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A Review on IoT-Cloud based EEG Depression Detection System: A Case Study

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Abstract: A debilitating mental disease, major depressive disorder (MDD), may develop functional impairments and become a social problem. An accurate and early diagnosis of depression may be difficult. Automated systems to help human lives thrive with the development of machine learning technology, especially deep learning. In this paper, we suggest a method based on deeper learning to identify automated electroencephalograms (EEGs). Firstly, as a time/space representation, the raw EEG data is processed. The EEG signal's spatial-temporal structure is the input into a convolutional neural network (CNN). Using transfer learning are three different CNN models; a shallow model, an Alexnet and a ResNet model. Through the order to proceed with the diagnosis of moderate depression for depressed people, the proposed system plays a vital role by informing family members and doctors in emergency situations so that we can safeguard the patients' lives. Major Depressive Disorder in adolescents is associated with decreased functioning in adulthood, recurrence and an increased risk of death due to suicide. A study of typically developing preschool-aged children found that while irritability and sadness were the most sensitive predictors of depression (identified in 98% of preschoolers), anhedonia was the most specific, apparent only in the depressed group.50 Younger children may present with somatic complaints and behavior problems and may demonstrate a persistent engagement in activities or play with themes of death or suicide.This approach may enable physicians to remotely monitor major depression patients in distant and disadvantaged regions. In this paper, however, we provide a comprehensive review of many current methods for detecting and preventing depression as soon as possible and highlight their strengths, constraints, and difficulties to guarantee the safety of patients and to save precious lives.

Keywords: *Cloud layer, IoT, Major depressive disorder, EEG data.*

1. Introduction

In recent days, depression, coupled with different medical problems, is a constant sense of sadness, exhaustion, and anxiety. A person may feel sad or low for a few days because of various everyday issues, but if that feeling continues for even three to four weeks, it becomes a kind of mental disorder known as depression [1]. Depression is an illness that is not transmissible and may be healed by proper medications and by changes in lifestyle occasionally. But if identified and mistreated, suicides may occur. The Internet of Things is creating its foundation from every point of view in our daily life, especially in the medical health-care sector. It is significantly growing regarding market prospects and different big market competitors are investing in it. During their treatment, most patients had to remain in the hospital. This led to higher health care costs and strained health facilities in rural and distant areas [11]. Because of the technical progress made in recent years in connection with IoT, many diseases and health monitoring may now be diagnosed through tiny devices such as smartwatches [2]. In addition, technology has turned a hospital-centered healthcare system into a patient-centered one. For instance, they may do many clinical analyses at home without the help of a health care expert, such as blood pressure measurement, blood glucose, pO2, level.

In addition, it may transmit clinical data via sophisticated telecommunications services to health facilities in distant regions. The usage, along with fast-growing technologies such as machine learning, big data analysis, the Internet of things (IoT), wireless sensing, mobile technology, and cloud computing, has enhanced healthcare facilities' accessibility.Technologies like IoT, cloud and other technologies have driven the development of inexpensive, sophisticated and smart healthcare sensors as intelligent wearable devices–cloud integration. There are a wide variety of sensors that are used for medical purposes, such as blood glucose measurement, blood pressure, and electroencephalogram (EEG). Complex, real-time and large data like EEG often needs sophisticated processing and extensive storage. Therefore, we are using services like big data, cloud computing, and deep learning. We need an intelligent health framework that addresses not just the data processing problems, but also meets the needs of all stakeholders in the intelligent city and delivers dependable, low-cost healthcare services.

