α (8 Hz–12 Hz), β (12 Hz–30 Hz), low γ (30 Hz–70 Hz) and high γ (70 Hz–128 Hz) [40]. On the other hand, the second spectral band group '8' is comprised of a set of eight bands, such as δ (0.1 Hz–4 Hz), θ (4 Hz–8 Hz), α (8 Hz–12 Hz), β (12 Hz–30 Hz), low $\gamma - 0$ (30 Hz–50 Hz), low $\gamma - 1$ (50 Hz–70 Hz), high $\gamma - 0$ (70 Hz–100 Hz), and high $\gamma - 1$ (100 Hz–128 Hz) [40]. This separation of spectral EEG into various bands has been achieved by selecting different frequency bands in FFT of EEG segments.

Feature extraction

This step involves the extraction of various features characterizing each spectral band of a given EEG segment for a particular seizure class label. The extracted features plays a key role to achieve a competent prediction of epileptic seizures. The present work utilizes two distinct features for each spectral band of EEG segments, viz., mean spectral amplitude and spectral power [41, 42], for preictal and interictal class labels. The whole process of extracting mean spectral amplitude and spectral power features from various spectral bands of a 30 s duration EEG segment has been depicted in Fig. 2.

Mathematically, the mean spectral amplitude, expressed in μV /Hz for an N-point signal $x(n)$ having discrete Fourier transform $X(k)$ for a specific spectral band, is represented by the following Eq. 1.

$$S(k) = \frac{1}{N} \sum_{k=0}^{N-1} |X(k)| \tag{1}$$

On the other hand, the spectral power measured in μV^2/Hz for an N-point signal x(n) can be expressed by the following Eq. 2.

$$P = \frac{1}{N} \sum_{k=0}^{N-1} |X(k)X^{*}(k)| \tag{2}$$

where, $X^{*}(k)$ presents complex conjugate of $X(k)$ in frequency domain.

Deep learning based classification

The present research work applies two different deep learning algorithms to classify given EEG signals into different seizure states in various simulation experiments, which includes convolutional neural network (CNN) and long short-term memory network (LSTM).

The architectural overview of CNN employed for the task of seizure prediction has been shown in Fig. 4. This CNN classifier is fed with an input spectral feature map of $23 \times n$, where n belongs to a total number of features having a value of 12 for 'B6' group and a value of 16 for 'B8' group. Its architecture includes two convolutional layers having 32 kernels with 3×3 sizes and padding, one max-pooling layer having 32 kernels of size 2×2, a drop-out layer having dropping probability of 0.25, a flatten layer having 's' neurons and two fully connected 'dense' layers having numbers of neurons equal to 10 and 2 respectively. All of these layers are embedded into a classification layer of 'SoftMax' activation to provide a binary classification of interictal and

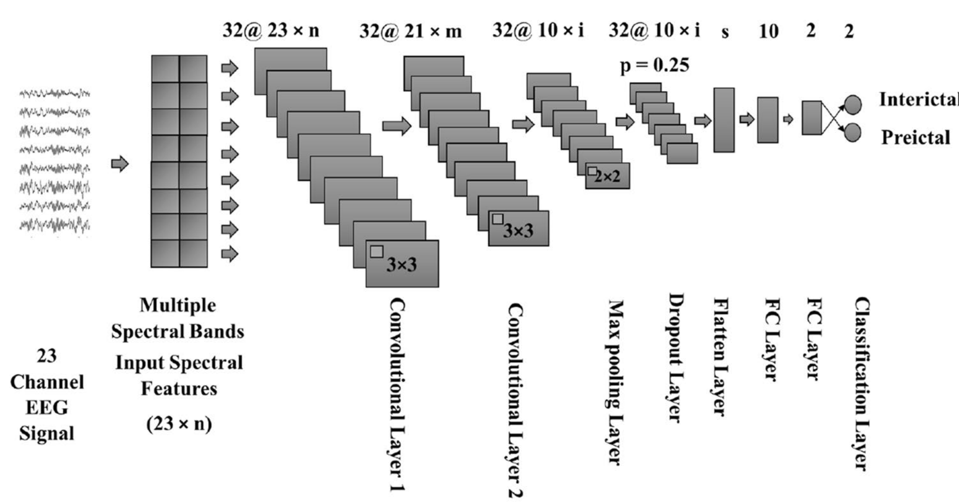

Fig. 4 The proposed CNN architecture for seizure prediction

preictal seizure states. The parameters n, m and i shown in Fig. 4 represent the number of data features for given layers. This CNN architecture performs training with the help of ‘rmsprop’ optimizer using a learning rate of 0.001, decay function with a value of 1×10^{-5} and loss function of binary cross-entropy using a batch size of 8 data samples for 100 epochs to achieve accurate seizure prediction.

