Seminar Report

On

EEG based automatic depression assessment using deep learning techniques

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CERTIFICATE

This is to certify that Mr. Raghav Gaggar of B.Tech., School of Computer Engineering & Technology, Trimester – IX, PRN. No. S1032171346, has successfully completed seminar on

EEG based automatic depression assessment using deep learning techniques

To my satisfaction and submitted the same during the academic year 2019 - 2020 towards the partial fulfillment of degree of Bachelor of Technology in School of Computer Engineering & Technology under Dr. Vishwanath Karad MIT- World Peace University, Pune.

Prof. Dr. Shamla Mantri — Seminar Guide

Prof. Dr. M.V.Bedekar — Head, School of Computer Engineering & Technology

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ABBREVIATION

- WHO : World Health Organization
- EEG : Electroencephalogram
- ECG : Electrocardiogram
- MDD : Major Depressive Disorder
- MRI : Magnetic Resonance Imaging
- AI : Artificial Intelligence
- ML : Machine Learning
- DL : Deep Learning
- RNN : Recurrent Neural Network
- CNN : Convolutional Neural Network
- DCNN : Deep Convolutional Neural Network
- LSTM : Long Short-Term Memory Networks

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ABSTRACT

EEG based depression assessment using deep learning is a niche research domain. EEG is specifically used since it has shown to have the most prominent changes when a person becomes depressed. Depression is at an all-time high and according to WHO, it is going to become the second largest disability, or the cause of malady worldwide by 2020. Using the brain signals of the concerned person as the dataset, deep learning techniques can be applied to check whether the person is having depression and its severity, if tested positive after the diagnosis. Deep learning is gaining grounds in this research topic since it has the ability to automatically and adaptively do the feature extraction, which used to be hand thus making the whole process fully automated. The research will also open future avenues for suggesting possible behavioral interventions for a depressed person.

KEYWORDS

Electroencephalography, deep learning, depression, emotion recognition.

TECHNICAL CONTENT

1. Introduction

Depression is a common mood disorder characterized by persistent feeling of loss, anger, sadness. It is a serious disorder that can occur in people of all age groups. Depression has affected a big part of the population, and nowadays observed to affect people of all age groups, including young kids also. Hence, depression assessment has become a rapidly growing research domain. Depression can be manifested in many forms. EEG, ECG signals, visual, vocal cues and some others are popularly used to detect depression and its severity, in a person. But little progress has been made in neuroscience and biomedical fields due to lack of sufficient data. But noteworthy progress has been made wherever the necessary data is available in this field. Earlier, we observed that machine learning algorithms were used for biomedical signals processing, but now deep learning has been recently gaining grounds. The earlier papers used to code the feature extraction part and the classification part separately to achieve the required goal. But with deep learning, this whole process can be automated and made into a single structure which takes raw EEG signals and gives the desired output. In fact, the newest deep learning systems built to solve this problem can also learn both local features and long-term dependencies for input signals.

1.1 Clinical background of depression

Depression is a mental illness often correlated with loss of interest, guilt feeling, low self-esteem, poor concentration, and in the worst case, having suicidal thoughts [1]. It is graded as mild, moderate, or severe depending on the severity of the symptoms. It is estimated that roughly more than 300 million people of all ages suffer from depression worldwide [2]. Depression can be treated with psychotherapy or medical prescription if diagnosed properly but remains a persisting health issue in the society as it often goes undiagnosed [2]. According to the Diagnostic and Statistical Manual of Mental Disorders of the American Psychiatric Association (APA), now in its fifth edition (DSM-5), subtypes of depressive disorders include: Major Depressive Disorder (MDD), Persistent Depressive Disorder (Dysthymia), Disruptive Mood Dysregulation Disorder (DMDD), Premenstrual Dysphoric Disorder (PDD), Substance/Medication-Induced Depressive Disorder (S/M-IDD), Depressive Disorder

Due to Another Medical Condition (DDDAMC), and Other Specified Depressive Disorder (OSDD) or Unspecified Depressive Disorder (UDD) [1].

At present, the doctors use the Diagnostic and Statistical Manual of
Mental Disorders (DSM), for diagnosing of depression. But different doctors may prefer different standards, and this could lead to different diagnostic results. Hence, we need to come up with an automated diagnostic service.

1.2 EEG signals

Studies have shown that electroencephalogram (EEG) signals are a major indication of a person's emotional state. EEG signals are spontaneous biopotential signals which are recorded from the scalp. These signals are recorded through electrodes and represent the rhythmic electrical activities of the brain cells. The characteristics
of EEG signals are usually described using waveforms, amplitudes, frequencies, and cycles. Hence, these can be used as a differentiating factor for the signals. The processing of EEG data generally includes preprocessing, feature extraction, feature selection and classification. In the preprocessing stage, the work basically includes electrooculogram removal, event extraction, EEG subsection, pseudotrace removal and so on [3].

1.3 Structure of the report

The structure of the remaining report is as follows : Section 2 will cover the literature survey done with respect to the concerned topic. Section 3 will focus on the details of design/technology. Discussion on the report's findings and future scope in this area is discussed in the conclusion section.

2. Literature Survey

2.1 Methodology followed in previous studies

Few remarkable studies have been done related to the topic in hand. People have used EEG, ECG and magnetic resonance imaging (MRI) for the diagnosis of various diseases. EEG is frequently used to detect seizure. Petrosian et al. had applied recurrent neural network (RNN) and extracted features from EEG time series data for seizure prediction [4]. Mirowski addressed this issue by using convolutional neural network (CNN) to extract features from EEG data [5]. Acharya et al. developed CNN model can detect the seizure EEG signals with accuracy of 88.7% [6].

Wulsin used deep belief net (DBN) for anomaly detection using EEG [7]. Yildirim et al. proposed a CNN for 1D data, giving the solution to detect the abnormal EEG signals with detection error rate of 20.66% [8]. A paper also explored the effectiveness of deep extreme machine learning (DEML) on two brain-computer interface (BCI) data sets [9]. They have highlighted the advantages of using DEML in classification of BCI data sets. Another paper proposed a deep learning network with 100 hidden nodes in each layer to detect emotions from EEG signals [10]. They achieved a low classification performance having an accuracy of 53.42%. Supratak et al. used DeepSleepNet comprising of CNN and bidirectional-LSTM model which learnt single-channel EEG data for automated sleep stage classification [11].

Oh et al. made an automated classification of arrhythmia into 5 types using unprocessed ECG signals using a combination of CNN and LSTM [12]. In another study bidirectional LSTM network was used for the same purpose [13]. In a paper, deep 1D-CNN detected 17 classes of cardiac arrhythmia and attained an overall accuracy of 91.33% for the same [14].

