Mobile Networks and Applications
https://doi.org/10.1007/s11036-018-1113-0

Cognitive IoT-Cloud Integration for Smart Healthcare: Case Study for Epileptic Seizure Detection and Monitoring

Musaed Alhussein [1] · Ghulam Muhammad [1] · M. Shamim Hossain [2] · Syed Umar Amin [1]

Abstract

We propose a cognitive Internet of Things (IoT)–cloud-based smart healthcare framework, which communicates with smart devices, sensors, and other stakeholders in the healthcare environment; makes an intelligent decision based on a patient's state; and provides timely, low-cost, and accessible healthcare services. As a case study, an EEG seizure detection method using deep learning is also proposed to access the feasibility of the cognitive IoT–cloud smart healthcare framework. In the proposed method, we use smart EEG sensors (apart from general healthcare smart sensors) to record and transmit EEG signals from epileptic patients. Thereafter, the cognitive framework makes a real-time decision on future activities and whether to send the data to the deep learning module. The proposed system uses the patient's movements, gestures, and facial expressions to determine the patient's state. Signal processing and seizure detection take place in the cloud, while signals are classified as seizure or non-seizure with a probability score. The results are transmitted to medical practitioners or other stakeholders who can monitor the patients and, in critical cases, make the appropriate decisions to help the patient. Experimental results show that the proposed model achieves an accuracy and sensitivity of 99.2 and 93.5%, respectively.

Keywords IoT-cloud · Smart healthcare · Seizure detection · EEG · Deep learning

1 Introduction

The Internet of Things (IoT), which can be considered an interconnected network of intelligent sensor devices, often has limited storage and low processing power capability. IoT, together with cloud computing, which has a large storage and sufficient processing power capability, has made essential services, such as smart healthcare [1, 2], possible in a smart city environment. However, monitoring and communicating remotely with patients are necessary in such environments. In addition, the need to provide low-cost, high-quality, and patient-centric smart healthcare to patients has emerged.

The advancements in the field of IoT [3] and cloud technologies [4] has resulted in a tremendous demand for real-time, intelligent, and remote healthcare services under the paradigm of smart cities. Furthermore, the integration of IoT and cloud technologies has provided a seamless and ubiquitous framework for smart healthcare monitoring. At present, residents in smart cities have access to smart sensor devices and advanced mobile technologies. In an environment such as that of a smart city, finding specialized doctors, healthcare centers, and hospitals nearby is difficult. The movement of patients in critical conditions is also quite difficult. Hence, we need to create a smart healthcare monitoring framework by integrating the resources available at our disposal to improve the quality and accessibility of healthcare services. In such a smart healthcare monitoring framework, we can transmit and process medical-related multimedia signals from smart sensors and mobile devices to provide timely assistance and quality healthcare services to patients. However, such healthcare data and signals are often naturally large and challenging to handle because of their complexity.

The healthcare industry has emerged as one of the major industries with tremendous demands. Apart from providing patients with critical and crucial services, this industry is also generating large revenues for the government and the private sector. The smart healthcare industry has recently witnessed a competition among various healthcare providers in providing mature and sophisticated services and devices with high

✉ M. Shamim Hossain
mshossain@ksu.edu.sa

[1] Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia

[2] Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia

Published online: 18 September 2018

accuracy and dependability and low cost [5]. Therefore, the IoT–cloud integration within healthcare has recently been the focus of considerable research initiative. Several types of IoT devices built for healthcare include smart wearable devices, such as blood pressure devices, portable insulin syringe, stress monitoring devices, weight tracking and general fitness devices, hearing aids, and EEG and ECG monitors.

Although healthcare data, such as EEG, are complex in nature, we have had numerous technological advances in the fields of big data analytics and cloud computing to manage the complexity of such data and provide the processing power and storage capability needed by such information. However, many interconnected IoT devices and sensors and extensive multimedia, healthcare, and communication data make it difficult to build a smart healthcare framework that can cater to the needs of all stakeholders in a smart city environment.

However, the concept of smart IoT–cloud integration is impossible without human brain-like intelligence. With big data and its real-time processing coming into the picture, the research community faces multiple challenges to develop a smart and intelligent IoT–cloud framework, which would be able to make its own decisions. Consequently, the cognitive computing framework was introduced and proposed to turn IoT into a brain-powered cognitive IoT (CIoT) [6], which would possess a high level of intelligence. When we consider complex and big data, such as healthcare data, for a smart city paradigm, the CIoT becomes considerably important. Ecidently, having a cognitive IoT–cloud smart healthcare framework would require that the IoT devices inside a patient's body (i.e., attached or around him/her) cooperate to sense his/her body signals, movements, voice, disease biomarkers, or monitored signals, such as EEG and ECG; and deduce the state of the patient. The cognitive healthcare framework is sufficiently intelligent to make the corresponding decisions to make the patient comfortable and decide the future course of activities by involving different stakeholders of the smart city. Similar to the assumption that making life in a smart city comfortable without intelligence is unachievable, an IoT framework without cognitive capability is only a waste of resources. Therefore, considerable research effort has been exerted [5] to develop such a healthcare framework, which caters to the needs of the patients, medical practitioners, hospitals, and all other service providers.

A previous study [1] highlighted the challenges of providing smart healthcare services using smart sensors and cloud connectivity in a smart city environment. Temperature, traffic, humidity, and other related parameters should be controlled through smart sensors to provide effective smart healthcare services [6]. In [7], the researcher presented a patient status monitoring framework, in which medical data are accessed through voice and facial expression, to address such complex medical-related data. In [8, 9], the authors proposed an emotion recognition system that can be utilized in a cloud framework. Previous studies [10, 11] showed that when cloud technologies, IoT, and smart sensors are integrated, real-time smart healthcare services can be provided in a smart city. Another study focused on integrating edge computing with cognitive technology for smart healthcare [12]. Therefore, such a smart healthcare monitoring framework should be able to effectively process multimedia signals and sensor data and in real time to provide quality healthcare services.

Epilepsy has been called a neurological disorder that can occassionally cause jerking in several parts of the human body, loss of consciousness, and in severe cases, convulsions in the entire body. This disorder can affect a patient's quality of life, cause social and economic problems in people of all ages, and lead to premature death in extreme cases [13]. Approximately 50 million people are affected by epileptic seizure globally [13]. However, only approximately 70% of patients can be treated with medication, while approximately 8% of patients who do not respond to medication require surgical intervention. If epilepsy is detected at an early stage, epileptic seizures can be suppressed using antiepileptic drugs or by electrical stimulation [14].

