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Cognitive Smart Healthcare for Pathology Detection and Monitoring

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ABSTRACT We propose a cognitive healthcare framework that adopts the Internet of Things (IoT)–cloud technologies. This framework uses smart sensors for communications and deep learning for intelligent decision-making within the smart city perspective. The cognitive and smart framework monitors patients' state in real time and provides accurate, timely, and high-quality healthcare services at low cost. To assess the feasibility of the proposed framework, we present the experimental results of an EEG pathology classification technique that uses deep learning. We employ a range of healthcare smart sensors, including an EEG smart sensor, to record and monitor multimodal healthcare data continuously. The EEG signals from patients are transmitted via smart IoT devices to the cloud, where they are processed and sent to a cognitive module. The system determines the state of the patient by monitoring sensor readings, such as facial expressions, speech, EEG, movements, and gestures. The real-time decision, based on which the future course of action is taken, is made by the cognitive module. When information is transmitted to the deep learning module, the EEG signals are classified as pathologic or normal. The patient state monitoring and the EEG processing results are shared with healthcare providers, who can then assess the patient's condition and provide emergency help if the patient is in a critical state. The proposed deep learning model achieves better accuracy than the state-of-the-art systems.

INDEX TERMS Cognitive, IoT-cloud, deep learning, smart healthcare, EEG.

I. INTRODUCTION

The Internet of Things (IoT) has transformed from being an interconnection of embedded computing devices to an interconnection of smart sensor devices. However, when applied to the smart city environment, it tends to open issues, such as low storage and limited processing capacity. Meanwhile, cloud computing offers fast processing and large storage capability. Therefore, we need IoT–cloud integration to cope with highly demanding smart healthcare services [1]. Real-time communication and patient monitoring have always been the central idea of smart healthcare services. However, with IoT–cloud technologies, the need for a cognitive framework that provides patient-centric and high-quality smart healthcare at low cost increases. With artificial intelligence (AI) and deep learning techniques, introducing human-like intelligence to smart healthcare frameworks is timely.

IoT and cloud technologies have recently seen substantial advancements and have helped provide real-time smart healthcare services. With IoT–cloud integration, the demand for a ubiquitous smart healthcare framework that provides seamless and fast response is considerable. Deep learning and AI can provide cognitive behavior and improve decision-making capability. Besides smart sensor devices, advanced mobile devices and technologies are at the disposal of smart city stakeholders. Nevertheless, locating or accessing specialized medical practitioners and hospitals is quite difficult in a complex smart city environment. Sometimes, patients with critical cases need immediate care and fast response to live. Thus, complex multimedia signals must be transmitted and processed with minimum delay, and the result produced must be sufficiently accurate for medical practitioners to depend on it for initial analysis. Therefore, an integrated smart healthcare framework that could address these issues by utilizing the technologies and resources available in a smart city environment is necessary.

The healthcare industry is now one of the fastest growing fields with substantial demands. Not only does it provide important and critical services to patients; it also brings large revenues to the health sector. Healthcare providers compete in providing dependable and low-cost healthcare services to smart city residents [2]. Hence, the integration of IoT–cloud technologies has also been under research focus recently. Sophisticated and low-cost smart IoT healthcare devices and smart healthcare sensors are being employed for this purpose, including smart wearable devices for monitoring blood sugar, insulin, blood pressure, body temperature, stress, weight, ECG, and EEG.

Real-time signals, such as EEG, that are acquired through smart sensors and IoT devices, are usually complex and require advanced techniques, such as deep learning, big data analytics, and cloud processing. These advances provide the necessary processing and storage capability required for data storage, processing, and analysis. However, in the case of a smart city environment where real-time multimodal big data are being produced by numerous smart IoT devices and sensors, developing a smart healthcare framework that could satisfy all stakeholders by providing quality and low-cost services is a challenge.

