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A Deep Learning Technique for Detection of Depressionusing EEG Signal Dataset

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Abstract- Electroencephalogram (EEG) signal-based emotion recognition has attracted wide interests in recent years and has been broadly adopted in medical, affective computing, and other relevant fields. Depression has become a leading mental disorder worldwide. Evidence has shown that subjects with depression exhibit different spatial responses in neurophysiologic signals from the healthy controls when they are exposed to positive and negative. Depression is a common reason for an increase in suicide cases worldwide. EEG plays an important role in E-healthcare systems, especially in the mental healthcare area, where constant and unobtrusive monitoring is desirable. EEG signals can reflect activities of the human brain and represent different emotional states. Mental stress has become a social issue and could become a cause of functional disability during routine work. This paper proposed an adaptive approach based on deep learning for detecting depression using EEG. The algorithm first extracts features from EEG signals and classifies emotions using machine and deep learning techniques, in which different parts of a trial are used to train the proposed model and assess its impact on emotion recognition results.

Keywords- EEG, Emotion, Stress, Deep Learning, Machine Learning, E-healthcare.

I. INTRODUCTION

WHO estimates that the burden of mental health problems in India is 2443 disability-adjusted life years (DALYs) per 100 00 population; the age-adjusted suicide rate per 100 000 population is 21.1. The economic loss due to mental health conditions, between 2012-2030, is estimated at USD 1.03 trillion.

Stress is commonly recognized as a state in which an individual is expected to perform too much under sheer pressure and in which he/she can only marginally contend with the demands. These demands can be psychological or social. It is known that psychosocial stress exists in daily life, which has resulted in poor quality of life by affecting people's emotional behavior, job performance, mental and physical health [1]. Psychosocial stress is a leading cause of several physiological disorders. For example, it increases the likelihood of depression, stroke, heart attack and cardiacarrest [4]. Electroencephalography (EEG) is an efficient modality which helps to acquire brain signals corresponds to various states from the scalp surface area. These signals are generally categorized as delta, theta, alpha, beta and gamma based on signal frequencies ranges from 0.1 Hz to more than100 Hz. It is a test that detects electrical activity in the brain using small, metal discs (electrodes) attached to the scalp. Routinely, EEG is used in clinical circumstances to determine changes in brain activity that might be useful in diagnosing brain disorders, especially epilepsy or another seizure disorder.

The types of EEG waves [2,3] are identified according to their frequency range – delta: below 3.5 Hz (0.1–3.5 Hz), theta: 4–7.5 Hz, alpha: 8–13 Hz, beta: 14–40 Hz, and gamma: above 40 Hz. The EEG may show unusual electrical discharge when some abnormality occurs in the brain.

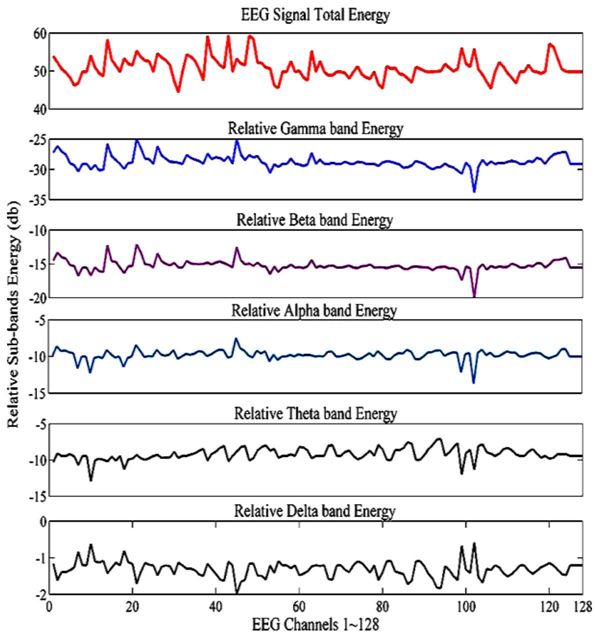


Fig 1. EEG Signal. [1]

Stress is your body's reaction to a challenge or demand. In short bursts, stress can be positive, such as when it helps you avoid danger or meet a deadline. EEG nonlinear dynamics features and frontal asymmetry of theta, alpha, and beta bands have been selected as biological indicators for chronic stress, showing relative greater right anterior EEG data activity in stressful individuals.