There has also been a rise in brain-related diseases, resulting in researchers developing EEG diagnostic systems for intelligent medical applications [3]. Several recent research projects such as stroke therapy, Alzheimer's illness, depression and bleeding have focused on this area [4]. Such medical problems need patient surveillance and emergency help in real-time. In addition, intelligent health systems for the diagnosis of various conditions should be clever, confident and accurate [12]. Medical representatives should be able to access medical records and offer professional services. In the event of an emergency, intelligent

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ambulances and intelligent health centers.We are proposing an intelligent health care system for the diagnosis of depression based on EEG data to meet the challenges stated above. Our technology analyses, analyses and classifies EEG depression data as normal or abnormal. Any brain-related diseases may cause an abnormal EEG. Our system utilizes intelligent multimodal IoT sensors to store EEG data in real time and to transmit it for processing to the cloud server. The data received includes EEG, to assess the medical condition of the patient. We then sent the data and then informed the emergency unit or doctors concerned about the need for emergency services. The doctors examine electronic medical records to monitor the status of the patient.

2. Related Works

Several works have been originated in the literature which deliberates cloud and edge in the healthcare system.

In [5], researchers developed a strategy predicated on the differential evolution of crossover mutations. Two sets of evaluated EEGs extract the 864 features of three bands are optimized, and kNN classified for optimum features. The test results have shown that this technique is better and has better accuracy and efficacy than other approaches for differentiating slightly depressed individuals from normal people [13]. Differential evolution is an effective global optimization method that addresses the problem of detecting depression.

The authors presented a method for the diagnosis of depression using features derived from EEG data [6]. As a feature were alpha, alpha1, alpha2, beta, delta, and theta power. Additionally, used as a feature were alpha1, alpha 2 along with theta asymmetry. When a feature combination has been employed, Multi-Cluster Feature Selection (MCFS) is used for function selection. The classifiers utilized were Support Vector Machine (SVM), Regression Logistic (LR) and Decision Tree (NB) (DT). In all applicable grade categories, Alpha2 had better grade accuracy than Alpha1 and Alpha power [14]. From t-testing, they observed a significant difference in the theta strength of normal people in the left and right hemisphere, while they detected no significant difference in patients with depression. In normal people, average theta asymmetry is greater than in MDD patients, but the difference between theta asymmetry is not significant in normal individuals and MDD patients [15]. Alpha2 and theta asymmetry exhibited 88.33% of SVM's maximum accuracy in classification.

In [7], the authors presented a deep hybrid model that would identify depressions using EEG data, combining convolutional neural network (CNN) [23][24] and long-short term memory (LSTM) architectures. The deep model learns the temporal characteristics of the data using layers of convolution to provide learning with the help of LSTM. These tasks yielded 99.12% and 97.66% accuracy for EEG signals in the right and left brain. The proposed CNN-LSTM model may therefore be concluded that it can detect depression accurately and rapidly using EEG data. Depression may be reliably detected using EEG signals and assisted by doctors in the psychiatric stations of the hospital.

The researchers presented an EEG-derived synchronizing likelihood (SL) machine learning architecture as input data for automated MDD diagnosis [8]. It was supposed to be more accurate than measures like interhemispheric coherence and common information to distinguish between MDD patients and good health controls on EEG-based SL. The classification models for the EEG features and study groups (MDD patients and healthy control) have been used in the work, as well as in the classification models (SVMs), logistic regression (LR), and Naïve Bayesian (NB) to model a connection between research participants and EEG functionalities. The findings showed superior to probability classification rates. In particular, the research showed a higher accuracy of SVM classification compared to other conventional methods [16].

In [9], the authors set up a process to examine the difference between depressed people and ordinary people regarding facial expressions and used machine learning techniques to analyses the classes of EEG-features. The results showed that the eight nonlinear features used had improved classification performance and reached 99.1% accuracy, which exceeded the best results in prior research [17]. Thus, the combination of linear and non-linear characteristics proved beneficial. The quick spread of wearable devices is a technique that gives physicians an efficient approach to monitoring the risk of depressed patients, along with bioelectric signals in human health care. It may not only decrease the probability of misdiagnosis but also improve the effectiveness of doctor-patient interactions by using an automated depression detection system [18]. And the authors' method provided a better understanding of their depressive conditions for regular individuals who are continuously living with low mood and taking the required countermeasures on time.