Another deep learning algorithm, which has been employed for the task of seizure prediction is long short-term memory network (LSTM) [17]. The present work employs a single-layer LSTM network consisting of 50 LSTM units, which are determined by comprehensive experimentation for the accurate classification of interictal and preictal seizure states. The other layers in this network include a drop-out layer having a dropping probability of 0.25 and an output layer of ‘sigmoid’ activation. Its architecture designed for seizure prediction has been shown in Fig. 5. This model is fed with an input feature map of $23 \times n$, where n represents the number of features for different spectral band groups. The proposed LSTM model has been trained using ‘rmsprop’ optimizer and binary cross-entropy loss function with a batch size of 32 input samples for 100 epochs to obtain optimum classification accuracy for seizure prediction.

Results

This section illustrates the results of several simulation experiments to ensure the relevancy of the proposed patient-specific approach for the prediction of epileptic seizures. These experiments are performed on EEG recordings taken from 24 cases of CHB-MIT database using Python on a machine having hardware configuration of Intel i7 processor (8th Generation) operating at a clock speed of 2.20 GHz, NVIDIA GEFORCE GTX 1060 graphics processing unit (GPU) of 6 *GB* and having Windows 10 operating system.

In this work, the ‘B6’ spectral bands group provides an input spectral feature map of 23 × 12 having two features for each of six bands. On the other hand, the ‘B8’ spectral bands group offers an input spectral feature map of 23 × 16 consisting of two features for each of eight spectral bands. The task of classification has been performed using the proposed architectures of CNN and LSTM algorithms. When the two deep learning algorithms are employed for classification using input spectral feature map of ‘B6’ group, then these algorithms are abbreviated as CNN-B6 and LSTM-B6 respectively. Similarly, in case of the input spectral feature map of ‘B8’ group, these algorithms are denoted by CNN-B8 and LSTM-B8 respectively. In order to effectively analyse the performance of CNN and LSTM algorithms, the processed EEG datasets of all 24 cases have been fragmented into training datasets having 90% training data samples and test datasets consisting of 10% testing data samples for each patient. To ensure the appropriate training of these algorithms without any overfitting, they are validated using validation datasets, comprising 10% samples of training datasets.

The classification performance of given classifiers has been analysed for the task of epileptic seizure prediction using different performance measures. These performance measures include accuracy (ACC) [43], sensitivity (SENS) [43], specificity (SPEC) [43], false discovery rate (FDR) [44], false omission rate (FOR) [44] and classification time (Class. Time) of the given algorithms. In this work, the classification time to be considered is the time taken by classification algorithms to predict the output seizure state classes for given test input EEG samples.

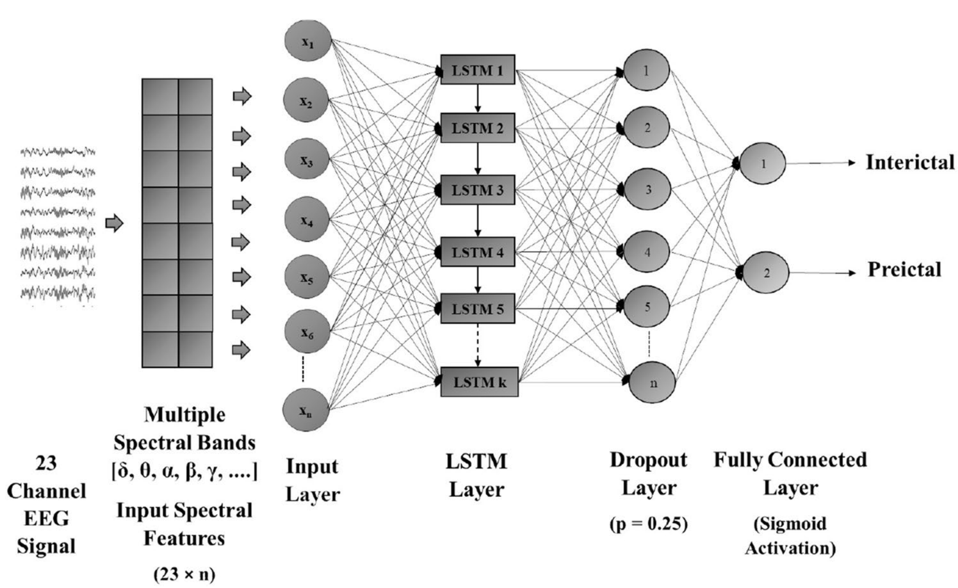

Fig. 5 The proposed LSTM architecture for seizure prediction

Table 1 Performance evaluation of CNN and LSTM for seizure prediction using 6 spectral bands group (B6)