However, the main problem is that epileptic patients need immediate and quality care. Any delay in treatment or reaching specialized medical centers or hospitals can be catastrophic for patients who are affected by seizures. Therefore, a smart healthcare monitoring system is essential for epileptic patients and could generally solve this problem. Medical practitioners can monitor and advise patients regularly. In serious cases, other smart city services, such as smart ambulances and mobile clinics, can be used to provide urgent medical assistance to patients.

This study proposes an automatic and advanced method for EEG-based seizure detection and monitoring to be used as a component of the proposed cognitive healthcare IoT (CHIoT) framework. In the proposed seizure detection method, we use scalp EEG, which is recorded by smart EEG sensors, as the input signal. Our system also uses other healthcare smart sensors to record the psychological and physiological signals and transmit them to the cloud via the Internet. Apart from EEG, these signals include patients' movements, gestures, and facial expressions to determine their state. Thereafter, the cognitive system makes a real-time decision on the activities and the medical attention and services to be provided to patients based on their state and whether to send the data to the deep learning module. If the cognitive system believes that a patient is having a seizure, then this system makes the decision to inform other stakeholders and sends the EEG data to the deep learning module. Signal processing and seizure detection occur in the cloud and signals are classified as seizure or non-seizure with a probability score. The results are transmitted to medical practitioners or other stakeholders who can monitor the patients and, in critical cases, make the appropriate decisions to assist the patient. EEG signals have a low signal-to-noise ratio and are sensitive to external and internal noises. Eye blinking and muscle movement artifacts can cause numerous problems in extracting good features. Therefore, we use a novel deep learning model composed of a deep convolutional neural network (CNN) and stacked autoencoder. The deep CNN is used to extract features, while the stacked autoencoder is used to improve the subject-specific features and accuracy. The major contributions of the proposed CHIoT framework are as follows. (1) The cognitive IoT–cloud technology is integrated with the smart healthcare monitoring framework. (2) To the best of our knowledge, this study is the first to use the smart CHIoT framework for epileptic seizure detection and monitoring. (3) A novel integration of deep CNN and stacked autoencoders, which is better than the state-of-the-art model for seizure detection, is proposed in this research.

The remainder of this paper is organized as follows. Section 2 discusses several related studies on CHIoT, smart healthcare, and EEG seizure detection. Section 3 describes the proposed smart healthcare monitoring framework. Section 4 presents the experiments, results, and discussion. Lastly, Section 5 concludes this research.

2 Related work

In this section, we discuss a few of the state-of-the-art methods for smart healthcare and the recent methods for seizure detection.

2.1 Cognitive healthcare-IoT

CHIoT is an advancing field that is creating a plethora of applications to improve healthcare and revolutionizing the entire concept of connected healthcare devices. Moreover, CHIoT has a tremendous scope in providing smart services, such as remote monitoring of patients; tracking, detection, and generation of alerts; medical equipment operation and control; and smart pill disbursal. CHIoT enables us to deal with medical emergencies in an improved manner and provide rapid response anywhere. CHIoT connects with smart sensors, which are inside, on the surface, or around a patient's body; and monitors and interprets multimodal health data, including the patient's physiological and psychological signals, through these smart sensors. Research initiatives have integrated CHIoT with 5G technology to make it considerably phenomenal in the smart healthcare perspective [15]. Several of the consumer-based cognitive systems have integrated smart platforms, such as Microsoft Kinect, to fuse smart cognitive behavior in healthcare IoT frameworks. The Kinect platform is based on gesture and activity recognition to understand human behavior cognition. In one of such research initiatives, the authors [15] proposed a speech emotion recognition-based 5G cognitive system for providing health services. However, given that the domain is new and still developing, improvements in framework design and enhancement of the end services, intelligent behavior, and smart processing of multimodal health data are needed to fuel further exploration and interest in this field.

All objects in CHIoT, such as sensors and devices, are interconnected and cooperate to understand the physical and social environments, store and process the learned information and the extracted knowledge, and learn to adapt themselves. The framework has intelligent decision-making capability that requires minimum human intervention.

Many cognitive IoT frameworks for various applications [3, 12, 15–17] are presented in the literature. In [18], the authors propose a cognitive framework to assist in smart city development and make it considerably sustainable. In [19], a three-layer cognitive ring is proposed to achieve a good performance and high intelligence and merges human cognition with the system design. In [20], a cognitive system, which could model human knowledge and process relative information, was proposed. In [18], the authors developed a cognitive system that has the open question answering capability and makes use of text data and natural language processing. In [21], big data are analyzed to build a cognitive system. Many researchers have also applied cognitive computing to different applications in the healthcare domain. A few researchers have used it for physiological [5, 22, 23] and psychological applications [15]. In [10], an emotion-aware cognitive system is proposed based on cloud computing. In [19], an emotion-aware cognitive system is also proposed, although it uses human facial expression recognition. In [22], another emotion-aware cognitive system is proposed but uses voice and facial expression recognition.

2.2 Smart healthcare

Smart healthcare is attracting considerable interest from government organizations, private companies, and researchers from different fields because of its social and economic benefits. Accordingly, numerous studies [18], models [24], and services [19, 25] related to smart healthcare have emerged because of the integration of IoT–cloud technologies. In such a type of smart healthcare model, medical practitioners, including healthcare staff members, can analyze healthcare data in real time. In another study [5], the author discussed a smart healthcare framework, in which smart city residents can use smart devices to find a route to healthcare centers. In another study [19], the author discussed an interconnected smart healthcare framework involving processing of electronic health records. In [21], the researchers proposed a smart glucose monitoring system for diabetic patients, which involved daily activities and locations. In [25], the author proposed a robot-controlled automatic ambulance to treat patients with cardiac arrhythmia requiring immediate care. Other studies have explored medical forgery in smart healthcare [26]. The effective use of communication technology, data analytics, smart sensors, and cloud resources is crucial for the smart healthcare environment [27].

Our proposed framework for smart healthcare monitoring caters to the various needs and challenges discussed in the literature and provides a solution for deploying an automatic EEG-based seizure detection system. In particular, we use smart sensing, IoT-aware, and cloud technologies. In the subsequent section, our seizure detection and classification methods are discussed.

2.3 EEG seizure detection

This section reviews state-of-the-art seizure detection methods.