In [10], the researchers developed a model for the sensor-based bio-signal detection of mental stress status. The proposal is to establish a deep, multilevel neural network using hierarchs of the neural network of convolution. Multivariate series data, including biological sensors based on both chest and wrist, is used to train high-level features for each bio-signal feature using a hierarchy of networks. A model-level fusion approach suggested that high-level features be combined into a single representation and stress they classified states as baseline, stress and amusement into three categories [19]. On the WESAD data set for mental health, the model is assessed and compared well with state-of-the-art methods that achieve 87.7% exceptional efficiency.

We propose a perceptive and intelligent depression detection system based on EEG in this study. [22] By integrating the IoT-cloud with the smart health system, we provide perceptive intelligence. Our perceptual method addresses important issues in intelligent healthcare.

3. Materials and methods

An EEG-based depression detection cloud-based framework has been developed. There are three major components to the framework. We show the overall framework as shown in Figure 1. A headset of electrodes captures the EEG signals. We use the IoT device as a headset. Alternatively, various IoT devices may be developed to gather EEG data from various brain components. They sent EEG signals through a LAN network to a mobile edge computing (MEC) server. The MEC to various edge processors, who prepare the signal delivered signals.

Preprocessing of EEG signals:

Preprocessing comprises the removal of noisy sources and transformation into the required domain for easy processing. With the help of IoT-friendly processing devices, they reduce the strain of sending huge amounts of data to cloud storage.

Cloud infrastructure layer:

The radio access network (RAN) transmits the 2D signals to a primary cloud. There are many components in the primary cloud, including a cloud manager and resource manager. The cloud management provides users and stakeholders with authentication and allocates tasks to the resource engine. We perform all the operations with the support of data storage.

Application layer:

The signal choice (depression or non-depression) is subsequently sent to the stakeholders' users through cloud services. In the same way, measures taken to provide healthcare companies for users depend on the decision.

Database: In the tests of this study, Shah et al. (2018) the TUH EEG Corpus is considered. In the database, 2,383 participants were registered, including 1,385 with normal EEG records and 998 with an abnormal EEG record. We decomposed the database into three for training and evaluation. In the train subset, 1.237 were classified, and we classified 893 as abnormal. The numbers were 148 and 105 in the evaluation subset.

More than once in the train subset, some subjects occur. There was no overlap between training and evaluations. EEG signals were obtained in many sessions for some subjects. We observed data in the database in both normal and abnormal classifications for 512.01 and 526.05 hours. The figures in theevaluation subset were 55.46 and 47.48 hours, respectively. The subjects have been evenly distributed between males and females.

Proposed EEG depression detection system:

A pre-processing phase followed by the feature extraction process, CNN, and finally, the classification process is included in the proposed EEG pathology detection method. This section provides information about the stages. We follow two steps for the preprocessing of raw EEG data.

Stage 1: The Fourier transform transforms every electrode on Stage 1 into a frequency domain signal. The frequency-domain signal is applied with three band-pass filters. From 1 to 7 Hz, from 8 to 30 Hz, and 31 to 100 Hz are the frequency bands. Thus, each EEG signal has three band-limited signals.

Stage 2: For all electrodes, the band-limited signals are row-specific. We have 21 rows of 21 EEG electrodes with a 21 to 6000-dimension matrix for every band. We give the matrices to a CNN model once preprocessing is done. The study investigated three models of CNN. As an initial step, we have developed the shallow CNN model Rode et al. (2021). The second is the AlexNet Ni et al. (2021), the third is the ResNet Lim et al. (2021), which we employ as a pre-trained model.