Patient ID.	CNN-B6						LSTM-B6					
	ACC (%)	SENS (%)	SPEC (%)	FDR (%)	FOR (%)	Class. time (ms)	ACC (%)	SENS (%)	SPEC (%)	FDR (%)	FOR (%)	Class. time (ms)
1	100	100	100	0	0	41.6	100	100	100	0	0	73.8
2	100	100	100	0	0	38.6	100	100	100	0	0	77.8
3	100	100	100	0	0	39.9	100	100	100	0	0	86.2
4	97.67	95.83	100	0	5	38.1	100	100	100	0	0	86.2
5	100	100	100	0	0	38.5	95.24	91.67	100	0	10	83.8
6	88.17	83.78	91.07	13.89	10.53	42.9	91.4	94.59	89.29	14.63	3.85	86.3
7	94.44	93.33	95.24	6.67	4.76	44.9	86.11	91.67	83.33	26.67	4.75	83.1
8	100	100	100	0	0	44.9	98.33	96.55	100	0	3.13	76.7
9	100	100	100	0	0	44.9	93.75	95.24	92.59	9.09	3.85	83.7
10	94.94	91.49	88.89	11.11	0	41	97.47	94.59	100	0	4.55	84.8
11	95	100	91.67	11.11	11.11	37.2	95	100	88.89	8.33	0	79.8
12	100	100	100	0	0	41.6	100	100	100	0	0	86.7
13	97.92	95.24	100	0	3.57	40.6	100	100	100	0	0	73.8
14	95.95	95	97.06	2.6	5.71	41.6	89.19	96.97	82.93	17.95	2.86	94.7
15	100	100	100	0	0	40.7	100	100	100	0	0	90.6
16	97.67	95.833	100	0	5	40.1	90.7	85.71	95.45	5.26	12.5	83.5
17	100	100	100	0	0	39.8	100	100	100	0	0	84.6
18	97.96	95	100	0	3.33	39.2	87.75	79.16	96	5	17.24	89.1
19	100	100	100	0	0	39.3	100	100	100	0	0	76
20	100	100	100	0	0	39.6	100	100	100	0	0	90.7
21	100	100	100	0	0	43.9	92.86	86.96	100	0	13.64	83.3
22	100	100	100	0	0	37	87.09	92.31	83.33	20	6.25	75.8
23	100	100	100	0	0	40.8	100	100	100	0	0	80.6
24	99.12	98.08	100	0	1.61	44.9	97.35	98.15	96.61	3.39	1.72	97.5
Avg.	98.3	97.6	98.5	1.9	2.1	40.9	95.9	96	96.2	4.6	3.5	83.7
SD	2.9	3.9	3.3	4.2	3.4	2.4	4.9	5.6	6	7.7	5	6.2

The performance of CNN-B6 and LSTM-B6 has been presented in Table 1, which shows the prediction efficiency of both of these algorithms in case of six spectral band features group ‘B6’ in terms of the abovementioned performance measures for 24 subjects of epilepsy. Similarly, Table 2 illustrates the performance of CNN-B8 and LSTM-B8 algorithms for predicting seizure activities in given 24 subjects.

Figure 6 illustrates the performance comparison of CNN-B8, LSTM-B8, CNN-B6 and LSTM-B6 algorithms in terms of average values of different performance measures such as accuracy, sensitivity, specificity, FDR, FOR and classification time. These performance measures indicate the averages of their individual values in all 24 epileptic subjects of the given database for the proposed spectral bands specific deep learning algorithms.