The scalp EEG technique is commonly used for epileptic seizure detection, prediction, classification, diagnosis, and onset detection. The EEG recordings are often analyzed by trained neurologists who scan hours of EEG recordings for characteristic patterns of seizures. This activity can be time-consuming, tedious, and expensive even when done for a single patient. Numerous researchers have developed automated techniques for seizure detection and prediction to address these issues [28–31]. Automated techniques also face many problems because of the inherent nature of the EEG signal. The EEG seizure patterns are different from patient to patient. An epileptic seizure pattern in one patient may appear to be a normal EEG in another patient. Hence, building a generic automated method that functions correctly for every epileptic patient is relatively a difficult task [29] because of the overlap between seizure and non-seizure patterns.

In several methods [30], EEG signals are transformed into images. In [31], the authors transformed EEG signals into images by projecting the patient electrodes into 2D. These studies employed hand-crafted features for automated seizure detection and classification. These techniques are specific because epileptic seizures are nonstationary and the EEG pattern varies significantly in epileptic patients [32].

Deep learning techniques have recently achieved promising results [33] in computer vision and speech recognition, thereby proving that automatically extracted features work better than manual extracted features. Deep learning methods have also been applied to detect epileptic seizures. Deep neural networks trained with dropout are used in [34] for patient-specific epileptic seizure detection. Deep belief networks are used in [35] to detect seizures in multichannel and high-resolution EEG data. Deep CNN and stacked autoencoders are used in [36] for the analysis and classification of the EEG data.

The majority of the deep learning methods discussed previously exhibit a good performance but are incomparable to the deep learning models in other fields, such as computer vision. Therefore, considerable enhancement is needed in deep learning methods applied to EEG analysis and seizure detection.

Deep CNN is a variant of deep networks that learn local and spatial features in data using convolutions. Deep CNN often has multiple successive convolutional layers [30]. In the initial layers, these networks extract features that are spatial and of low level using the raw input. Thereafter, the networks in the deeper layers progressively extract considerably global, high-level features. CNN has been successfully used for such inputs as images, which are 2D. By contrast, the EEG signal has different properties and comprises dynamic time series data from electrode recordings on the three-dimensional scalp surface. The EEG signal has the disadvantage of having a low signal-to-noise ratio. That is, this signal is affected by noise from artifacts that lack task-related information. Therefore, the existing CNN architectures should be modified and adapted to the EEG data. We use a novel deep learning model composed of a deep CNN and stacked autoencoder.

First, we use the deep CNN model to extract features from the raw input data. Thereafter, we use these features as input to the stacked autoencoder. During the supervised training phase of the deep CNN model, the network parameters are pretrained for the EEG seizure data set. These features are eventually used by the stacked autoencoder to learn general subject-specific features. In this manner, we are able to achieve good specificity and accuracy for the cross-patient dataset.

3 Proposed cognitive IoT-cloud framework and seizure detection technique

This section presents the proposed IoT–cloud-based smart healthcare monitoring framework and discusses the EEG-based seizure detection and classification method.

3.1 Cognitive IoT-cloud smart healthcare scenario

The use of smart healthcare systems in an interconnected smart city environment enables residents and medical practitioners to use smart sensor devices and cloud and cognitive IoT aware technologies to access their electronic health records. Through smart wearable technology and communication, patients can regularly update their health-related data. The cognitive system can analyze these data in real time and perform the best action to provide services to patients. These uploaded data can also be remotely viewed and analyzed by medical staff members who can also provide assistance and advice to the concerned patients. This type of patient-dependent healthcare monitoring is essential for smart healthcare to achieve its major objectives, such as low healthcare cost, high efficiency, easy accessibility, error-free diagnosis, reduced hospital and medical staff member visits, and enhanced quality of life. Accordingly, we present a scenario for our proposed smart healthcare monitoring framework for a smart city environment.

Residents should use smart city infrastructures and register with a smart healthcare service provider to enable the cognitive system and the medical practitioner and staff members to communicate with the service provider and obtain access to a patient's health record in a remote manner. The person's location information is also available in the system and can be used in case of an emergency. The smart healthcare service provider has a communication link with all specialized medical practitioners, including those involved in epilepsy. Many healthcare smart sensors can be used to record the real-time psychological and physiological data from patients. These signals include a patient's movements, gestures, and facial expressions. The cognitive system continuously calculates the patient's state in real time. The epileptic patient also has to wear a smart EEG sensor, which comes in the form of a comfortable and lightweight skull cap. Through sensor electrodes, the EEG sensor continuously records the concerned patient's EEG. When the cognitive system detects that the patient is having seizures, the recorded data are sent to the cloud for further processing in real time. From the cloud, the data are sent to the healthcare professionals for further analysis. The medical staff members can further investigate and advise the patient accordingly. The signals are processed continuously based on the severity of the seizure detection and classification result. The cognitive system sends a warning to the medical staff members and related stakeholders through the smart healthcare provider. In case of emergencies, a smart ambulance can rush through traffic to provide urgent care to a patient. In such cases, ambulances are assisted by a smart traffic light system, which ensures that these vehicles move easily through traffic. Therefore, the smart city healthcare framework can provide remote, real-time, and critical healthcare services to residents and patients while they remain in their respective locations.

3.2 System architecture

In our proposed smart healthcare monitoring framework (see Fig. 1), different types of health-related multimedia and EEG signals are obtained using smart IoT sensors. We have a local area network (LAN) layer, which comprises short-range smart communication devices. This LAN layer acts as an interface to transmit the obtained signals, such as EEG, from IoT devices' layer to a hosting layer consisting of heterogeneous smart devices, such as a smartphone or laptop. Thereafter, these smart devices transmit the received data through the wide area network (WAN) layer to the cloud. The WAN interface uses smart communication technologies, such as 4G, 5G, or WiFi, to transmit data to the cloud. Once all health-related data and signals, including EEG, reach the cloud, user authenticity is verified by the system and the data are processed by the seizure detection system. Figure 1 shows that the IoT sensors may include different types of healthcare-related sensor devices, such as wristbands, smartwatch, wearable sensors, and headgears; and can measure diverse health-related data, such as heart rate, blood pressure, respiratory rate, body temperature, body movement, ECG, and EEG. These smart sensors' devices can be worn by patients or may be embedded in smart city environments, such as smart homes, medical centers, offices, or automobiles. These smart sensor devices can also communicate with each other using short-range communication. The LAN interface layer is built upon smart communication protocols for short- to medium-range communication and interconnection between devices. These protocols include Zigbee, Bluetooth, Z-wave, and LoWPAN.