Acharya et al. developed a 13-layer CNN model to detect depression accurately by using EEG signals, having able to get an accuracy of 93.54% (left hemisphere of the brain) and 95.96% (right hemisphere) [15]. In a previous paper, some of the authors of this paper presented a 13-layer CNN for the automated identification of seizure using EEG signals [6]. High sensitivity and specificity of 95% and 90% were reported, respectively, based on 300 EEG signals, a large data set. Moreover, some of the authors have employed CNN in previous studies using Electrocardiogram (ECG) signals to diagnose various cardiac disorders [16-19]. In these studies, authors have obtained high diagnostic performances (more than 90%) even with noisy ECG signals. Based on prior experience with other biological signals, the same 13-layer CNN model is employed in this research. My base paper developed an even more accurate automated depression detection system with EEG signals as dataset, with accuracy of 97.66% (left hemisphere) and 99.125% (right hemisphere) [20]. It used a CNN-LSTM based hybrid deep learning algorithm to solve the purpose. CNN model is good in extracting temporal features and poor in learning sequential information. To overcome this problem, my base paper used the hybrid algorithm.

The overall procedure in my base paper to automatically detect depression is illustrated in Figure 1 below.

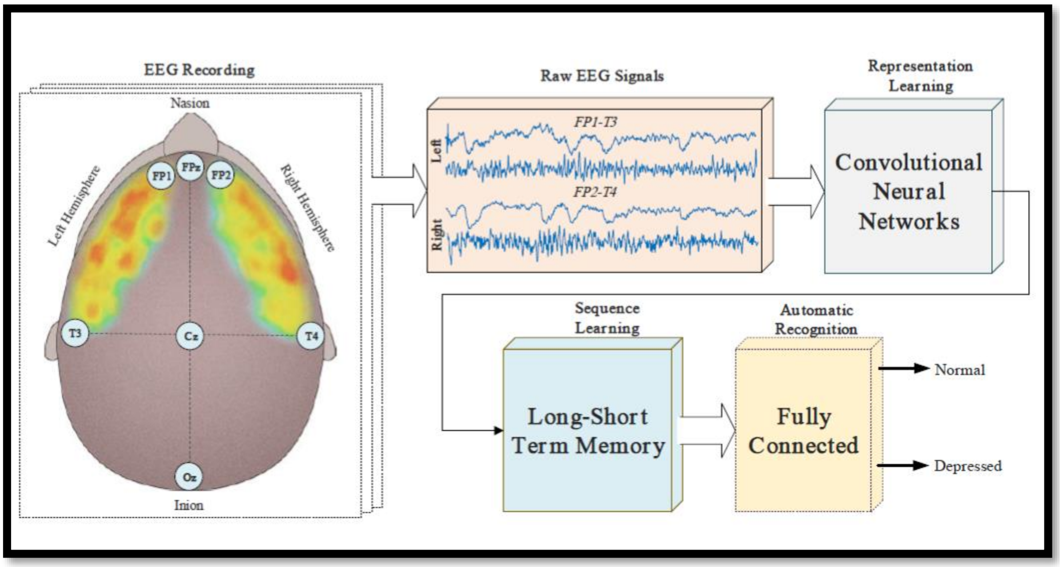

Figure 1. Procedure followed for EEG based automatic depression detection [20].

Table 1 below gives an overview of the studies done on automated depression detection using EEG signals.

Table 1. Overview of past studies on EEG based automatic depression assessment

Name of paper	Year of study	Model used	Accuracy (In %)	Advantages of the method	Disadvantages of the method
Fractality analysis of frontal brain in major depressive disorder[21]	2012	Evolutionary Pruning Neural Network (EPNN)	91.30	Discovered Higuchi Fractal Dimensions showing meaningful differences between MDD and healthy groups.	Hand – crafted feature extraction had to be done.
Classification of EEG signals in normal and depression conditions by ANN using RWE and signal entropy [22]	2012	Artificial Neural Network (ANN)	98.11	This paper attempts to classify EEG signals of normal and depressed patients based on well established signal processing techniques involving Relative Wavelet Energy (RWE).	The deep learning model used was not capable of learning short or long term dependencies.

Depression diagnosis support system based on EEG signal entropies [23]	2014	Probabilistic Neural Network (PNN)	98.20 (Left) 99.50 (Right)	The feature extraction method revolves around a novel processing structure that combines wavelet packet decomposition (WPD) and non-linear algorithms.	Hand – crafted feature extraction had to be done.
A novel depression diagnosis index using nonlinear features in EEG signals [24]	2015	Support Vector Machine (SVM)	98.00	A novel Depression Diagnosis Index (DDI) is presented through judicious combination of the nonlinear features.	The deep learning model used was not capable of learning short or long term dependencies
EEG-based computer-aided technique to diagnose major depressive disorder (MDD) [25]	2017	Support Vector Machine (SVM)	98.40	Dataset used was relatively bigger	Hand – crafted feature extraction had to be done.

Automated diagnosis of depression EEG signals using linear prediction coding and higher order spectra features [26]	2017	Bagged Tree	94.30	Seven different feature ranking are used to test and rank the extracted features.	There is loss of interpretability of the model.
Major depression detection from EEG signals using kernel eigen-filter-bank common spatial patterns [27]	2017	Support Vector Machine (SVM)	81.23	Robust spectral-spatial EEG feature extractor called kernel eigen-filter-bank common spatial pattern (KEFB-CSP)	Accuracy is relatively less
Automated EEG-based screening of depression using deep convolutional neural network [15]	2018	Convolutional Neural Network (CNN)	93.54 (Left) 95.96 (Right)	Fully automated design	CNN is poor in learning sequential information.

Automated Depression Detection Using Deep Representation and Sequence Learning with EEG Signals (My base paper) [20]	2019	CNN-LSTM	97.66 (Left) 99.12 (Right)	The deep learning model used was capable of learning both local characteristics and also short and long term dependencies.	The dataset used was still not robust enough, despite many previous studies on this topic. Also, the method used is complex and intensive in terms of computation.

In order to detect single channel depression EEG signals, Bachmann at al. used combination of linear and nonlinear methods [28]. Puthankattil and Joseph used relative wavelet energy and entropy features extracted from the EEG signals to detect the depression [22]. Ahmadlou et al. used combination of wavelet filter bank and fractal dimension features to detect the depression automatically [29]. Faust et al. used nonlinear features extracted from the wavelet packet decomposition sub-bands of the EEG signals [23]. Acharya et al, have developed an index to detect the normal and depression subjects using a single integer developed using nonlinear features [24]. Bairy et al. [26] used features extracted from the linear predictive coding (LPC) residuals to discriminate depression signals from normal EEG signals.