Discussion

This section discusses the analysis of results obtained from different simulation experiments for the prediction of epileptic seizures using spectral features based deep learning approach. Table 1 provides the performance of LSTM-B6 and CNN-B6 algorithms for seizure prediction task in terms of accuracy, sensitivity, specificity, FDR, FOR and classification time for 24 epileptic subjects. For CNN-B6, the accuracy, sensitivity and specificity values vary in the range of 88.17% to 100%, 83.78% to 100% and 88.89% to 100% respectively for 24 different cases of EEG recordings. Similarly, the values of FDR and FOR are changed from a maximum value of 13.89% to a minimum value of 0% and a maximum value of 11.11% to a minimum value of 0% respectively. This algorithm takes an average classification time of 40.9 ms only with a standard deviation (S.D.) of ± 2.4 ms. On the other hand, the LSTM-B6 shows its performance for classification of seizure states in terms of variation in accuracy, specificity and specificity values in the range of 86.11% to 100%, 85.71% to 100% and 82.93% to 100% respectively. The FDR and FOR values of this algorithm change from 26.67% to 0% and 17.24% to 0% respectively. The average classification time taken by LSTM-B6 algorithm is 83.7 ms with a standard deviation of ± 6.2 ms.

After carrying out the simulation experiments of CNN and LSTM algorithms using eight spectral band features group ‘B8’ for 24 subjects, the classification performance of these algorithms has been described in Table 2. The operation of CNN-B8 algorithm for the desired task has been elaborated in terms of accuracy, sensitivity and specificity values, which varies from 86.11% to 100%, 84.21% to 100%, and 83.33% to 100% respectively. Similarly, the performance of this algorithm has been analysed in terms of FDR and FOR values, which ranges from 26.66 to 0% and 20% to 0% respectively. The classification time taken by CNN-B8 gives its average value of 41.6 ms with a variation of ± 2.7 ms. Moreover, the task of seizure prediction with eight spectral feature bands group ‘B8’ has also been implemented using the proposed architecture of LSTM-B8. The simulation results obtained from this algorithm reveal its classification performance in terms of accuracy, sensitivity and specificity values as mentioned in Table 2, which varies in the range of 87.76% to 100%, 79.49% to 100% and 84.21% to 100% respectively for 24 epileptic subjects. The FDR and FOR values for the same are changed from 18.18 to 0% and 19.05% to 0% respectively. This algorithm takes a classification time of 87.8 ms with a change of ± 9.6 ms to predict the given number of test samples in the given 24 cases of recorded EEG signals.

Furthermore, Fig. 6 illustrates that CNN-B6 algorithm performs better among other algorithms in terms of maximum accuracy of 98.3%, maximum specificity of 98.5% and a minimum FDR of 1.9% only. Similarly, CNN-B8 algorithm also performs well for the classification of seizure states with a maximum sensitivity of 98.3% and minimum FOR of 1.8%. The performance of LSTM-B6 and LSTM-B8 algorithms is inferior to that of CNN-B6 and CNN-B8 algorithms for different performance measures. Thus, it ensures the suitability of spectral bands specific CNN algorithms for seizure prediction over LSTM algorithms. Similarly, this figure also reveals that the classification time taken by CNN-B6 and CNN-B8 is approximately less than half of that taken by LSTM-B6 and LSTM-B8, thereby proving them fast methods for seizure prediction.

Since both CNN-B6 and CNN-B8 variants of the proposed CNN model show nearly equal performance for the seizure prediction task. So, both of these techniques are proved to be efficient for the prediction of epileptic seizures in this patient-specific approach. This analysis has been further extended to the comparison of the proposed approach with other popular seizure prediction approaches, which are published during recent years and utilize the same CHB-MIT database of EEG signals. This comparative evaluation is presented in Table 3. This table evidently discloses the superiority of the proposed spectral bands specific CNN approach in terms of various performance measures. Hence, the analysis of CNN and LSTM algorithms for two different spectral band groups and comparison with recently published seizure prediction techniques reveal the worth of the proposed CNN-based patient-specific approach for accurate and real-time prediction of epileptic seizures.

Conclusion

With the emergence of the Internet of Things (IoT) technologies, the healthcare sector is going through revolutionary changes, which impacts the lives of millions of

Table 2 Performance evaluation of CNN and LSTM for seizure prediction using 8 spectral bands group (B8)