The hosting layer comprises heterogeneous smart devices, such as smartphone, tablets, personal digital assistant, laptops, or workstations, which collect data to be processed locally. These devices have processing capabilities to detect general health abnormalities through dedicated applications or programs. Health problems can include abnormal blood pressure, heart rate, or body temperature. These data are eventually sent to the cloud for further processing through the WAN interface. The WAN interface is used for long-range communications using WiFi, 4G, or 5G technologies. Once the data reaches the healthcare service providers, they can analyze the patients' health records to make any necessary immediate decision. Thereafter, the data (e.g., EEG signals) are further processed using the proposed seizure detection and classification system. After final processing, the result is returned to the medical practitioners for a detailed analysis. In non-emergency cases, the visiting medical centers require time and involve high cost. Hence, we can save money, time, and hospital space by using such a smart healthcare framework.

The cloud comprises the cloud manager, data center, feature extraction server, detection server, and classification server. The cloud manager first authenticates whether a resident is registered with a smart healthcare provider. The cloud manager is also responsible for verifying the identity of all stakeholders in the smart healthcare system, such as doctors, medical staff members, hospital representatives, and patients. The cloud manager also controls the data flow to and from the various servers and manages communication, storage, and other resources. The cloud manager sends the data to the cognitive engine, which uses multimodal data including EEG, psychological and physiological data and determines whether the patient needs emergency care. The sensor signals also include patient's movements, gestures, facial expressions to know about the patient's state. The cognitive system then makes a real-time decision based on patient's state, about the activities and the medical attention, services to be provided to

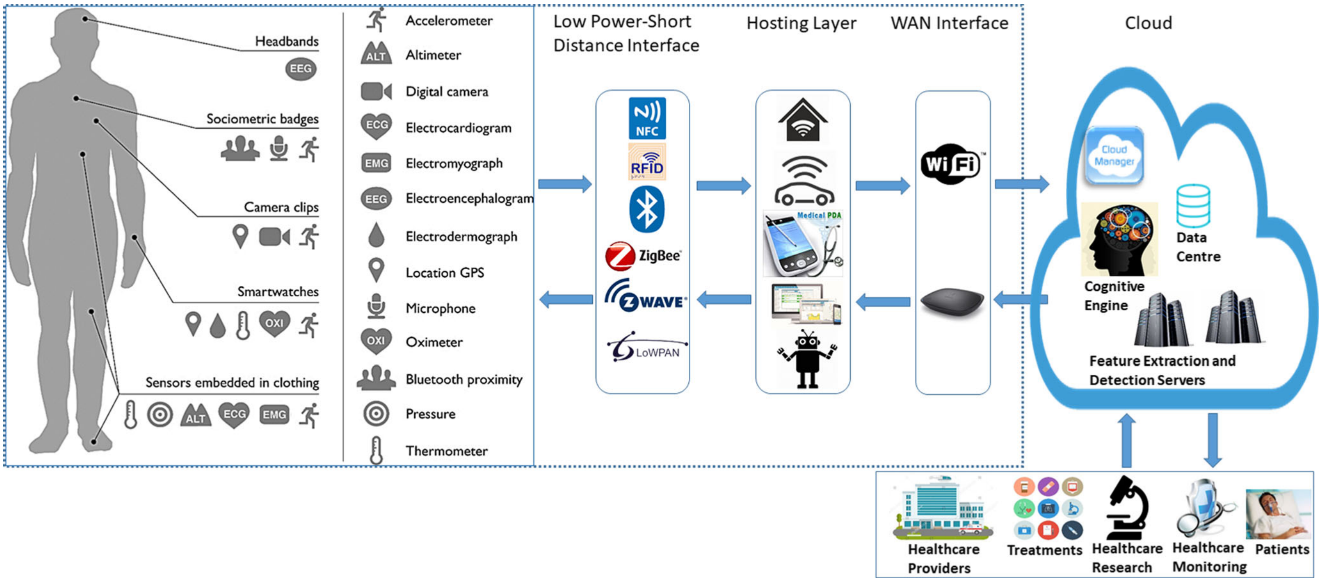

Fig. 1 Cognitive IoT-cloud smart healthcare framework

the patient and whether to send data to the deep learning module. If cognitive system believes that the patient is having a seizure, then it makes the decision to inform other stakeholders and the EEG data is sent to a deep learning module. Deep learning techniques are used to extract features in the feature extraction server. After the signals are preprocessed, signal processing techniques are used to extract features from the feature extraction server. The detection server detects and classifies seizure data and sends the detection results to the cloud manager. The data, features, results, and other model parameters are eventually stored in the data center. Healthcare professionals make the final decision on the type of service to be provided to epileptic patients using the different types of signal from various smart sensors and the EEG classification results. These healthcare service details are shared with all smart city stakeholders using smart communication that can access and analyze the patient health reports for further care of the residents.

3.3 Seizure detection and classification

3.3.1 Dataset

We used the CHB-MIT dataset for our study, collected at the Children's Hospital Boston, which is the largest freely available dataset for EEG epileptic seizure data [37]. It has 686 multiple channel scalp EEG recordings from paediatric patients who were affected by intractable seizures. The data is recorded from 23 epilepsy patients, which includes 5 males and 18 females in the age group of 10 to 22 years. The 10–20 international EEG electrode montage system is used to record the dataset. There are 969 h of scalp EEG recordings containing 173 epileptic seizures. The sampling rate used is 256 Hz and a resolution of 16-bit is used. Out of the total 686 EEG recordings, only 198 contain one or more seizures. In most of the EEG recordings, the seizure activity lasts about 25 s.

3.3.2 Input representation

There are many techniques used for the EEG input representation in the deep learning models. Since deep learning models like convolution neural networks need 2D inputs, therefore, a lot of researchers have converted EEG recordings into images and topo-maps [30, 31]. Some deep learning models used electrode voltage to transform the EEG recordings into topographical images organized in a time series [31]. However, there is evidence that EEG signal is correlated over time series data, [38], therefore in this study we used raw EEG data as input, represented as a two-dimensional array in which the in width we have the time steps (samples) and in the height there are all the electrodes. The input is represented as a two-dimensional array in which the width has all time steps and the height has all electrodes.