PREVALENCE PER 100,000

DEPRESSIVE DISORDERS		CONDUCT DISORDERS	
Tamil Nadu	4,796	Jharkhand	983
Andhra Pradesh	4,563	Bihar	974
Telangana	4,356	Meghalaya	961
Odisha	4,159	Uttar Pradesh	927
Kerala	3,897	Nagaland	924

ANXIETY DISORDERS		IDIOPATHIC DEVELOPMENTAL INTELLECTUAL DISABILITY	
Kerala	4,035	Bihar	6,339
Manipur	3,760	Uttar Pradesh	5,503
West Bengal	3,480	Madhya Pradesh	5,216
Himachal Pradesh	3,471	Assam	5,121
Andhra Pradesh	3,462	Jharkhand	4,940

Fig 2. Mental health data (Indian health report).

Facial expression recognition (FER) is currently one of the most active research topics due to its wide range of applications in the human-computer interaction field. An important part of the recent success of automatic FER was achieved thanks to the emergence of deep learning approaches. However, training deep networks for FER is still a very challenging task, since most of the available FER data sets are relatively small. Although transfer learning can partially alleviate the issue, the performance of deep models is still below of its full potential as deep features may contain redundant information from the pre-trained domain.

Emotions often facilitate interactions among human beings, but the big variation of human emotional states make a negative effect on the reliable emotion recognition [6]. Multimodal emotion recognition is an emerging interdisciplinary field of research in the area of affective computing and sentiment analysis. It aims at exploiting the information carried by signals of different nature to make emotion recognition systems more accurate. This is achieved by employing a powerful multimodal fusion method [8]. The main motivation of this work is to make a optimize model of prediction of the depression using EEG signal.

This paper is organization into 5 sections; the 1st section describes the overview or introduction of the concept. The 2nd section presents the literature review or previous work done in this field. The 3rd section shows the proposed methodology and the steps involving it. The 4th section presents the simulation work and results analysis. The 5th section presents the conclusion and future scope of theresearch.

II. LITERATURE REVIEW

A. Seal et al.,[1] suggest that CNN trained on recordwise split data gets overtrained on EEG data with a small numberof subjects. The performance of DeprNet is remarkable compared with the other eight baseline models. Furthermore, on visualizing the last CNN layer, it is found that the values of right electrodes are prominent for depressed subjects, whereas, for normal subjects, the values of left electrodes are prominent.

S. Sun et al.,[2] presents combined multi-types features (All: L+ NL + PLI + NM) outperformed single-type features for classifying depression. Analyzing the optimal features set we found that compared to other type features, PLI occupied the largest proportion of which functional connections in intra-hemisphere were much more than that of in inter-hemisphere. In addition, when using PLI features and all features, high frequency bands (alpha, beta) could achieve obviously higher classification accuracy than low frequency bands (delta, theta). Parietal-occipital lobe in the high frequency bands had great effect in depression identification.

W. Zheng et al.,[3] investigate stable patterns of electroencephalogram (EEG) over time for emotion recognition using a machine learning approach. Up to now, various findings of activated patterns associated with different emotions have been reported. However, their stability over time has not been fully investigated yet. In this paper, we focus on identifying EEG stability in emotion recognition.

W. Fang et al.,[4] presents the operation was validated using ADVANTEST V93000 PS1600, and the training process and real-time classification processing time took 0.12495 ms and 0.02634 ms for each EEG image, respectively. The proposed EEG-based real-time emotion recognition system included a dry electrode EEG headset, feature extraction processor, CNN chip platform, and graphical user interface, and the execution time costed 450 ms for each emotional state recognition.