Even with the use of technological advances, the concept of smart healthcare in a complex scenario, such as that of a smart city, is difficult to achieve without human-like intelligence. With the increasing sophistication and complexity of data, we need a healthcare framework that has intelligent decision-making capability. Therefore, many researchers have attempted to introduce the concept of cognitive behavior in the development of smart and intelligent IoT frameworks [3]. Given that healthcare frameworks are multimodal and require complex decision-making, having a cognitive behavior becomes increasingly important [3]. In a smart city paradigm, a smart healthcare framework uses IoT sensors attached to or around a patient to acquire data, such as movements, voice, EEG, ECG, and body temperature, and determines the patient's state. Such a framework also considers all health indicators and determines whether emergency response or specialized medical care is required. The framework also keeps all concerned smart city stakeholders informed about patient state outcomes and monitoring results. The concept of smart healthcare is vague without cognitive capability, and smart city resources can never be fully utilized without such intelligence. Therefore, researchers are now exerting significant effort in this direction [2].

A research [1] highlighted the challenges of using smart sensors with cloud computing for smart healthcare in a smart city environment. Environmental factors, such as humidity and temperature, must be monitored to provide quality smart healthcare. Several researchers [3] utilized IoT and cloud to access medical records and monitor patient status. Hossain *et al.* [4] proposed a cloud-based IoT framework that is based on emotion recognition. Several researchers [5] built cloud-IoT-based real-time smart healthcare frameworks for smart cities, and another research integrated edge computing and cognitive behavior for the same application [6]. All these recent approaches have attempted to integrate various technological advances to improve smart healthcare services for the smart city paradigm.

EEG is a commonly used technique of recording brain activity because of its low cost and non-invasive nature. It is widely used in diagnostic applications for brain-related diseases, such as epilepsy and stroke. EEG-based patient diagnostics are also widely studied for smart healthcare applications. Given that EEG requires significant time and expert knowledge for analysis, any real-time smart healthcare service that processes EEG data requires considerable training to produce reliable performance. Therefore, smart healthcare frameworks use machine learning or deep learning techniques for EEG analysis and decision-making. Brain-related ailments have increased over the years. Consequently, numerous researchers are implementing EEG diagnostics and monitoring applications within smart city healthcare services. These diagnostics include screening for ailments, such as Alzheimer's [7], stroke [8], epilepsy [9], depression [10], and brain injuries [11].

Patients with brain-related ailments require immediate response in case of emergency. Any delay in providing treatment or unavailability of trained medical practitioners can be dangerous for such patients. Therefore, a smart healthcare framework that monitors patient status is crucial for such individuals. However, any such system should be intelligent and mature to be dependable. Specialized doctors could access reports and medical records and can give their feedback and advise regularly. In emergency situations, transport services, such as smart ambulances, or mobile assistance, such as smart clinics, can attend to patients.

To solve these issues, we propose a cognitive healthcare IoT framework for EEG-based pathology detection. The proposed system classifies normal and pathological EEGs from patients with various types of brain-related ailments. The pathology detection method uses scalp EEG recorded through EEG sensors. The framework employs multimodal sensors to acquire the signals and transmits them to the cloud for further processing. Multimodal data consist of gestures, movements, EEG, facial expressions, and voice, among others. These signals are initially processed to determine the patient's state. Then, the data are transmitted to the cognitive system, which processes the data real time and decides future activities and course of action based on the patient's state. Subsequently, the EEG signal is transmitted to the deep learning system, which performs pathology detection. Then, the cognitive system again receives the overall processed result and decides on the emergency response before finally sending the results to the concerned stakeholders for further analysis. The signal is processed and classified as normal or pathologic on the cloud. Finally, medical specialists can study the result generated and monitor the patients. If the patient requires emergency assistance, then future services can be decided.

EEG has a characteristic low signal-to-noise ratio that makes its analysis very challenging. Also, the signal is prone to the effect of noise artefacts, such as eye and muscle movements. Hence, the proposed system uses deep learning for EEG feature extraction and classification. Overall, this study offers the following contributions. (1) A cognitive healthcare framework is proposed using the integration of IoT–cloud technologies. (2) This is the first study to propose a smart healthcare framework for pathology detection and monitoring. (3) The deep learning model provides state-of-the-art results for pathology detection.

The rest of the paper is organized as follows. Section 2 presents literature reviews related to cognitive and smart healthcare frameworks and pathology classification based on EEG. Section 3 presents the proposed cognitive healthcare framework. The experimental results are discussed in Section 4. Finally, the conclusion is presented in Section 5.

II. RELATED STUDY

Here, at first, we report a few related approaches for cognitive smart healthcare and EEG pathology detection.