3.3.3 Deep CNN

Deep CNN learns local and spatial features in such signals by using convolutions and nonlinearity and have the ability to represent higher-level features as a combination of lower level features. The pooling layers help the network to represent intermediate feature maps in a concise way by retaining the most important information using downsampling. Hence deep CNN models are best for end-to-end learning, which use raw data to extract features automatically. CNN takes raw data as input and learns spatial features in the initial layers, and

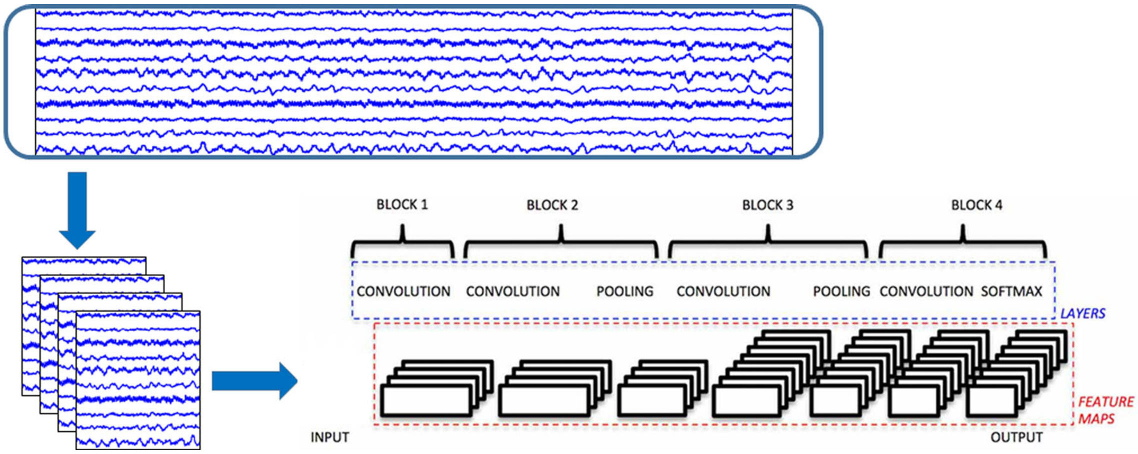

Fig. 2 Using sliding window to crop the signal and Deep CNN Architecture

progressively in the deeper layers, and it is able to learn temporal features.

Our deep CNN model is based on the architecture [33], which has convolution and max-pooling blocks followed by fully connected layers. We changed the first convolution layer to manage the multi-channel EEG input, as suggested in [39]. We tried with a different number of convolution and max-pooling layers, with different types of training, normalization strategies, and activation functions. Since our input is 2D, having time and electrodes dimension so we make CNN first convolve overtime followed by convolution over electrodes. Convolution layers are followed by the max-pooling layer. Then we have another normal convolution-max-pooling block. The next convolution layer is followed by fully connected softmax classifier as shown in Fig. 2. In CNN we have a convolutional layer which is composed of filters or kernels. Each of these kernels is slid over the input signal and in this way, the kernel is convolved with the input signal. We also have a parameter called stride, which decides the amount of convolution of the kernel with the input signal. The output for three-dimensional convolution, which is a set of kernel or feature maps, can be shown with eq. (1) below.

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

$x = (x_1, \ldots x_k)$ is the input for the network layer where (i, j) are the dimension of the weight filter, (i', j') are the location of the input on the 2D map where the weight filter is convolved, $w = (w_1, \ldots w_n)$ is the learned weight, k is the number of channels and k' is the number of filters. The max-pooling operation can be shown with following eq. (2):

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

Where p is called the padding operator,(i, j) are pooling location in the 2D map, (i', j') are the pooling window dimension. For activations function we used the Exponential linear units as shown below in eq. (3):

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

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

The eq. (4) above shows softmax operation or the normalized exponential function, which is used to represent a probability distribution of D dimensional vector.

Batch normalization is applied to intermediate outputs of layers to set them to unit variance and zero mean so that we can apply training examples in batches. It is also applied to the output of convolutional layers before we apply nonlinearity on it. Dropout sets randomly some inputs to zero, in each iteration of the training phase. It helps to achieve generalization and prevents overfitting. Dropout is used with a 0.5 probability at the beginning.

3.3.4 Stacked autoencoders

An autoencoder is usually a three-layer neural network with an input layer, one hidden layer and an output layer [40], with the output layer having the same number of neurons as the input layer in order to reconstruct its own inputs. Therefore, autoencoders are unsupervised learning methods. An autoencoder is trained so that the input x is mapped to the hidden layer, this stage is called the encoding stage, then the output of hidden layer z is mapped to the output layer, to reconstruct the input, this stage is called the decoding stage. These steps are shown in the following equations.

$$z = \sigma(Wx + b)$$

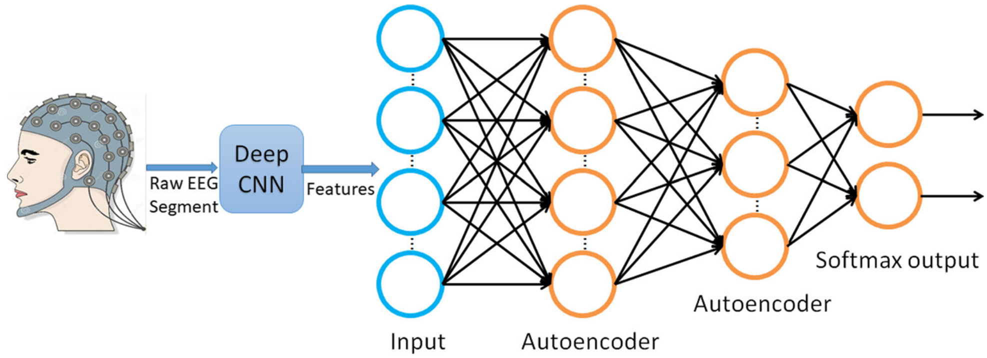

Fig. 3 Deep Learning model using CNN and stacked autoencoder

$$x' = \sigma'\left(W'x + b'\right)$$

Where W and W' are weight matrix, b and b' are bias vectors. The functions σ and σ' are element wise activation functions. The weights are said to be tied if we set $W = [W']^T$. Then training the autoencoders helps to minimize reconstruction error, $E(x, x')$.

$$\mathrm{argmin}_{W,b}\left[E\left(x, x'\right)\right]$$

After the autoencoder is trained and we obtain the learned hidden layer features, these features are used for classification tasks. We can also use these features as input to the next layer in stacked autoencoder. A stacked autoencoder consists of multiple layers of autoencoders. Stacking autoencoder is the greedy layer-wise training technique for pre-training a deep neural network. It trains each autoencoder layer in turn. The encoding and decoding step in autoencoder is run for each layer of the stacked model while the parameters of all other layers are frozen. After training step is complete then a supervised fine-tuning step is also performed in which all the network parameters are trained simultaneously using backpropagation algorithm [40], to improve results. In this study, we use stacked autoencoder with 2 hidden layers.