2.2 Dataset used in previous studies

The dataset used by most of the studies listed in the Table 1 comprises of 15 normal and 15 depressed patients. The EEG signals used by Acharya et al. [15] and in my base paper [20] were obtained from the Psychiatry Department, Medical College, Calicut, Kerala, India. It had EEG signals of 15 normal and 15 depressed subjects obtained from left half

(FP1-T3 channel) and right half (FP2-T4 channel) of the brain. The EEG signals were sampled at a sampling rate of 256 Hz and the power line was eliminated with a 50 Hz notch filter. Artifacts resulting from muscles and eye movements within the EEG signals were manually removed by experts. The EEG data of 30 subjects were evaluated in two separate categories as left and right hemisphere EEG data belonging to normal and depressed classes. It consists of 4798 depression and 4318 normal EEG records (files) with each file having 2000 samples. Figure 2 below illustrates the difference in the EEG signals of a healthy and depressed person.

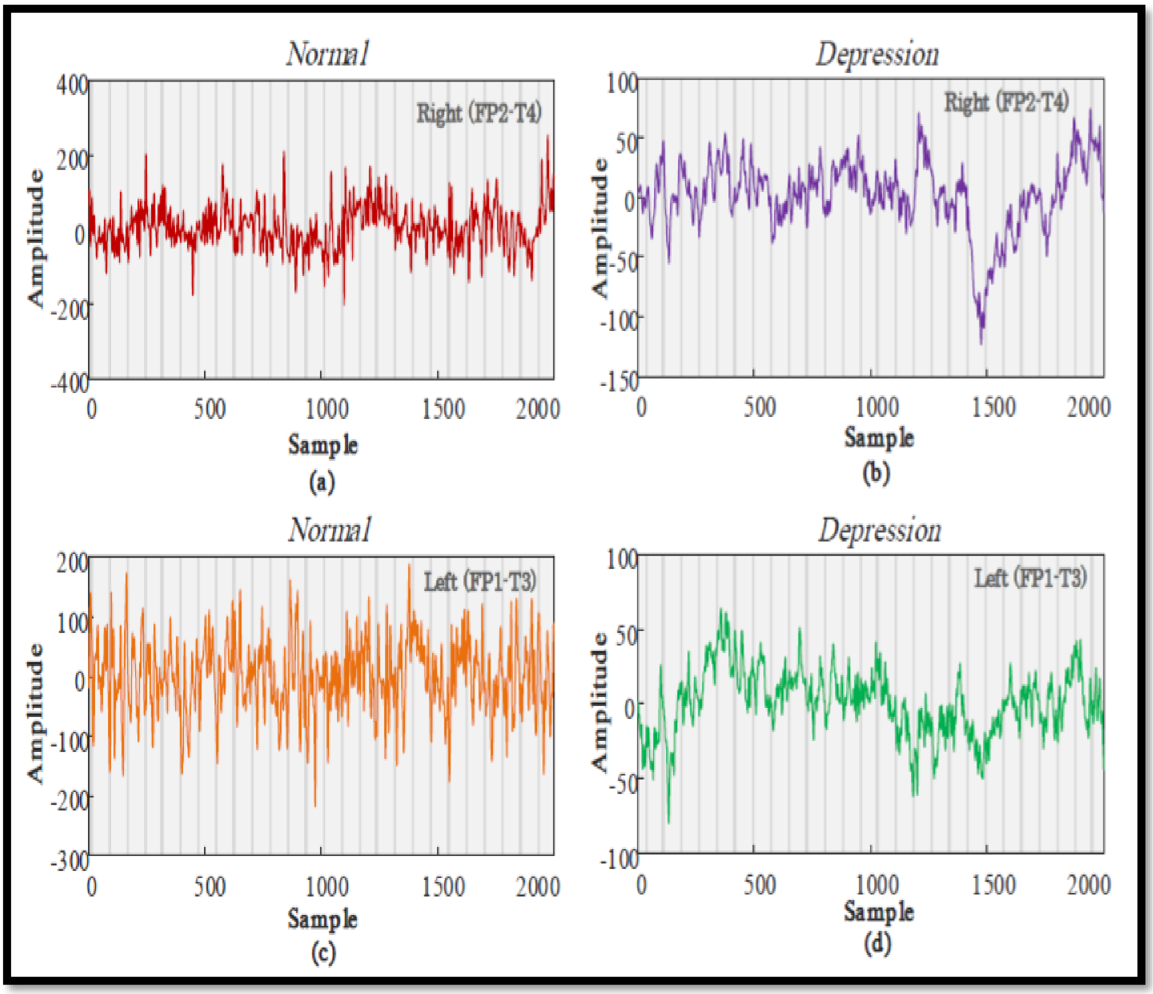

Figure 2. Sample EEG signals: a) right hemisphere normal, b) right hemisphere depression, c) left hemisphere normal and d) left hemisphere depression [20].

2.3 Details of the recent deep learning architectures used to solve the problem

A CNN has three types of layers - convolution, pooling, and fully - connected, which appear in it in this order. In the study by Acharya et al. [15], the CNN model is made up of 5 convolutional layers, 5 pooling layers, and 3 fully - connected layers shown in Figure 3. The filter is a weighted vector used for convolving the input and gets adjusted during training. The filter for the convolution and pooling operations are set at 5 and 2, respectively. Filters of 5 and 2 are selected because they provided the most accurate results. Also, the stride (number of sampling point window is shifted in each operation) is fixed at 1 and 2 for the convolution and pooling operations.

Table 1. Parameters of the CNN architecture (for both left and right hemisphere records) [15].

Layers	Type	Number of neurons	Filter size	Stride
0-1	Convolution	1996 x 5	5	1
1-2	Max-pooling	998 x 5	2	2
2-3	Convolution	994 x 5	5	1
3-4	Max-pooling	497 x 5	2	2
4-5	Convolution	493 x 10	5	1
5-6	Max-pooling	246 x 10	2	2
6-7	Convolution	242x 10	5	1
7-8	Max-pooling	121 x 10	2	2
8-9	Convolution	117x 15	5	1
9-10	Max-pooling	58 x 15	2	2
10-11	Fully-connected	80	-	-
11-12	Fully-connected	40	-	-
12-13	Fully-connected	2	-	-

The network is trained using the backpropagation algorithm [60] with a batch size (the number of training samples in an iteration) of 5. An optimization algorithm, adaptive moment estimation (Adam) [61] is adopted in this work to update the parameters of the proposed network structure. It was observed it enables the network to converge at a fast rate thereby improving the efficiency of the training process.