Residual Blocks:

Let us concentrate, as described in Figure 2, on a local part of a neural network. Input is denoted by x. We presume that the fundamental mapping that we require through learning is f (x) which is taken as the input for the activation function. The part in the dotted line box on the left of Figure 2 needs to learn to map directly (x). The segment on the right of the dotted line box has to learn the mapping of the rest of $f(x) - x$, since its name comes from the residual block. If $f(x) = x$ is the mapping that we want, residual mapping becomes much simpler to learn: just the weights and biases of the higher weights (i.e., a full-connected layer and a convolutional layer) need to be pushed to zero inside the pointed-line box. The image on the right in Figure 2 shows the residual ResNet block, where a residual connection is termed a solid line with input layer x to the additional operator. Residual blocks allow the inputs to propagate faster across layers through the residual connection.

VGG's complete 3×3 convolution layer architecture is followed by ResNet. The last block comprises the same output channel number of 2 convolution layers of 3×3. A batch of normalizing layers and a ReLU activation function follow each convolutional layer. We then skip the two convolution processes and add the input earlier to the final ReLU role. If we change the number of channels, an additional 1×1 convolution layer is necessary for the input to be converted into a suitable arrangement. Early warning systems will serve as a lifesaving to thousands of major-depression patients in the era of internet of things (IoT). This model will play an important part in medical treatment by promoting early diagnosis of moderate depression for depression victims, such that patients, their families and physicians in nearby hospitals can only be alerted to this chronological condition in the major stage of the patient, and so the lives of patients can be rescued. This prototype could allow doctors to track major depression patients in remote and underprivileged areas remotely. However, the computer-aided approach used to learn facts about practical communication matrices that can easily be found in patients withmajor depression.

4. Results and Discussions

ResNet has the benefit that the gradient flows from later layers to older levels directly via the identity function to substantially solve the problem of gradient. We have substituted cascade blocks with the original residual blocks of 16Gb RAM and Intel-7 core. Figures3-5 shows various performance measures in terms ofa confusion matrix obtained by the Alexnet, Shallow CNN and proposed ResNet. Confusion matrix is a very popular measure used while solving classification problems. It can be applied to binary classification as well as for multiclass classification problems .The data for confusion matrix is taken from the TUH EEG Corpus A rich archive of over 30,000 clinical EEG recordings collected at Temple University Hospital (TUH).In this we took 276 instances as total for study.