Table 1 Structure of CNN

Layers	Type
1	Convolution (10 × 1, 20 filters)
2	Convolution (20 × 23, 20 filters)
3	Max-pooling (2 × 1, stride 2)
4	Convolution (10 × 20, 40 filters)
5	Max-pooling (2 × 1, stride 2)
6	Convolution (10 × 40, 80 filters)
7	Fully connected(2 classes)

3.3.5 Proposed model architecture

Even when recording EEG in controlled environments there are always some differences among subjects and among recording sessions. Therefore it is difficult to identify common features for cross-subject recordings. In the case of EEG, since the signal to noise ratio is poor, it is sensitive to external and internal noise. Eye blinking and muscle movement artifacts can cause a lot of problems in extracting good features. Therefore we use a novel deep learning model composed of deep CNN followed by stacked autoencoder.

In our model, during the pre-training stage, CNN is employed to train all the weights and biases in the network simultaneously. In this supervised learning strategy, the deep CNN maps each of the time steps in the input data to one of the given classes (output labels) and the error is used to train the network parameters. Hence the important features are learned, noise artifacts in the EEG dataset are ignored, and it does not over-fit to noise in the data.

We used cropped training technique that uses sliding windows within the input. By using this technique we achieve a large number of training examples. We used this technique as the CHB-MIT database has only 173 seizure events, hence especially for seizure class we have limited training data, and hence there are chances that our deep CNN model could overfit. It not only increases stabilize the dataset but also increases classification accuracy. Figure 2 illustrates the use of the sliding window in the proposed architecture.

Figure 3 shows the overall architecture of the deep learning model. Since the sampling rate for the dataset is 256 Hz therefore in a 2-s window we have about 500 samples for all channels, which are presented to the first convolution layer. The

Table 2 Structure of Stacked Autoencoder

Layers	Type
1	Input layer (1000 neurons)
2	Autoencoder (500)
3	Autoencoder(200)
4	Softmax, Fully connected(2 classes)

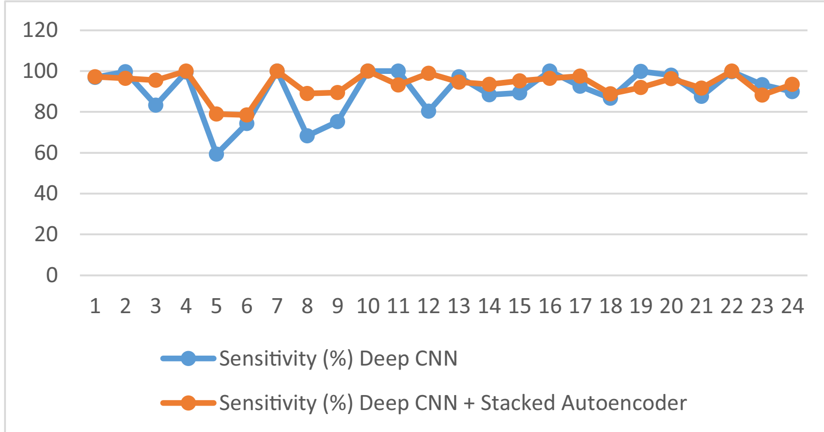

Fig. 4 Sensitivity: Deep CNN model comparison with Deep CNN + Stacked Autoencoder

first convolution layer uses 20 filters of size 10 × 1, which are slid over every sample, therefore this convolution is over time for each electrode at a time. The second convolution is over all electrodes or channels having 20 filters of size 20 × 23 as there are 23 channels. Then within this block, we have max pooling layer having a filter of size 2 × 1 with stride 2. After this, we again apply a convolution and max-pooling block having 40 filters of size 10 × 20 and max-pooling filter of the same size of 2 × 1 with stride2. In the last block, we apply convolution without max-pooling with 80 filters of size 10 × 40 and finally a fully connected layer with softmax function to give the output probability for the two classes.

The structure of CNN and stacked autoencoder are shown in Table 1 and Table 2, respectively. In our model the training takes place one patient at a time, therefore the softmax classifier gives us patient-specific probability distribution over output classes, which is 2 here.

We first use deep CNN model as explained earlier for the extracting features from the raw input data, then these features are used as input to the stacked autoencoder. During the supervised training phase of deep CNN model, the network parameters are pre-trained for the EEG seizure dataset. Then these features are used by the stacked autoencoder to learn general subject-specific features. These learned features from CNN are used individually for each patient but in cross trial manner. This is achieved by having the stacked autoencoder to reconstruct a different trial of the same patient. In this way, we also increase the training set as there are many trials available for each patient. After training the stacked autoencoders using trials from the same patient, we again trained them with trials from different patients but belonging to the same class. In this way were able to achieve good sensitivity and at the same time good accuracy for the cross-patient dataset.

4 Results

We used PyTorch deep learning framework to build deep CNN-stacked autoencoder model and used GTX 960 GPU card on Intel Pentium i7 machine. We tested the performance of the model using sliding window strategy to increase the dataset size. Since we took 2 s window as an input to our model for testing the output label was the mean of the labels for all the events in a single trial.

There are improvements in the result when using autoencoders with CNN as compared to only CNN method.

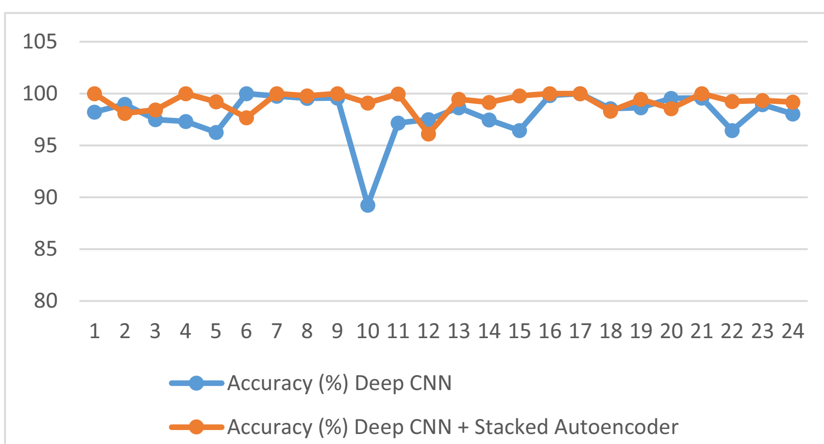

Fig. 5 Accuracy: Deep CNN model comparison with Deep CNN + Stacked Autoencoder

Table 3 The performance of some methods for seizure detection

Study	Problem	Design choices	Accuracy	Sensitivity
[37]	Patient Specific Seizure Detection and Prediction	SVM	96%	–
[31]	Cross patient Epileptic Seizure detection	CNN + RNN	95%	85%
[42]	General seizure detection across different subjects without prior knowledge	k-NN	93%	88%
[43]	Patient Specific Seizure Detection	stacked autoencoders	–	100%
[44]	Context-learning based EEG analysis for seizure detection	SVM	88.8%	–
[45]	DWT to improve accuracy and to reduce computational cost of seizure detection	DWT	92.30%	–
Our Model	Patient Specific and Cross Patient Seizure Detection and Classification	CNN + stacked autoencoders	99.20%	93.5%