A. COGNITIVE SMART HEALTHCARE

Cognitive smart healthcare has recently revolutionized healthcare services, especially for smart city applications. IoT and interconnected smart healthcare sensors, together with cloud technology, have transformed the concept of smart healthcare. These healthcare applications include remote tracking and monitoring of patients, intelligent disease detection, emergency response, mobile healthcare, smart health records, smart alerts, smart pill dispensing, and remote medical equipment operation and control. Such a system would help in medical emergencies by providing immediate response. It is connected with multiple smart healthcare sensors inside, on, and around the human body, receiving and monitoring real-time multimodal data. Some researchers have used 5G technology to further enhance the communication in such cognitive healthcare frameworks [12]. They have integrated cognitive healthcare systems with AI technologies, such as Kinect, which has been extensively used for activity recognition.

One of the basic requirements in cognitive smart healthcare frameworks is the cooperation of interconnected IoT devices and smart sensors in learning the environment and processing the extracted information. It should work with minimum intervention for humans and possess an intelligent decision-making ability.

Several cognitive smart IoT frameworks have been mentioned in the literature for different domains. In [15], a cognitive framework was proposed to make smart city modelling more sustainable. A multilayer cognitive framework was proposed in [16], which shows high intelligence with a human behavior cognition. Another cognitive framework for human knowledge modelling, which can process relative knowledge, was proposed in [13]. An NLP-based cognitive framework, which has a question answering ability, was proposed in [15]. Researchers used cognitive behavior to analyze big data in [17]. Cognitive intelligence has also been embedded in healthcare applications, such as psychological [12] and physiological [18] applications. In [5], an emotion-aware cognitive system that uses cloud computing was presented. An emotion-based cognitive system that detects facial expressions was proposed in [16], and another such framework [18] detects emotions using voice with facial expressions.

B. SMART HEALTHCARE

Given their immense economic and social advantages, smart healthcare systems have recently been gaining significant attention. Many research studies [15], frameworks [14], [34], [35], and services [16], [19] that focus on IoT–cloud integration, have been proposed for smart healthcare. In [2], a smart healthcare framework was proposed to help patients find routes to hospitals using smart devices. Several studies [16] proposed frameworks for electronic health records processing and maintenance. A cognitive smart framework for glucose monitoring was proposed in [17] to monitor the activities of diabetic patients. Cognitive ambulance, which are driven by robots and used to treat cardiac patients who need emergency help, was also proposed in [19]. Some frameworks have also detected medical forgery in the smart healthcare domain [20].

The cognitive smart healthcare framework proposed in this study aims to solve the issues and challenges related to this field and presents an EEG pathology detection system. We integrate cognitive behavior with IoT–cloud technologies for smart healthcare. In the next section, works related to EEG pathology classification are discussed.

C. EEG PATHOLOGY CLASSIFICATION

With recent advancements in machine learning techniques, the research focus on automatic EEG diagnosis tools has increased. Diagnosis is applied to various brain diseases and disorders, such as Alzheimer's [7], stroke [8], epilepsy [9], depression [10], and brain injuries [11]. These EEG diagnostic tools are based on different machine learning techniques, such as support vector machines (SVMs), principle component analysis, random forests, logistic regression, and neural networks. Researchers have switched to deep learning techniques to improve EEG classification accuracy. EEG pathology detection could help detect patients with abnormal EEG and provide necessary help, and the underlying cause or diseases could be analyzed further.

The only large EEG pathology dataset available that could be used for deep learning is Temple University Hospital (TUH) [21], which has 3000 abnormal clinical EEG recordings. Only two studies have explored pathology detection on this dataset. In [22], researchers from TUH employed CNN-based deep network with many fully connected layers to obtain an accuracy of 78.8%. In another study [23], researchers used deep and shallow CNNs for pathology detection with an accuracy of 86%. Automated machine learning methods also face many issues as EEG signal is complex and has a low signal-to-noise ratio. EEG pathology recording patterns are different from patient to patient and disease to disease. Hence, finding a cross-patient automated EEG diagnosis tool is very challenging. Also, normal and pathological EEG patterns can overlap, and thus difficult to separate them.