To avoid overfitting and improve the generalization, the dropout technique is applied to the fully - connected layers 11 and 12. During training for each mini-batch, some of the neurons from these layers are selected randomly and dropped. This forces the model to learn from a subset of input features and not the entire input features. The rate is set to 0.9. i.e. a probability of 90% a neuron will be kept and a probability of 10% that a neuron will be dropped out during the training.

The proposed CNN model is trained using 90% of the EEG dataset. The remaining 10% of the dataset is used to test the model.

In my base paper[20], the CNN learns the local features of input EEG signals (representation learning). The aim of sequential learning is to model short-term and long-term memory. Although, the short-term memory is very well modeled by standard recurrent neural networks (RNN), it cannot be effective in long-term dependencies due to vanishing gradient problems. The biggest problem encountered when training artificial neural networks with back propagation is the vanishing gradient problem, which makes it difficult to train the previous layers and learn the network[30]. To overcome this long-term dependency problem, there is a need for neural networks that can remember the input information given over a long time and decide which data to remember. The solution to the problem was LSTM. In the LSTM architecture, unlike the RNN architecture, there are special hidden units called memory cells that are used to remember the previous input for a long time. The deep learning architecture used in it is described in Figure 4.

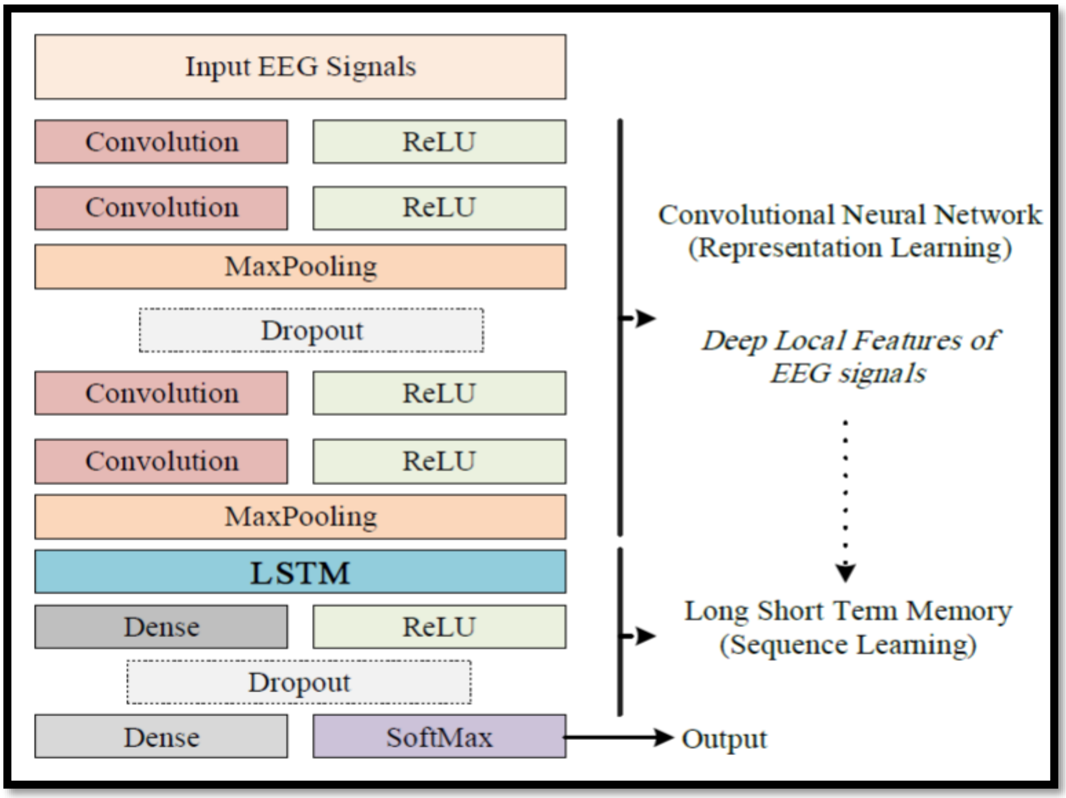

Figure 3. Overview of architecture used in my base paper[20].

In the dataset, raw signals belonging to 30 subjects are scaled to a range of [0, 1].

The training and validation datasets are used to train the deep learning model. The test set is the data which was never used by the model during training. Therefore, the test performance of the trained model can be observed more effectively through test data.

2.4 Evaluation methods used for the deep learning architectures

Both the papers discussed above in section 2.3 [15][20] used k-fold (k was equal to 10 in both papers) cross validation process for evaluating the architecture used. In this technique, the data is randomly divided into k equal parts. k-1 parts are used in the training phase of the model and the remaining part is used in the testing phase. This process repeats until all parts are evaluated in the test phase.

Acharya et al. [15] used the ten-fold cross-validation strategy on the test dataset (10% of the EEG data). The testing of the proposed model is repeated 10 times. Then, an overall performance is computed by averaging the results from all 10 iterations.

My base paper also used random splitting technique for better evaluation. In random splitting technique, the data is divided randomly into training, validation and testing. It is a widely used technique especially in deep learning studies where data is large. In this study, the dataset for each group is divided into 70% training, 15% validation and 15% test sets and this procedure is shown in Figure 5.