It can be seen that the average values for sensitivity are close to 93% and average recognition accuracy is 99.2%. For some patients, the sensitivity was less as is the case for patient 5 and 6. It shows that the EEG is highly variable across patients.

When we applied cropped training strategy on the CHB-MIT dataset, the deep CNN-stacked autoencoder model gave us an overall accuracy of 99.5%, which is better than the state of the art on the same dataset. The sensitivity of the system was comparable with state of the art, which means this deep CNN- stacked autoencoder architecture can be used as a patient-specific as well as cross-patient seizure detector. The sensitivities and the accuracies are shown in Figs. 4 and 5, respectively.

Our result was better than the state of the art when compared with patient-specific approaches as well as cross-patient techniques. Researchers in [37] built a patient-specific detector for detection of epilepsy seizures and reported an accuracy of 96%, which is less than our model's accuracy. Our model also got better accuracy and sensitivity than REVEAL algorithm discussed in [41], which had good results for cross-patient seizure detection. One of the studies [31] used recurrent and convolution deep learning method for seizure detection reported a sensitivity of 85% for cross-patient detection, is also less than our model's sensitivity of 90%. In [42], they used supervised k-NN classifier for seizure detection across subjects and reported a classification accuracy of 93% and sensitivity of 88%, which is also less than what we report. In [43], the authors used stacked autoencoders with logistic classifiers for patient-specific seizure detection on the CHB-MIT dataset, to achieve 100% sensitivity. In [44], authors proposed context-learning for seizure detection by extracting hidden inherent features within EEG fragments and the temporal features from EEG contexts. They used SVM to achieve an accuracy of 88.8%. Discrete Wavelet Transform (DWT), was applied to selected frequency bands, in [45] to attain an accuracy of 92.30% on the CHB-MIT dataset. Table 3 compares accuracies and sensitivities of the proposed CNN-stacked autoencoder model with the discussed state of the art models, showing our method outperforms them in accuracy and is comparable in terms of sensitivity.

5 Conclusion

This study proposes a cognitive smart healthcare monitoring framework based on the integration of IoT and the cloud. An epileptic seizure detection and classification system inside the framework is built using deep CNN and stacked autoencoders. The proposed system also uses other healthcare smart sensors to record the psychological and physiological signals and transmit them to the cloud via the Internet. These signals include patients' movements, gestures, and facial expressions to determine their state. Thereafter, the cognitive system makes a real-time decision on the activities and the medical attention and services to be provided to patients based on their state and whether to send the data to the deep learning module. If the cognitive system believes that a patient is having a seizure, then it makes the decision to inform other stakeholders and sends the EEG data to the deep learning module. Signal processing and seizure detection occur in the cloud and signals are classified as seizure or non-seizure with a probability score. The results are transmitted to medical practitioners or other stakeholders who can monitor the patients. In critical cases, these medical practitioners make the appropriate decisions to assist patients.

This study also evaluated deep CNN and stacked autoencoders for EEG epileptic seizure detection and classification. Deep CNN is able to extract a robust and wide range of features from EEG, while stacked autoencoders facilitate the removal of noise artifacts from the signal. Deep CNN and stacked autoencoders also increase the overall accuracy of the system and assist in building a generic cross-patient classifier.

Experiments showed that the proposed system is accurate and sensitive for cross-patient seizure detection. However, we should address several issues before such framework can be operative in a secure manner. These issues include interoperability, availability, scalability, and security. We attempted to solve the issues of interoperability in the proposed framework. Security should be provided at the end of the healthcare service provider. For future research direction, we can create a cognitive framework to handle big data of EEG in the cloud.

Acknowledgements This work is supported by the Deanship of Scientific Research at King Saud University, Riyadh, Saudi Arabia through the Research Group Project No: RG-1436-016