Deep learning has been widely used to detect seizures. A CNN with a dropout technique was proposed in [24] for detecting seizures. A study [25] used multichannel EEG and CNN for seizure detection. In another study [26], CNN was used together with autoencoders for EEG classification. Given that CNN has been successfully applied to various EEG applications, we use popular pretrained CNN models (VGG16 [27] and AlexNet [28]) for EEG pathology detection. First, we pre train these CNN models on normal EEG datasets to find general features using EEG signals. Then, the extracted features are used to train and fine-tune the CNN models on the Abnormal TUH EEG pathology dataset specific features.

III. COGNITIVE SMART HEALTHCARE FRAMEWORK

Our proposed cognitive IoT–cloud smart healthcare framework and EEG pathology classification case study are presented in this section.

A. COGNITIVE SMART HEALTHCARE SCENARIO

The frameworks for smart healthcare designed for a smart city environment help residents, doctors, and other stakeholders in monitoring their health through smart sensor devices. They can access electronic health records from anywhere at any time using cloud and IoT technologies. Cognitive capability makes decisions intelligent and dependable. Smart wearable sensors enable residents to monitor and update health records. The cognitive framework analyzes, records, and processes information real time and help patients select the best medical service available. Health records are uploaded on the cloud and are remotely accessible by medical practitioners who can advise the patients accordingly.

The major goals of smart healthcare frameworks are accurate diagnosis, low cost, reduced hospital visits, easy access, and enhanced overall quality of life. To achieve these objectives, we present a proposed healthcare framework that is based on IoT–cloud technologies. The infrastructure for a smart city needs its residents to register for its services. The registration process sets up a secure channel between residents and healthcare service providers and enables all authorized stakeholders to use the cognitive module to remotely retrieve patient details and health records. The patient's location is continuously tracked to offer help in case of emergency. Psychological and physiological signals are recorded in real time and the patient's state is continuously monitored. Patients' movements, facial emotions, voice, and gestures are also recorded. Patients with brain disorders wear a smart EEG skull cap. The cognitive system accesses the patient's state and transmits the EEG signal to the cloud to be processed by the deep learning system. The deep learning module detects the EEG pathology and sends back binary classification results. Based on these results the cognitive system plans future activities. These data, in the form of health records, are shared with healthcare practitioners for detailed analysis. In case of emergencies, alerts and warnings are generated by the cognitive system, and a smart ambulance or mobile clinic can locate and come to the patient in minimum time. The smart traffic system also assists in medical services to reach the spot in minimum time via the shortest route. In this manner, the cognitive smart healthcare framework remotely offers critical healthcare services to all its residents.

B. SYSTEM ARCHITECTURE

The architecture of the proposed cognitive smart healthcare system is shown in Figure 1. Multimodal signal acquisition is carried out through smart IoT sensors. The local area network (LAN) consists of low-range communication devices. This layer transmits the acquired signals from the smart IoT sensor and device to another layer called the hosting layer. The hosting layer has different types of smart devices, such as multimedia mobiles or laptops, which can store and send signals. The smart devices are connected to the wide area network (WAN), which sends the data received from the smart devices to the cloud unit.

The WAN layer employs advanced communication networks, such as Wi-Fi, 4G, or 5G, to transmit data in real time to the cloud. The cloud manger in the cloud layer authenticates the patient's data and sends them to the cognitive engine for processing.

Smart IoT sensors consist of wearable and fixed sensors that can measure medical signals, such as body temperature, heartbeat, blood pressure, voice, facial expressions, body movement, and EEG. Some of these sensors are embedded in the patient's surroundings. These devices can also communicate with other devices using IoT. The LAN consists of short-range communication protocols, such as Bluetooth, LoWPAN, and Zigbee.

The hosting layer has smart devices, such as multimedia smartphones, laptops, tablets, and personal digital assistants. These devices store data locally and have dedicated programs for simple computations on the received signals. The users can obtain preliminary and general health feedback using these limited processing devices. Data are transmitted to the cloud processing unit via the WAN layer.