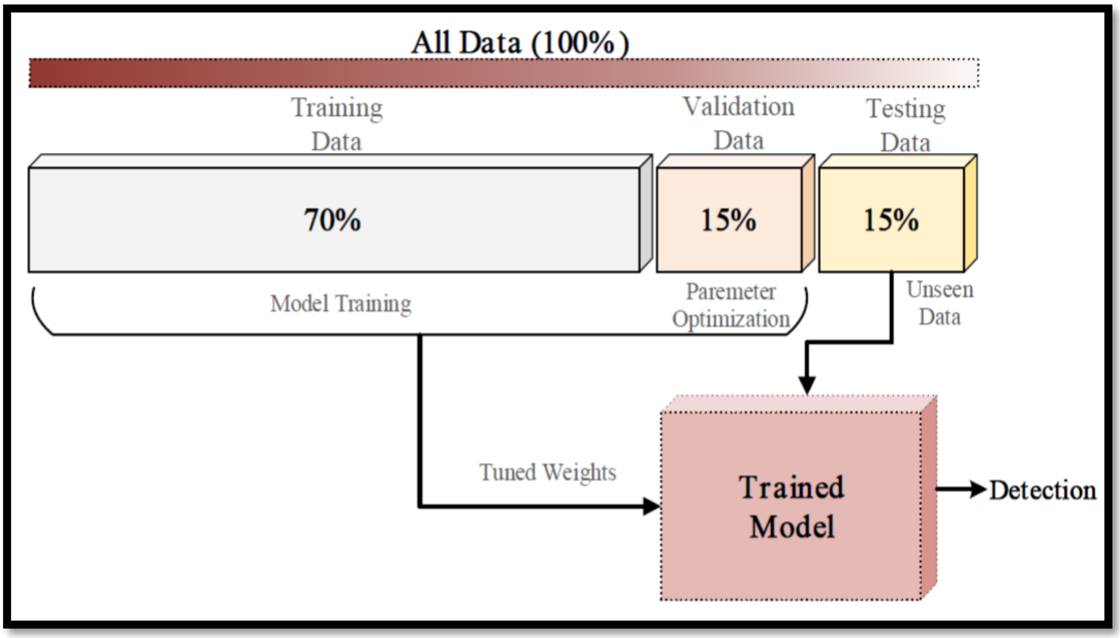

Figure 4. The way data in hand was used for the deep learning model discussed [20].

2.5 Results of evaluation

In [15], the proposed network was trained and tested on a computer with 2 Intel Xeon (2.40 GHz processor) with a 24 GB RAM. It required approximately 199.07 seconds to finish an epoch of training on the left hemisphere data and 198.68 seconds to finish one epoch of training on the right hemisphere data.

The overall result in this paper is described in Figure 6 below

Table 2. Overall performance by the architecture used in [15].

	TP	TN	FP	FN	Accuracy (%)	Sensitivity (%)	Specificity (%)
Left	1,984	2,055	104	175	93.54	91.89	95.18
Right	2,065	2,087	87	109	95.49	94.99	96.00

TP = true positive TN = true negative FP = false positive FN = false negative

In my base paper, experiment was performed on a Linux Server (Ubuntu 16.04.4) with a NVDIA GTX 1080 GPU. The model was implemented with Python using Keras deep learning libraries. The training took an average of 52 second for each epoch.

The overall result in this paper is described in Figure 7 and Figure 8 below.

Table 3. Overall performance by the architecture in testing right hemisphere (Fp2-T4) [20]

		Predicted					
	Classes	Depression	Normal	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Actual	Depression	342	5	99.12	99.70	98.55	99.70
	Normal	1	336		98.53	99.70	98.55

Table 4. Overall performance by the architecture in testing left hemisphere (Fp1-T3) [20].

		Predicted					
	Classes	Depression	Normal	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Actual	Depression	327	10	97.66	98.19	97.03	98.27
	Normal	6	341		97.15	98.27	97.03

2.5 Impact of the studies

Figure 9 below shows how depression assessment has been an increasingly important research domain

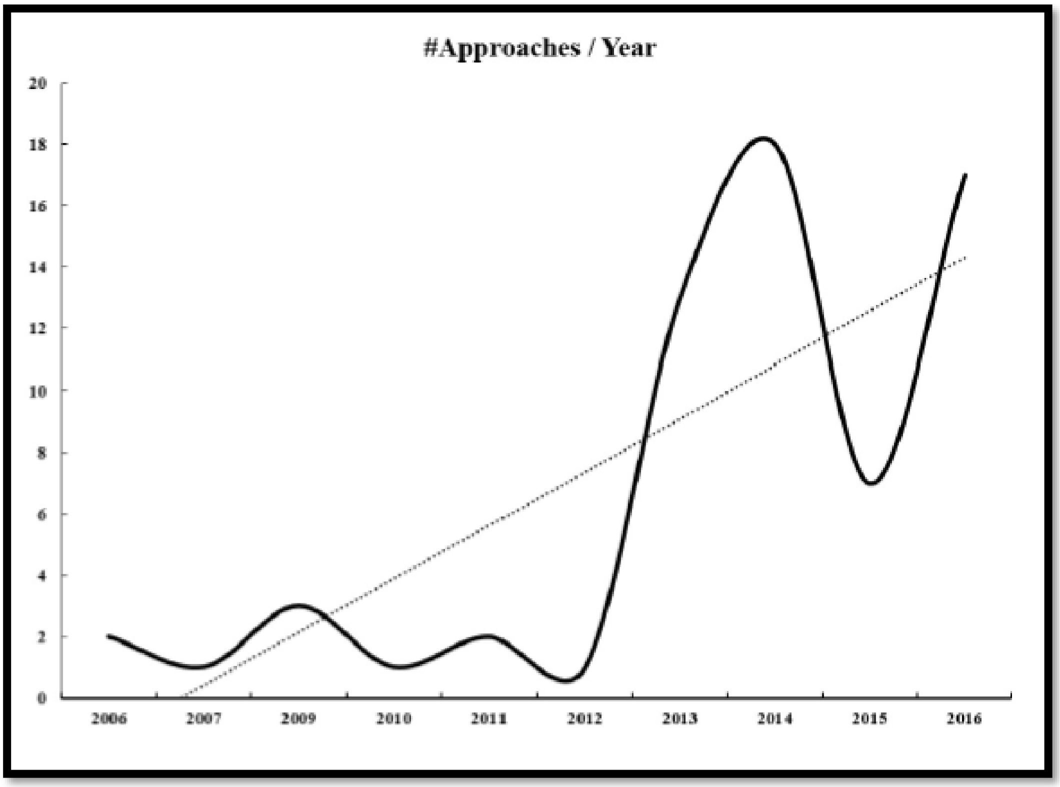

Figure 5. Number of studies in the field of depression assessment by year of publication [31]

In spite of the saturation achieved in this field in the number of studies done on it, the reviewed studies have come up with commendable results and have had a great impact both in research domain and commercially.

In Acharya et al. [15], he proposed CNN model can be implemented in a clinical setting to be used as a tool for objective diagnosis of depression using EEG signals. In the current clinical practice, the diagnosis of depression is based on questionnaires and the physical emotions displaced by the patients. Furthermore, the proposed diagnosis system can be installed as a web-based application to be used by non-specialist clinicians remotely. Once the EEG signals are obtained from the patients, they will be sent to the servers (located in the hospitals) in the cloud where the proposed CNN model can be used to make the diagnosis. The diagnosis can be sent immediately to the clinic.

Our right hemisphere is higher than the left as reported by Acharya et al. [15]. This is because the activation of frontal cortex of right hemisphere is higher during depression than left hemisphere. Hence, right hemisphere EEG will contribute more than the left hemisphere.