Patient ID.	CNN-B8						LSTM-B8					
	ACC (%)	SENS (%)	SPEC (%)	FDR (%)	FOR (%)	Class. time (ms)	ACC (%)	SENS (%)	SPEC (%)	FDR (%)	FOR (%)	Class. time (ms)
1	100	100	100	0	0	40.9	100	100	100	0	0	86.8
2	100	100	100	0	0	40.5	95.83	100	91.67	7.7	0	80.5
3	100	100	100	0	0	40.8	97.96	96.55	100	0	4.76	73.8
4	97.67	100	96.77	7.69	0	42.5	95.35	95	95.65	5	4.35	89.7
5	100	100	100	0	0	40.9	97.62	100	96.15	5.88	5.88	88.8
6	93.55	95.24	92.16	9.1	4.08	44.4	91.4	85.37	96.15	5.4	10.71	92.6
7	86.11	91.67	83.33	26.66	4.76	41.9	94.44	94.44	94.44	5.56	5.56	89
8	100	100	100	0	0	41.9	100	100	100	0	0	72.9
9	100	100	100	0	0	37.8	93.75	93.33	94.44	3.45	10.53	81.3
10	98.73	100	97.67	2.7	0	44.5	97.47	97.44	97.5	2.5	2.5	91.8
11	95	90.9	100	0	10	40	95	100	91.67	11.11	0	73.9
12	100	100	100	0	0	40.4	100	100	100	0	0	91.4
13	97.92	96.15	100	0	4.35	41.9	100	100	100	0	0	86.8
14	97.3	100	93.33	4.35	0	49.9	87.84	79.49	97.14	3.13	19.05	112
15	100	100	100	0	0	43.9	100	100	100	0	0	94.7
16	95.35	100	90.9	8.69	0	37.9	95.35	100	92.31	10.53	0	92.9
17	97.22	100	93.75	4.76	0	43	100	100	100	0	0	103
18	97.96	100	95.83	3.85	0	40.7	87.76	90	86.21	18.18	7.41	87.8
19	100	100	100	0	0	38.9	100	100	100	0	0	80.8
20	100	100	100	0	0	42.5	100	100	100	0	0	86
21	92.86	100	86.36	13.04	0	39.3	92.86	100	84.21	11.54	11.54	86.2
22	90.32	84.21	100	0	20	38.9	93.55	93.33	93.75	6.67	6.25	79.8
23	98.31	100	96.43	3.13	0	39.9	96.61	93.75	100	0	6.9	79.8
24	99.12	100	98.33	1.85	0	44.6	99.12	98.21	100	0	1.72	105
Avg.	97.4	98.3	96.9	3.6	1.8	41.6	96.3	96.5	96.3	4	4	87.8
S.D.	3.6	4	4.7	6.1	4.6	2.7	3.8	5.3	4.5	4.9	5	9.6

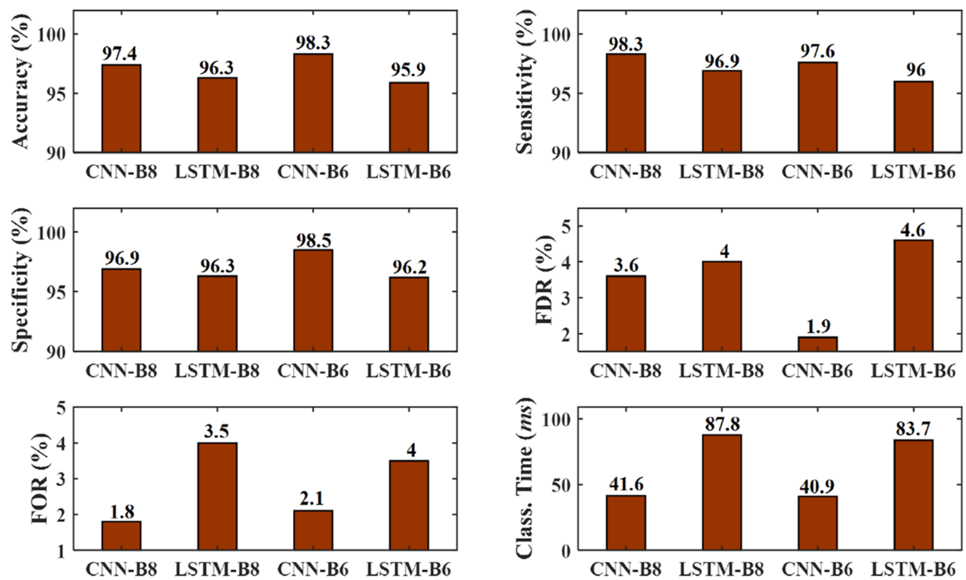

Fig. 6 Comparative analysis of CNN and LSTM models using different spectral bands groups for seizure prediction

patients with the prognosis of numerous health-related disorders. Epilepsy is one of these disorders, which can be controlled by the prediction of epileptic seizures well before their actual occurrence. The early seizure prediction enables the patients, their family members and the doctors or neurologists in nearby hospitals to take protective measures and gives them an opportunity to enjoy a healthier and improved quality of life by avoiding severe injuries or unpredicted deaths.