References

1. Yin Y, Zeng Y, Chen X, Fan Y (2016) The internet of things in healthcare: an overview. Journal of Industrial Information Integration 1:3–13
2. Chen M, Zhang Y, Qiu M, Guizani N, Hao Y (2018) SPHA: smart personal health advisor based on deep analytics. IEEE Communications 56(3):164–169
3. Hu, L et al (2016) Internet of Things Cloud: Architecture and Implementation. IEEE Commun Mag 54(12-Supp):32–39
4. Chen, M et al (2018) Edge-CoCaCo: Toward Joint Optimization of Computation, Caching, and Communication on Edge Cloud. IEEE Wireless Commun 25(3):21–27
5. Muhammad G, Rahman SKMM, Alelaiwi A, Alamri A (2017) Smart health solution integrating IoT and cloud: a case study of voice pathology monitoring. IEEE Commun Mag 55(1):69–73
6. Chen M, Herrera F, Hwang K (2018) Cognitive computing: architecture, technologies and intelligent applications. IEEE Access 6: 19774–19783
7. Hossain, MS (2016) Patient State Recognition System for Healthcare Using Speech and Facial Expressions. J Medical Systems 40(12):272:1–272:8
8. Hossain MS, Muhammad G (2016) Audio-visual emotion recognition using multi-directional regression and Ridgelet transform. Journal on Multimodal User Interfaces 10(4):325–333
9. Hossain MS et al (2015) Audio–visual emotion-aware cloud gaming framework. IEEE Transactions on Circuits and Systems for Video Technology 25(12):2105–2118
10. Zanella A (2014) Internet of things for smart cities. IEEE Internet Things J 1(1):22–32
11. Hossain MS, Muhammad G (2016) Cloud-assisted industrial internet of things (IIoT)-enabled framework for health monitoring. Comput Netw 101:192–202
12. Chen M, Li W, Hao Y, Qian Y, Humar I (2018) Edge cognitive computing based smart healthcare system. Futur Gener Comput Syst. https://doi.org/10.1016/j.future.2018.03.054
13. World Health Organization (2017) Available: http://www.who.int/mediacentre/factsheets/fs999/en/
14. Litt B, Echauz J (2002) Prediction of epileptic seizures. Lancet Neurol 1:22–30. https://doi.org/10.1016/S1474-4422(02)00003-0
15. Chen M, Yang J, Hao Y, Mao S, Hwang K (2017) A 5G cognitive system for healthcare. Big Data Cogn Comput 1(1):2
16. Qian Y, Chen M et al (2018) Secure enforcement in cognitive internet of vehicles. IEEE Internet of Things Journal 5(2):1242–1250
17. Hossain MS, Muhammad G, Al-Qurishi M (2018) Verifying the images authenticity in cognitive internet of things (CIoT)-oriented cyber physical system. MONET 23(2):239–250
18. Zhang M et al (2012) Cognitive internet of things: concepts and application example. Int J Comput Sci Issues 9(3):151–158
19. Hossain MS, Muhammad G (2017) Emotion-aware connected healthcare big data towards 5G. IEEE Internet of Things Journal 5(4):2399-2406 (2018)
20. Hossain MS, Muhammad G, Alamri A (2017) Smart healthcare monitoring: a voice pathology detection paradigm for smart cities. Multimedia Systems. https://doi.org/10.1007/s00530-017-0561-x
21. Samani H, Zhu R (2016) Robotic automated external defibrillator ambulance for emergency medical service in smart cities. IEEE Access 4:268–283
22. Muhammad G, Alsulaiman M, Amin SU, Ghoneim A, Alhamid MF (2017) A facial-expression monitoring system for improved healthcare in smart cities. IEEE Access 5(1):10871–10881
23. Chen M, Song J, Lai C, Hu B (2016) Smart clothing: connecting human with clouds and big data for sustainable health monitoring. Mob Netw Appl 21(5):825–845
24. Vlacheas P et al (2013) Enabling smart cities through a cognitive management framework for the internet of things. IEEE Commun Mag 51(6):102–111
25. Piniewski B et al (2010) Empowering healthcare patients with smart technology. Computer 43(7):27–34
26. Ghoneim A, Muhammad G, Amin SU, Gupta B (2018) Medical image forgery detection for smart healthcare. IEEE Commun Mag 56(4):33–37
27. Muhammad G (2015) Automatic speech recognition using interlaced derivative pattern for cloud based healthcare system. Cluster Computing (Springer) 18(2):795–802
28. Hills M (2014). Seizure detection using FFT, Temporal and Spectral Correlation Coefficients, Eigenvalues and Random Forest. Technical Report. Github
29. Park Y, Luo L, Parhi KK, Netoff T (2011) Seizure prediction with spectral power of EEG using cost-sensitive support vector machines. Epilepsia 52:1761–1770. https://doi.org/10.1111/j.1528-1167.2011.03138.x
30. Parvez MZ, Paul M (2015) Epileptic seizure detection by exploiting temporal correlation of electroencephalogram signals. IET Signal Processing 9(6):467–475. https://doi.org/10.1049/iet-spr.2013.0288
31. Thodoroff P, Pineau J, Lim A (2016). Learning robust features using deep learning for automatic seizure detection, Proceedings of the 1st Machine Learning for Healthcare Conference. PMLR 56:178–190
32. Panayiotopoulos, CP (2010) A Clinical Guide To Epileptic Syndromes And Their Treatment. Springer-Verlag, London, pp 654
33. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks. In: Pereira F, Burges CJC, Bottou L, Weinberger KQ (ed) Advances in neural information processing systems 25, pages 1097–1105. Curran Associates, Inc.. URL http://papers.nips.cc/paper/ 4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf
34. Pramod S, Page A, Mohsenin T, Oates T (2014) Detecting epileptic seizures from EEG data using neural networks. arXiv preprint arXiv 1412:6502
35. Turner JT, Page A, Mohsenin T, Oates T (2014) Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection. In 2014 AAAI Spring Symposium Series
36. Li D, Wang G, Song T, Jin Q (2016) Improving convolutional neural network using accelerated proximal gradient method for an epilepsy diagnosis. In Control (CONTROL), 2016 UKACC 11th International Conference on. IEEE, 1–6
37. Shoeb A (2009) Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. Ph.D. thesis, Massachusetts Institute of Technology
38. Canolty RT, Edwards E, Dalal SS, Soltani M, Nagarajan SS, Kirsch HE, Berger MS, Barbaro NM, Knight RT (2006) High gamma power is phase-locked to theta oscillations in human neocortex. Science 313:1626–1628
39. Schirrmeister RT, Springenberg JT, Fiederer LDJ, Glasstetter M, Eggensperger K, Tangermann M, Hutter F, Burgard W, Ball T (2017) Deep learning with convolutional neural networks for EEG decoding and visualization. Hum Brain Mapp 38:5391–5420. https://doi.org/10.1002/hbm.23730
40. Bengio Y, Lamblin P, Popovici D, Larochelle H (2007) Greedy layer-wise training of deep networks. Adv Neural Inf Process Syst 19:153

41. Wilson S, Scheuer M, Emerson R, Gabor A (2004) Seizure detection: evaluation of the Reveal algorithm. Clin Neurophysiol 10: 2280–2291
42. Fergus P, Hussain A, Hignett D, Al-Jumeily D, Abdel-Aziz K, Hamdan H (2016) A machine learning system for automated whole-brain seizure detection. Applied Computing and Informatics 12(1):70–89, ISSN 2210-8327. https://doi.org/10.1016/j.aci.2015.01.001
43. Supartak A, Li L, Guo Y (2014) Feature extraction with stacked autoencoders for epileptic seizure detection, 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, pp. 4184–4187. https://doi.org/10.1109/EMBC.2014.6944546
44. Xun G, Jia X, Zhang A (2015) Context-learning based electroencephalogram analysis for epileptic seizure detection, 2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Washington, DC, 2015, pp. 325–330. https://doi.org/10.1109/BIBM.2015.7359702
45. Chen D, Wan S, Xiang J, Bao FS (2017) A high-performance seizure detection algorithm based on discrete wavelet transform (DWT) and EEG. PLoS One 12(3):e0173138. https://doi.org/10.1371/journal.pone.0173138