The CNN – LSTM model used in my base paper is accurate and robust in detecting the depression using EEG signals. The proposed model detects unknown EEG signals fast and accurately. Therefore, the proposed model is useful and can be easily implemented for clinical applications.

Based on the results obtained by Acharya et al. [15] using the proposed model with a limited number of EEG data, it can be concluded that the CNN model can be used for computer-assisted diagnosis of depression rather reliably. Moreover, this proposed algorithm can serve as a second-opinion to validate the diagnosis made by a clinician.

In my base paper, a novel depression detection system based on EEG signals was presented. This model consists of a combination of LSTM network that is effective in learning long-term dependencies present in the CNN architecture, which is powerful in extracting the local features

But, there are still some research gaps that need to be filled. They are –

- Dataset can be made more robust by including EEG signals of people of different ethnicity, which were not a part of the dataset used.
- Only one feature (EEG signals) are used for our purpose. Multiple features can be combined to produce more reliable results.
- There is no gender based classification done on the data, which is supported by many of the approaches to perform better.

3. Details of design/technology

The algorithm used is a hybrid CNN-LSTM deep learning model.

3.1 CNN

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

A covnets is a sequence of layers, and every layer transforms one volume to another through differentiable function. Types of layers: Let’s take an example by running a covnets on of image of dimension 32 x 32 x 3.

Input Layer: This layer holds the raw input of image with width 32, height 32 and depth 3.

Convolution Layer: This layer computes the output volume by computing dot product between all filters and image patch. Suppose we use total 12 filters for this layer we’ll get output volume of dimension 32 x 32 x 12.

Activation Function Layer: This layer will apply element wise activation function to the output of convolution layer. Some common activation functions are RELU: max(0, x), Sigmoid: 1/(1+e^-x), Tanh, Leaky RELU, etc. The volume remains unchanged hence output volume will have dimension 32 x 32 x 12.

Pool Layer: This layer is periodically inserted in the covnets and its main function is to reduce the size of volume which makes the computation fast reduces memory and also prevents from overfitting. Two common types of pooling layers are max pooling and average pooling. If we use a max pool with 2 x 2 filters and stride 2, the resultant volume will be of dimension 16x16x12.

Fully-Connected Layer**:** This layer is regular neural network layer which takes input from the previous layer and computes the class scores and outputs the 1-D array of size equal to the number of classes [32].

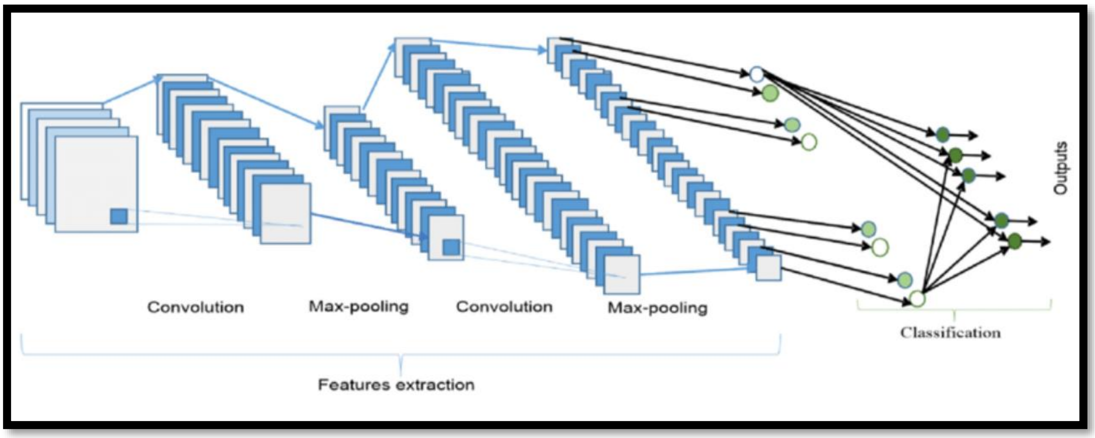

Figure 6. Architecture of CNN [33]

3.2 LSTM

Structure Of LSTM:

LSTM has a chain structure that contains four neural networks and different memory blocks called cells.

Information is retained by the cells and the memory manipulations are done by the gates**.** There are three gates –

Forget Gate**:** The information that no longer useful in the cell state is removed with the forget gate. Two inputs *x_t* (input at the particular time) and *h_t-1* (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias. The resultant is passed through an activation function which gives a binary output. If for a particular cell state the output is 0, the piece of information is forgotten and for the output 1, the information is retained for the future use.

Input gate**:** Addition of useful information to the cell state is done by input gate. First, the information is regulated using the sigmoid function and filter the values to be remembered similar to the forget gate using inputs *h_t-1* and *x_t*. Then, a vector is created using *tanh* function that gives output from -1 to +1, which contains all the possible values from h_t-1 and *x_t*. Atlast, the values of the vector and the regulated values are multiplied to obtain the useful information

Output gate**:** The task of extracting useful information from the current cell state to be presented as an output is done by output gate. First, a vector is generated by applying tanh function on the cell. Then, the information is regulated using the sigmoid function and filter the values to be remembered using inputs *h_t-1* and *x_t*. Atlast, the values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell [34].

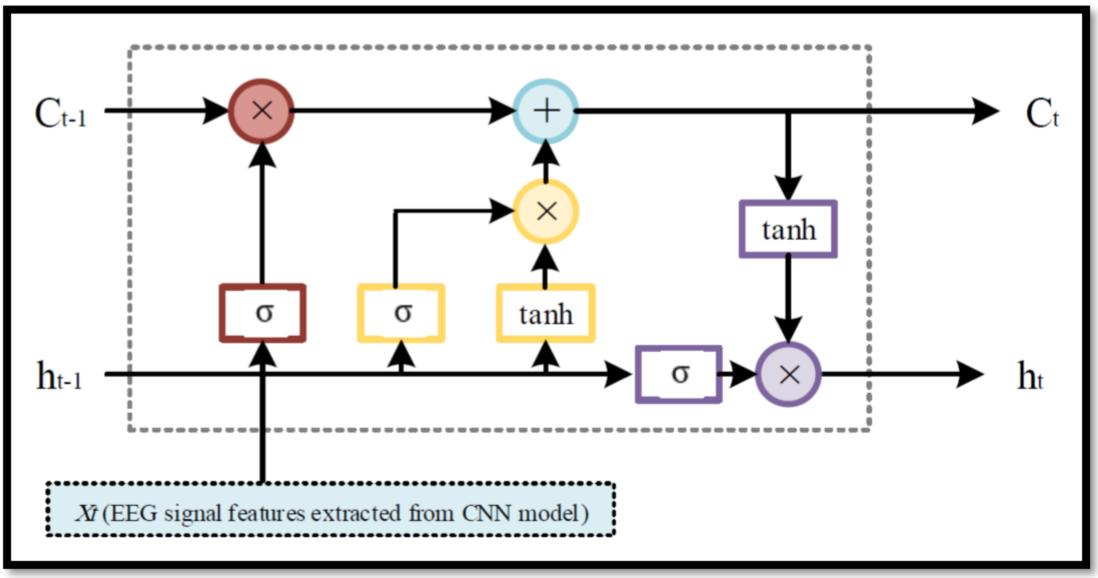

Figure 7. Architecture of LSTM [20]