The cloud layer consists of a cloud manager, a cognitive engine, and a deep learning server. The cloud manager is responsible for data flow and implements all the security protocols to verify the identity of all smart city stakeholders. After patient authentication, the cognitive engine processes the data and determines the state of the patient. It makes intelligent decisions and sends EEG signals to the dedicated deep learning server for EEG pathology detection. Deep learning models send detection results back to the cognitive engine, which in turn makes final decisions about the patient's state and accordingly informs the concerned stakeholders about

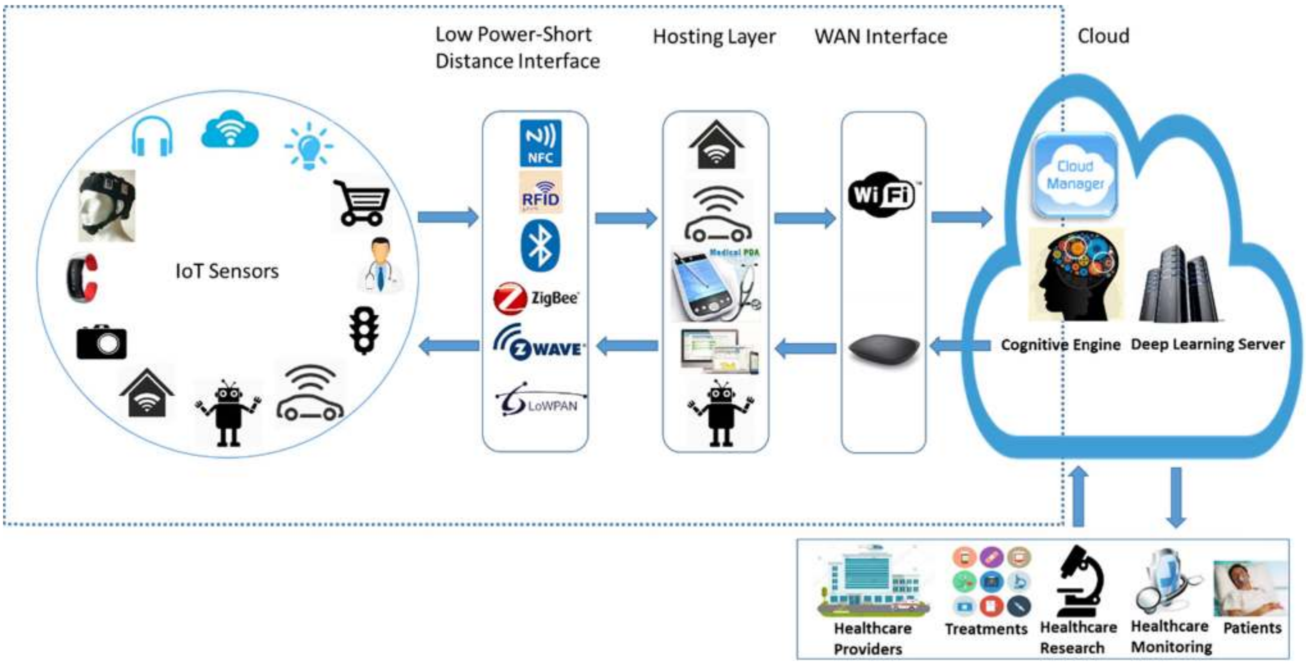

FIGURE 1. Cognitive Smart Healthcare Framework.

the results. Healthcare practitioners then analyze the health records and results, and then follow up with patients.

C. PATHOLOGY DETECTION AND CLASSIFICATION

We used TUH's abnormal EEG dataset [21], which has 3000 normal and pathology recordings and normal EEG recordings of more than 10000. The vast size of the dataset is very useful for training deep networks. Hence, the TUH Abnormal EEG Corpus is rich in annotations and is an excellent resource for differentiating pathology EEG from normal EEG recordings. Data are recorded from 21 standard electrode positions, and the sampling rate is 250 Hz. Each recording has approximately 20 min of EEG. Labelling is done manually.

In the literature, we found only two studies that utilized this dataset for automated EEG pathology detection. Both studies used CNN-based deep networks to achieve good results. Only two studies explored pathology detection on this dataset. In one of the two studies, [22] researchers from TUH employed a multilayer CNN model with many fully connected layers and achieved 78.8% accuracy. The other study [23] also employed CNN but with fewer fully connected layers and obtained an accuracy of 86%.