The proposed work presents a smart health monitoring framework for automated prediction of epileptic seizures, which explores the potential of deep learning techniques to predict the preictal state of the sensed EEG signals. The multichannel EEG signals are processed using filtering, segmentation and spectral separation into different bands, namely delta, theta, alpha, beta and sub-bands of gamma. Then, spectral features such as mean spectral amplitude and spectral power are extracted from each band, which are further fed to the proposed architectures of CNN and LSTM classifiers.

The analysis of simulation results show that the spectral bands specific CNN approach is more appropriate over the identical LSTM approach for seizure prediction due to its higher prediction accuracy and less classification time. Thus, it is evident that the proposed CNN architecture fed with several spectral band features is an efficient method for accurate and fast prediction of seizures in different real-time scenarios, enabling epileptic patients to have a better quality of life.

Table 3 Performance comparison of the proposed approach with other recently published techniques

Authors, year	Signal processing and feature extraction techniques	Classification technique	Results
Usman et al., 2017 [45]	Time and frequency domain features extracted using Empirical mode decomposition	SVM	Sensitivity = 92.23%
Truong et al., 2017 [46]	STFT	CNN	Sensitivity = 81.2%
Koutsouris et al., 2017 [47]	Various features related to Graph theory, time and frequency domain	CNN	Sensitivity = 87.75%, Specificity = 87.75%
Abdelhameed et al., 2018 [48]	2D-convolutional autoencoder to learn spatial features	Bi-LSTM	Sensitivity = 94.6%
Cui et al., 2018 [49]	Bag-of-waves features	ELM	Sensitivity = 88.24%
Kitano et al., 2018 [50]	Wavelet transform	SOM	Accuracy = 91%, Sensitivity = 98%, Specificity = 88%
Shahbazi and Aghajan, 2018 [51]	STFT	CNN+LSTM	Sensitivity = 98.21%
Hu et al., 2019 [52]	CNN based Mean amplitude spectrum feature extraction from 19 frequency bands of 13 channel EEG signals	CNN+SVM	Sensitivity = 86.25%
Ouyang et al., 2019 [53]	Temporal features related to statistical analysis and positive zero-crossing interval length series	SVM	Accuracy = 86.50%, Sensitivity = 92.75%, Specificity = 69.77%
Duan et al., 2020 [54]	CNN based feature extraction from correlation coefficients among electrodes for 8 distinct sub-bands of multi-time scale EEG segments	Bi-GRU(RNN)	Accuracy = 94.8%, Sensitivity = 91.7%, Specificity = 97.7%
Zhang et al., 2020 [55]	Use of Nonlinear partial directed coherence (NPDC) based functional brain network (FBN) for feature extraction	ELM	Accuracy = 89.2%
Zhang et al., 2021 [56]	Measuring synchronization in multichannel EEG using pearson correlation coefficient	CNN	Accuracy = 89.98%
Usman et al., 2021 [57]	CNN-based feature extraction from decomposed EEG signals using empirical mode decomposition	LSTM	Sensitivity = 93%, Specificity = 92.5%
Prathaban and Balasubramanian, 2021 [58]	3D EEG image generation using nonlinear conjugate gradient method and sparsity based EEG reconstruction	CNN	Accuracy = 98%
Proposed approach	Spectral power and mean spectral amplitude features extracted from different spectral bands of segmented EEG signals	CNN with spectral band features of six bands (CNN-B6)	Accuracy = 98.3%, Sensitivity = 97.6%, Specificity = 98.5%
		CNN with spectral band features of 8 bands (CNN-B8)	Accuracy = 97.4%, Sensitivity = 98.3%, Specificity = 96.9%

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Declarations

Conflict of interest The authors of this manuscript declare that they have no conflict of interest with any person or organization for carrying out this research work.

Informed consent This manuscript uses a publicly available 'CHB-MIT' EEG dataset, which was developed at the Children's Hospital Boston in collaboration with the Massachusetts Institute of Technology (MIT). The authors of this manuscript have cited the article corresponding to this dataset as per the recommendations of its developers. The appropriate informed consent has already taken by the developers of this dataset from the concerned organization before making it online.

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