3.3 CNN-LSTM hybrid

The CNN LSTM model is specifically designed for sequence prediction problems with spatial inputs, like images or videos. This architecture involves using Convolutional Neural Network (CNN) layers for feature extraction on input data combined with LSTMs to perform sequence prediction on the feature vectors. In short, CNN LSTMs are a class of models that are both spatially and temporally deep and sit at the boundary of Computer Vision and Natural Language Processing. These models have enormous potential and are being increasingly used for many sophisticated tasks such as text classification, video conversion, and so on [35].

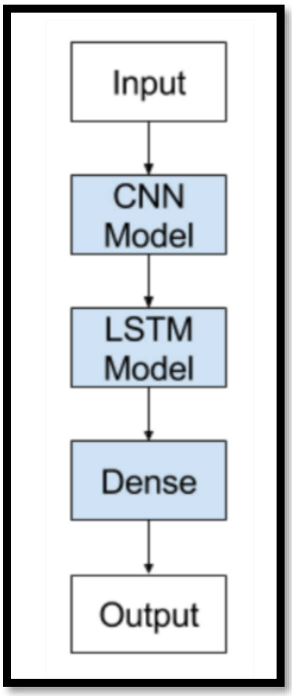

Figure 8. Generic architecture of CNN-LSTM model [35].

CONCLUSION

Thus, this research work gave a review of the various studies done on depression detection. It focused on areas like EEG, deep learning, depression and emotion recognition. It showed and explained detailed approaches followed by different papers for achieving the intended result. The proposed CNN – LSTM hybrid model did not require the semi-manually-selected extraction and selection of features for classification. Rather, the model could self-learn and picked up distinct features during the training of the algorithm. The algorithm attained a high accuracy of 97.66% and 99.12% using EEG signals from the left and right hemisphere, respectively. Based on the results obtained with a limited number of EEG data, it can be concluded that the CNN – LSTM model can be used for computer-assisted diagnosis of depression rather reliably. Moreover, this proposed algorithm can serve as a second opinion to validate the diagnosis made by a clinician.

There is a good future scope of research in this topic.

Some of the points that can be considered are –

- More robust models can be developed using huge database obtained from diverse races. The developed model can be used to detect the early stage of depression and other neurological disorders using EEG signals.
- Prognosis of depression is an area in research which is not very much explored and has a lot of scope for development.
- Wireless EEG caps have also come in the market. They can help a lot as until now we were restricted to settle in a place to record our EEG signals, which would not be required now.
- fMRIs and MEG, along with EEG can also be used to detect depression for more reliable results.

REFERENCES

[1]Who.int. 2020. [online] Available at: <https://www.who.int/mental_health/management/depression/wfmh_paper_depression_wmhd_2012.pdf> [Accessed 13 May 2020].

[2] (2015, Feb.)World Health Organization. [Online]. Available: http: //www.who.int/mental health/management/depression/en/

[3] Li, Y., Hu, B., Zheng, X. and Li, X. EEG-Based Mild Depressive Detection Using Differential Evolution. *IEEE Access*, 7, pp.7814-7822, 2019.

[4] Günther, J., Pilarski, P., Helfrich, G., Shen, H. and Diepold, K. First Steps Towards an Intelligent Laser Welding Architecture Using Deep Neural Networks and Reinforcement Learning. *Procedia Technology*, 15, pp.474-483, 2014.

[5] Mirowski, P., Madhavan, D., LeCun, Y. and Kuzniecky, R. Classification of patterns of EEG synchronization for seizure prediction. *Clinical Neurophysiology*, 120(11), pp.1927-1940, 2009.

[6] Acharya, U., Oh, S., Hagiwara, Y., Tan, J. and Adeli, H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. *Computers in Biology and Medicine*, 100, pp.270-278, 2018.

[7] Wulsin, D., Gupta, J., Mani, R., Blanco, J. and Litt, B. Modeling electroencephalography waveforms with semi-supervised deep belief nets: fast classification and anomaly measurement. *Journal of Neural Engineering*, 8(3), p.036015, 2011.

[8] Yıldırım, Ö., Baloglu, U. and Acharya, U. A deep convolutional neural network model for automated identification of abnormal EEG signals. *Neural Computing and Applications*, 2018.

[9] Ding, S., Zhang, N., Xu, X., Guo, L. and Zhang, J. Deep Extreme Learning Machine and Its Application in EEG Classification. *Mathematical Problems in Engineering*, 2015, pp.1-11, 2015.

[10] Jirayucharoensak, S., Pan-Ngum, S. and Israsena, P. EEG-Based Emotion Recognition Using Deep Learning Network with Principal Component Based Covariate Shift Adaptation. *The Scientific World Journal*, 2014, pp.1-10, 2014.

[11] Supratak, A., Dong, H., Wu, C. and Guo, Y. DeepSleepNet: A Model for Automatic Sleep Stage Scoring Based on Raw Single-Channel EEG. *IEEE*

Transactions on Neural Systems and Rehabilitation Engineering, 25(11), pp.1998-2008, 2017.

[12] Oh, S., Ng, E., Tan, R. and Acharya, U. Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats. *Computers in Biology and Medicine*, 102, pp.278-287, 2018.

[13] Yildirim, Ö. A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification. *Computers in Biology and Medicine*, 96, pp.189-202, 2018.

[14] Yıldırım, Ö., Pławiak, P., Tan, R. and Acharya, U. Arrhythmia detection using deep convolutional neural network with long duration ECG signals. *Computers in Biology and Medicine*, 102, pp.411-420, 2018.

[15] Acharya, U., Oh, S., Hagiwara, Y., Tan, J., Adeli, H. and Subha, D. Automated EEG-based screening of depression using deep convolutional neural network. *Computer Methods and Programs in Biomedicine,* 161, pp.103-113, 2018.

[16] U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan, and C. K. Chua, "Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network," *Knowledge-Based Systems*, vol. 132, pp. 62–71, 2017.