We used pretrained popular CNN models, namely, VGG 16 [27] and AlexNet [28], for pathology detection. These models were pretrained on normal EEG recordings available on the TUH corpus. After the models extract features for EEG, we perform transfer learning and fine-tuning using the abnormal TUH EEG corpus and remove the final classification layers. We use SVM as a final classification layer.

1) EEG PREPROCESSING AND REPRESENTATION

Different EEG representation techniques have been used for the input to deep learning systems [29]. CNN requires 2D inputs; thus, many studies have transformed EEG signals to images, and some have converted EEG into topographical maps [30]. Other studies utilized electrode voltage to convert EEG signals into time series topographical images [30]. However, some research shows evidence that EEG recordings are correlated over time series signals [31]. Hence, we take the EEG recordings as input, without conversion into images or topomaps. We take the EEG input prepared as a 2D array, which has all the recording samples or time steps, because its width and all the EEG electrodes are represented as the height of the array.

2) CNN MODEL

CNN models can learn temporal and spatial features from an EEG signal through convolutions and nonlinearity. CNN can store complex high-order features as a group low-order features. The intermediate features are represented by pooling layers in the form of feature maps in a compact manner and retain only important information. CNN models have shown excellent results for end-to-end feature learning where raw signals act as input and the model extracts spatial features initially, and as the learning progresses, the model can extract temporal features in the deep layers.

We use VGG-16 [27], which is a popular CNN architecture. The VGG-16 model is pre-trained on the TUH normal EEG recording dataset. After pretraining, the last fully connected layer is removed from the VGG-16 model, and SVM is added for classification. The VGG-16 model has five convolution blocks. The first two convolution blocks consist of two convolutional layers followed by a max pooling layer. The third and fifth blocks consist of three convolutional layers followed by a max pooling layer. After each convolution layer, we apply the rectified linear unit (ReLU) as an activation function. After all the convolution blocks, we have three fully connected layers. Finally, a softmax classifier is used. Each of the first two fully connected layers has 4096 hidden units, and ReLU is applied as activation function. After the first two fully connected layers, we apply dropout with a probability of 0.5. The last fully connected layer has two units and the softmax activation function. After the model is pretrained, transfer learning and fine-tuning are performed. In transfer learning, the learning rate is decreased, and the final fully connected layer is replaced by the binary SVM.

We also use the AlexNet model as described in [28]. The model is pretrained on the TUH normal EEG recording dataset. The AlexNet model has five convolution layers and three fully connected layers. After pretraining, the last fully connected layer is removed from the model, and SVM is added for classification. The first two and fifth convolution layers are followed by a max pooling layer. ReLU is applied after each convolution layer. Each of the first two fully connected layers have 4096 hidden units, and ReLU is applied as activation. After the first two fully connected layers, we also apply dropout with a probability of 0.5. The last fully connected layer has two units and a softmax activation function.

Transfer learning is applied for the VGG-16 model. The learning rate is decreased, and the final fully connected layer is replaced by a binary SVM. In SVM, a radial basis function (RBF) kernel is used because it has produced good results in many applications.

The VGG-16 and AlexNet models structure is provided in Tables 1 and 2, respectively.

The input to the CNN model had 1000 samples, each comprising 4 sec EEG signals at a frequency of 250 Hz. We used the stochastic gradient descent algorithm for optimization and the Adam [32] algorithm to optimize the CNN parameters.

TABLE 1. Structure of VGG-16.

Layers	Type of Layer (Size, Filters)
1	Convolution (10x21, 25)
2	Convolution (10x20, 25)
3	Max-pooling (2x1, stride 2)
4	Convolution (10x20, 50)
5	Convolution (10x20, 50)
6	Max-pooling (2x1, stride 2)
7	Convolution (10x20, 50)
8	Convolution (10x20, 50)
9	Convolution (10x20, 50)
10	Max-pooling (2x1, stride 2)
11	Convolution (10x20, 50)
12	Convolution (10x20, 50)
13	Convolution (10x20, 50)
14	Max-pooling (2x1, stride 2)
15	Convolution (10x20, 50)
16	Convolution (10x20, 50)
17	Convolution (10x20, 50)
18	Max-pooling (2x1, stride 2)
19	Fully connected(4096)
20	Fully connected(4096)
21	Fully connected(2 classes)

IV. EXPERIMENTS

In this section, we describe the database we used in the experiments and present the experimental results and discussion.