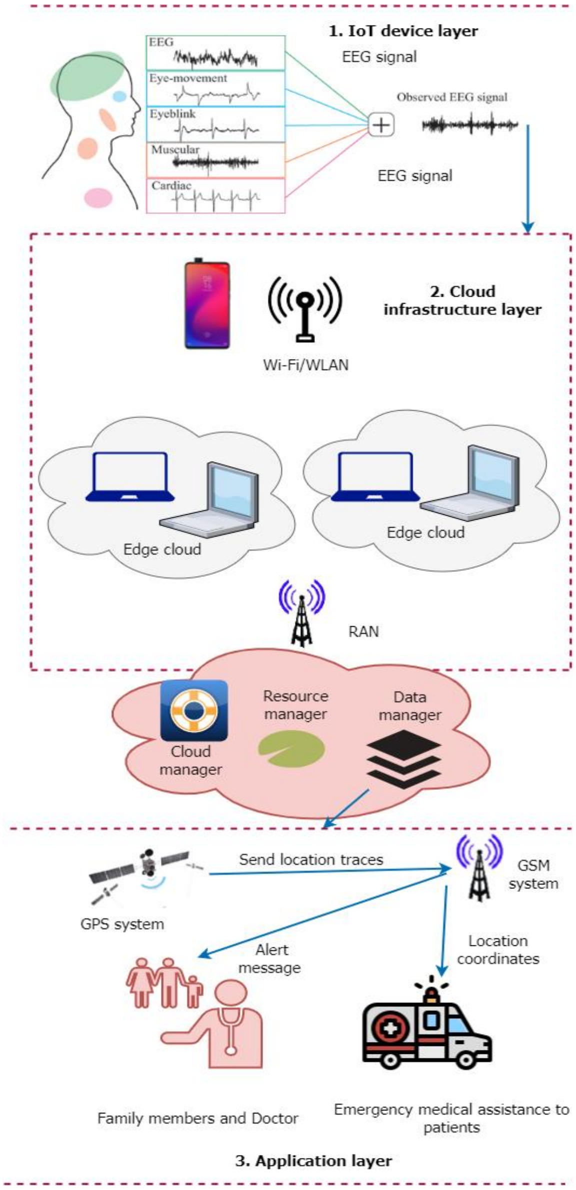

Fig 1. Overview of proposed framework with 5 phases of processing

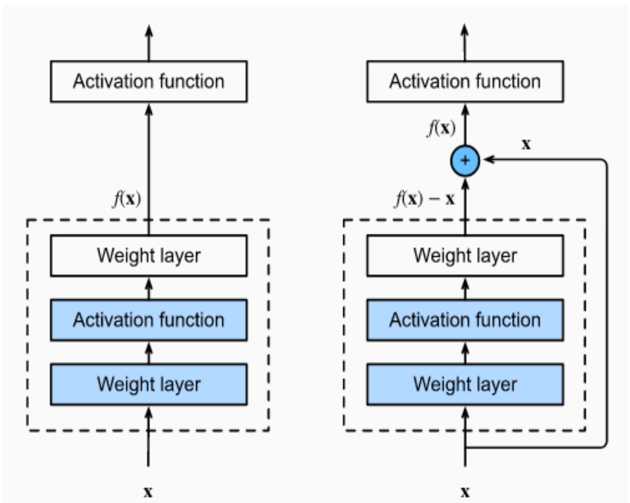

Fig.2 Original block (left) and a Modified residual block (right).