[17] U. R. Acharya, H. Fujita, S. L. Oh, U. Raghavendra, J. H. Tan, M. Adam, A. Gertych, and Y. Hagiwara, "Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network," *Future Generation Computer Systems*, vol. 79, pp. 952–959, 2018.

[18] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals," *Information Sciences*, vol. 415-416, pp. 190–198, 2017.

[19] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," *Information Sciences*, vol. 405, pp. 81–90, 2017.

[20] Ay, B., Yildirim, O., Talo, M., Baloglu, U., Aydin, G., Puthankattil, S. and Acharya, U. Automated Depression Detection Using Deep Representation and Sequence Learning with EEG Signals. *Journal of Medical Systems*, 43(7), 2019.

[21] M. Ahmadlou, H. Adeli, and A. Adeli, “Fractality analysis of frontal brain in major depressive disorder,” *International Journal of Psychophysiology*, vol. 85, no. 2, pp. 206–211, 2012.

[22] J. Kuncewicz and B. Ohtani, “Correction: Rhodium-doped titania photocatalysts with two-step bandgap excitation by visible light—influence of the dopant concentration on photosensitization efficiency,” *RSC Advances*, vol. 6, no. 94, pp. 91658–91658, 2016.

[23] O. Faust, P. C. A. Ang, S. D. Puthankattil, and P. K. Joseph, “Depression Diagnosis Support System Based On Eeg Signal Entropies,” *Journal of Mechanics in Medicine and Biology*, vol. 14, no. 03, p. 1450035, 2014.

[24] U. R. Acharya, V. K. Sudarshan, H. Adeli, J. Santhosh, J. E. Koh, S. D. Puthankatti, and A. Adeli, “A Novel Depression Diagnosis Index Using Nonlinear Features in EEG Signals,” *European Neurology*, vol. 74, no. 1-2, pp. 79–83, 2015.

[25] W. Mumtaz, L. Xia, S. S. A. Ali, M. A. M. Yasin, M. Hussain, and A. S. Malik, “Electroencephalogram (EEG)-based computer-aided technique to diagnose major depressive disorder (MDD),” *Biomedical Signal Processing and Control*, vol. 31, pp. 108–115, 2017.

[26] G. M. Bairy, O. S. Lih, Y. Hagiwara, S. D. Puthankattil, O. Faust, U. C. Niranjan, and U. R. Acharya, “Automated Diagnosis of Depression Electroencephalograph Signals Using Linear Prediction Coding and Higher Order Spectra Features,” *Journal of Medical Imaging and Health Informatics*, vol. 7, no. 8, pp. 1857–1862, Jan. 2017.

[27] S.-C. Liao, C.-T. Wu, H.-C. Huang, W.-T. Cheng, and Y.-H. Liu, “Major Depression Detection from EEG Signals Using Kernel Eigen-Filter-Bank Common Spatial Patterns,” *Sensors*, vol. 17, no. 6, p. 1385, 2017.

[28] M. Bachmann, L. Päeske, K. Kalev, K. Aarma, A. Lehtmets, P. Ööpik, J. Lass, and H. Hinrikus, “Methods for classifying depression in single channel EEG using linear and nonlinear signal analysis,” *Computer Methods and Programs in Biomedicine*, vol. 155, pp. 11–17, 2018.

[29] M. Ahmadlou, H. Adeli, and A. Adeli, “Fractality analysis of frontal brain in major depressive disorder,” *International Journal of Psychophysiology*, vol. 85, no. 2, pp. 206–211, 2012.

[30] Y. Bengio, P. Simard, and P. Frasconi, “Learning long-term dependencies with gradient descent is difficult,” *IEEE Transactions on Neural Networks*, vol. 5, no. 2, pp. 157–166, 1994.

[31] A. Pampouchidou, P. G. Simos, K. Marias, F. Meriaudeau, F. Yang, M. Pediaditis, and M. Tsiknakis, “Automatic Assessment of Depression Based on Visual Cues: A Systematic Review,” *IEEE Transactions on Affective Computing*, vol. 10, no. 4, pp. 445–470, Jan. 2019.

[32] S. Saha, “A Comprehensive Guide to Convolutional Neural Networks-the ELI5 way,” *Medium*, 17-Dec-2018. [Online]. Available: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53. [Accessed: 21-May-2020].

[33] M. Z. Alom, T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, M. Hasan, B. C. V. Essen, A. A. S. Awwal, and V. K. Asari, “A State-of-the-Art Survey on Deep Learning Theory and Architectures,” *Electronics*, vol. 8, no. 3, p. 292, May 2019.

[34] aakarsha_chughCheck out this Author's contributed articles., aakarsha_chugh, and Check out this Author's contributed articles., “Deep Learning: Introduction to Long Short Term Memory,” *GeeksforGeeks*, 17-Jan-2019. [Online]. Available: https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/. [Accessed: 21-May-2020].

[35] S. Pardeshi, “CNN-LSTM Architecture and Image Captioning,” *Medium*, 26-Nov-2019. [Online]. Available: https://medium.com/analytics-vidhya/cnn-lstm-architecture-and-image-captioning-2351fc18e8d7. [Accessed: 21-May-2020].

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Automated Depression Detection Using Deep Representation and Sequence Learning with EEG Signals

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Abstract

Depression affects large number of people across the world today and it is considered as the global problem. It is a mood disorder which can be detected using electroencephalogram (EEG) signals. The manual detection depression by analyzing the EEG signals requires lot of experience, tedious and time consuming. Hence, a fully automated depression diagnosis system developed using EEG signals will help the clinicians. Therefore, we propose a deep hybrid model developed using of convolutional neural network (CNN) and long-short term memory (LSTM) architectures to detect depression with EEG signals. In the deep model, temporal properties of the signals are learned with CNN layers and the sequence learning process is provided through the LSTM layers. In this work, we have used EEG signals obtained from left and right hemispheres of the brain. Our work has provided 99.12% and 97.66% classification accuracies for the right and left hemisphere EEG signals respectively. Hence, we can conclude that the developed CNN-LSTM model is accurate and fast in detecting the depression using EEG signals. It can be employed in psychiatry wards of the hospitals to detect the depression using EEG signals accurately and aid the psychiatrists.

Keywords: Depression detection, deep learning, CNN-LSTM, hybrid deep models, EEG signals.

1. Introduction

In recent years, deep learning architectures have achieved significant success in the areas of computer vision and natural language processing [1-4]. However, very little progress has been made in neuroscience and biomedical domains due to the availability of few data [5]. With rapid enhancement of available neurological data, there has been a significant improvement in the

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