A. DATABASE

In the experiments, we used the Temple University Hospital (TUH) EEG Abnormal Corpus v2.0.0 [33]. The data had two classes: normal and abnormal. The database was divided into evaluation and training sets. In the evaluation set, the normal class had 148 subjects, and the abnormal class had 105 subjects. In the training set, the normal class had 1237 subjects, and the abnormal class had 893 subjects. The total number of subjects in the database was 2383. No overlap existed between the patients in the evaluation and training sets. Some subjects appeared more than once in the training set. Several EEG signals from the same subject were recorded at different sessions. Therefore, the numbers of files in the evaluation and training sets were greater than the number of subjects in these sets. The total number of files in the database was 2993. Figure 2 shows the gender-wise distribution of the files in the two classes and in the two sets.

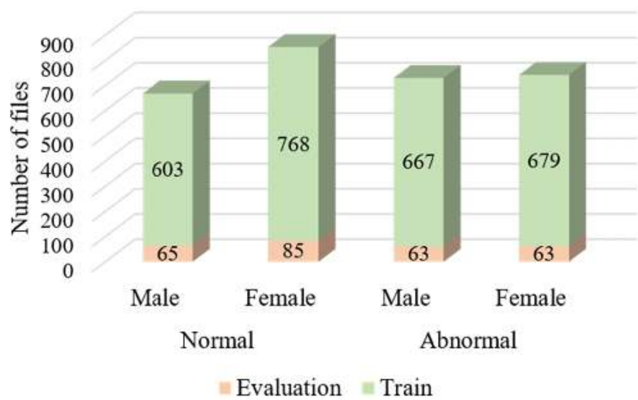

FIGURE 2. Gender-wise files distribution of evaluation and train sets in the database.

EEG recordings were obtained using a minimum of 21 standard electrodes. The sampling frequency was

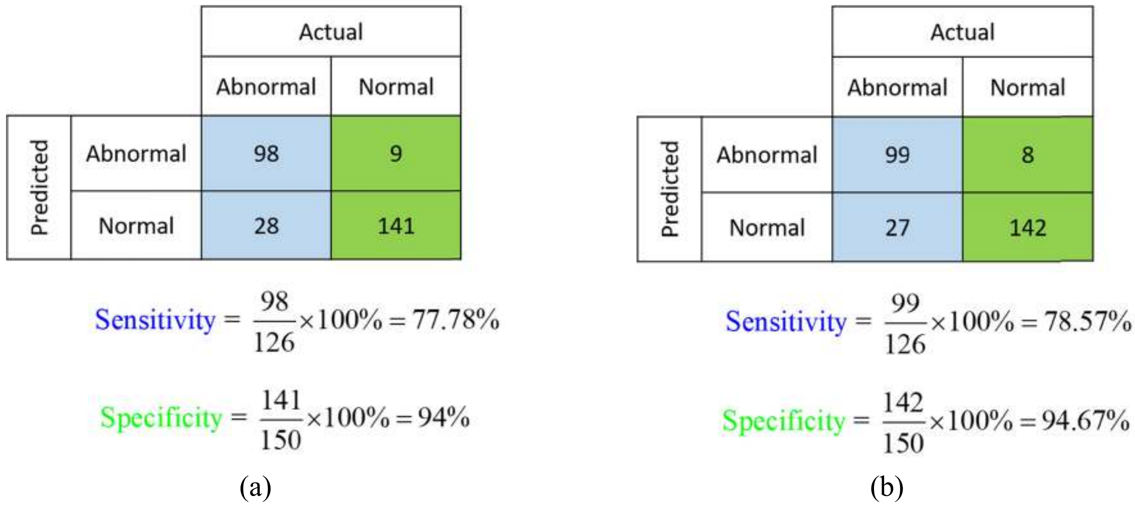

FIGURE 3. Confusion matrix of the system using (a) the VGG-16 model and (b) the AlexNet model.

TABLE 2. Structure of AlexNet.