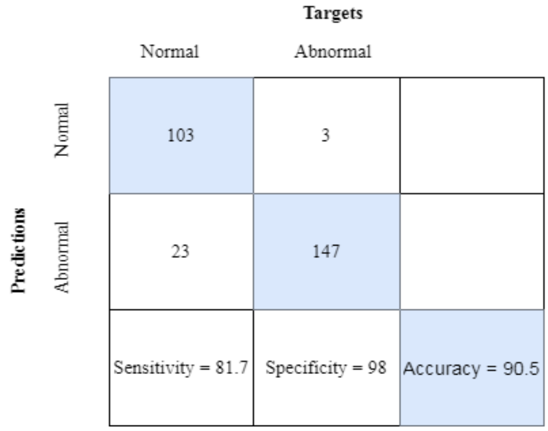

Fig 3. Confusion matrix of the Alex net

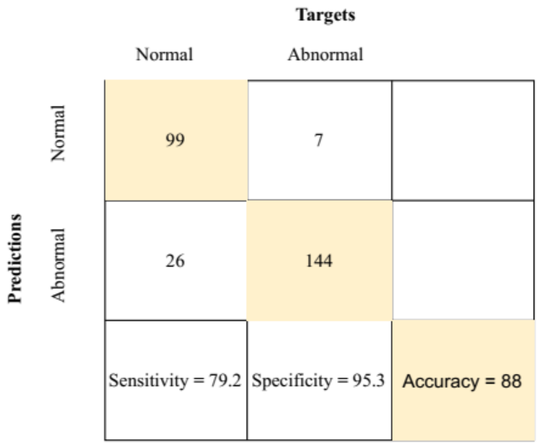

Fig 4. Confusion matrix of the Shallow CNN

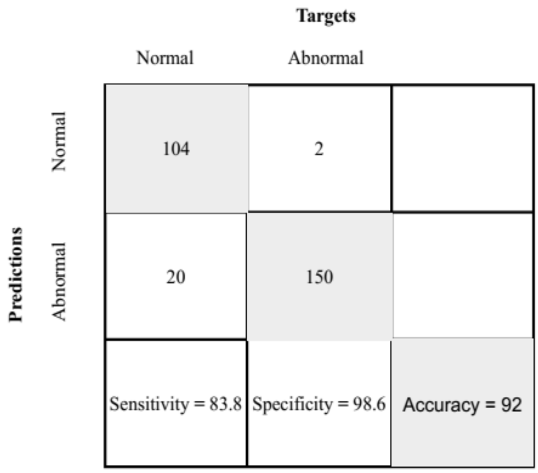

Fig 5. Confusion matrix of the Proposed ResNet

We conducted experiments for five minutes on each file on the train sub-set and the evaluation subset. Also, from Figure 6, it is confirmed that Proposed ResNet outperforms the other two models. The accuracy, Sensitivity and specificity of the Proposed ResNet are92%, 83.8% and 98.6% respectively. Because the sample numbers in the database are not large, a scratch model like the shallow model did not work effectively.

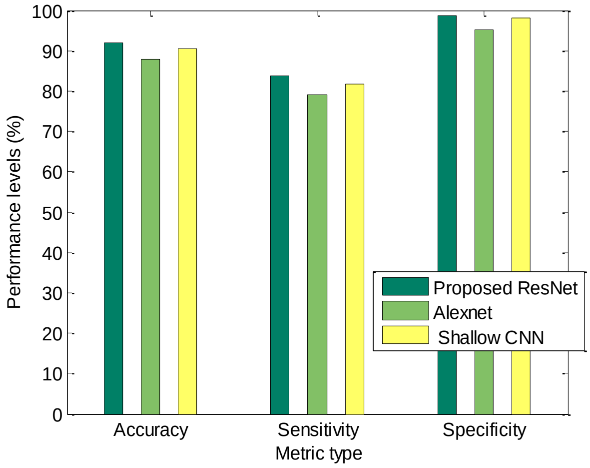

Fig 6. Showing relation between three CNN models for performance levels

We attempted to analyze the consequences of the duration of EEG signals in the train and the assessment data sets in the following experimental samples. Figure 7 illustrates the system accuracies as the signal length varies. The signal length in the evaluation subset ranged from 1 to 25 minutes. The accuracy was 76% when the length was only one minute and the accuracy was 85.4% with a duration of 20 minutes.

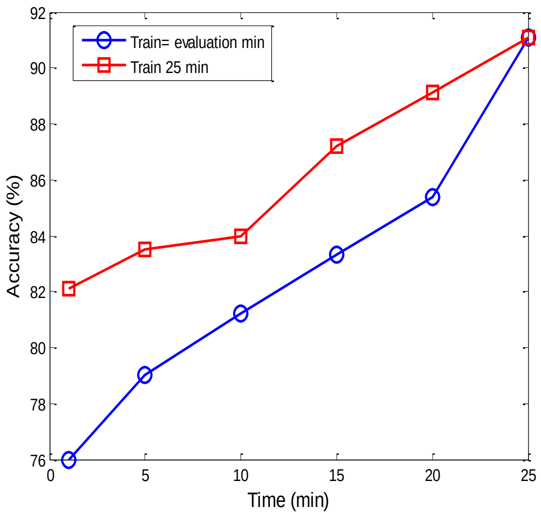

Fig 7. Graph showing training of model for 25 min w.r.t the accuracy

The duration of the signals in both the train and the test subsets remained the same in another trial. For signal lengths of four minutes in the train sub-set, the signal length was also four minutes in the evaluation subset. Figure 5 shows that the later trial gave more accuracy than the first. The accuracy was 82.1% for single-minute signals, and 89.1% for 20-minute signals.

5. Conclusion

A ResNet model was suggested for the EEG depression detection system. The EEG signals were pre-processed and their time-frames supplied to the ResNet model. The AlexNet investigation included the shallow CNN model and one deep CNN model. MLP was used to fusion CNN features from three different temporal slices of the EEG data. We have carried experiments on a database that is publicly accessible. Experimental findings showed the maximum accuracy of the system suggested by ResNet and that the other related systems were better.

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