Layers	Type of Layer (Size, Filters)
1	Convolution (10x21, 20)
2	Convolution (10x20, 20)
3	Max-pooling (2x1, stride 2)
4	Convolution (10x20, 50)
5	Max-pooling (2x1, stride 2)
6	Convolution (10x20, 50)
7	Max-pooling (2x1, stride 2)
8	Convolution (10x20, 50)
9	Max-pooling (2x1, stride 2)
10	Convolution (10x20, 50)
11	Max-pooling (2x1, stride 2)
12	Fully connected(4096)
13	Fully connected(4096)
14	Fully connected(2 classes)

250 Hz in most of the cases. Each recording file contained approximately 20 min of EEG data. Manual labeling was performed and indicated a 99% inter-rater agreement in the train set and 100% in the evaluation set.

For the experiments, we performed preprocessing on the datasets. We selected recordings from 21 electrodes, which were common in all the files. We removed the first minute of recording from all the files because they contained noise artifact. A maximum of 20 min of recording per file was selected.

B. EXPERIMENTAL RESULTS AND ANALYSIS

Two sets of experiments were performed. One set involved the proposed system using the VGG-16 model, whereas the other set involved the proposed system using the AlexNet model. In both cases, the SVM with the RBF kernel was used as the classifier.

Figure 3 shows the confusion matrices of the system using the VGG-16 and AlexNet models. The matrices indicate that the systems achieved 77.78% and 78.57% sensitivity and 94% and 94.67% specificity using the VGG-16 and AlexNet models, respectively.

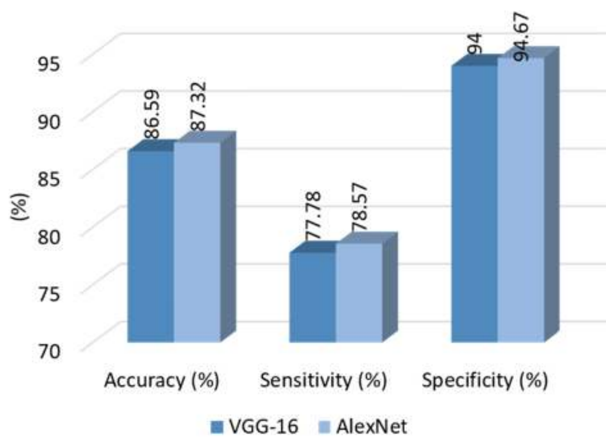

FIGURE 4. Percentage of Accuracy, sensitivity, and specificity of the system using VGG-16 and AlexNet.

Figure 4 shows the accuracy, sensitivity, and specificity of the system using the two models. The system achieved 86.59% accuracy with the VGG-16 and 87.32% accuracy with the AlexNet. Table 3 shows a comparison of the performance of the different systems. The system in [22] obtained 78.8% accuracy, whereas the system in [23] reported 85.4% accuracy with the use of deep ConvNet. These accuracies were obtained from the respective papers. The table shows that the proposed system with both models achieved higher

TABLE 3. Comparison of performances between the systems.

Systems	Accuracy (%)	Sensitivity (%)	Specificity (%)
[22]	78.8	75.4	81.9
[23], deep ConvNet	85.4	75.1	94.1
Proposed, VGG-16	86.59	77.78	94
Proposed, AlexNet	87.32	78.57	94.67

accuracy than did the two other systems. The proposed system also obtained better sensitivity and specificity than did the two others. This performance indicated the success of the proposed system.

V. CONCLUSION

We propose a cognitive healthcare model that combines IoT–cloud technologies for pathology detection and classification. We used two CNN models that were pretrained on a normal EEG dataset. We adopted raw time-domain EEG signals as input to the CNN model for pathology classification, which proved that end-to-end learning is suitable for EEG data.

Our models achieved better accuracies than did state-of-the-art algorithms. The framework uses intelligent sensors to acquire multimodal medical data. These signals are processed in the cloud unit. They include actions, movements, and emotions in addition to various types of medical data, including EEG signals. These signals are utilized to determine patients' condition. The cognitive module then decides based on the services and medical support that the patients need. The EEG signal is also transmitted to the deep learning system, which detects the EEG pathology and sends the result back to the cognitive system. The cognitive module informs all stakeholders about the condition of the patient so that follow-up procedures can be implemented. In a future work, we will investigate other deep learning models for the proposed system.

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