P. J. Bota et al., [5] shows the affective computing is a multidisciplinary field of research spanning the areas of computer science, psychology, and cognitive science. Potential applications include automated driver assistance, healthcare, human-computer interaction, entertainment, marketing, teaching and many others. Thus, quickly, the field acquired high interest, with an enormous growth of the number of s published on the topic since its inception.

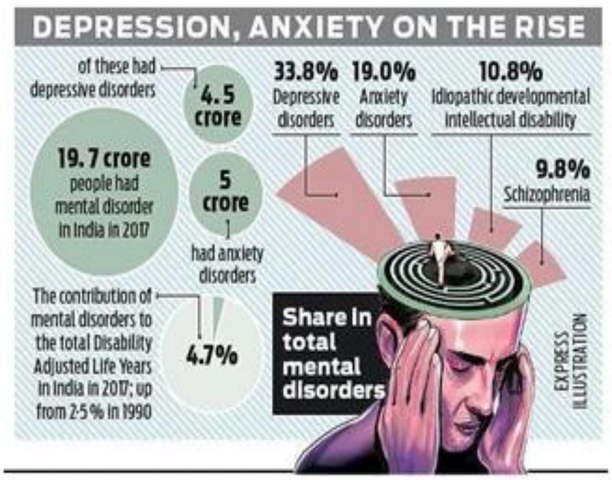


Fig 3. Depression statics.

S. Wang et al.,[6] the proposed method for emotion recognition is verified on the common facial expression datasets, the Extended Cohn-Kanade (CK+) dataset and the Japanese female facial expression (JAFFE). The results are satisfactory, which shows cloud model is potentially useful in pattern recognition and machines learning.

R. A. Khalil et al.,[7] presents the emotion recognition from speech signals is an important but challenging component of Human-Computer Interaction (HCI). Deep Learning techniques have been recently proposed as an alternative to traditional techniques in SER. This presents an overview of Deep Learning techniques and discusses some recent literature where these methods are utilized for speech-based emotion recognition.

S. Nemati et al.,[8] presents a hybrid multimodal data fusion method is proposed in which the audio and visual modalities are fused using a latent space linear map and then, their projected features into the cross-modal space are fused with the textual modality using a Dempster-Shafer (DS) theory-based evidential fusion method. The evaluation of the proposed method on the videos of the DEAP dataset shows its superiority over both decision-level and non-latent space fusion methods.

H. Zhang et al.,[9] presents the complex process of explicit feature extraction in traditional facial expression recognition, a face expression recognition method based on a convolutional neural network (CNN) and an image edge detection is proposed. Firstly, the facial expression image is normalized, and the edge of each layer of the image is extracted in the convolution process. The extracted edge information is superimposed on each feature image to preserve the edge structure information of the texture image.

P. M. Ferreira et al.,[10] propose a novel end-to-end neural network architecture along with a well-designed loss function based on the strong prior knowledge that facial expressions are the result of the motions of some facial muscles and components. The loss function is defined to regularize the entire learning process so that the proposed neural network is able to explicitly learn expression-specific features. Experimental results demonstrate the effectiveness of the proposed model in both lab-controlled and wild environments.

Y. Yang et al.,[11] proposes a hierarchical network structure with sub network nodes to discriminate three human emotions: 1) positive; 2) neutral; and 3) negative. Each sub network node embedded in the network that are formed by hundreds of hidden nodes, could be functional as anindependent hidden layer for feature representation. The top layer of the hierarchical network, like the mammal cortex in the brain, combine such features generated from sub network nodes, but simultaneously, recast these features into a mapping space so that the network can be performed to produce more reliable cognition.

S. Zhang et al.,[12] proposes to bridge the emotional gap by using a hybrid deep model, which first produces audio- visual segment features with Convolutional Neural Networks (CNNs) and 3D-CNN, then fuses audio-visual segment features in a Deep Belief Networks (DBNs). The proposed method is trained in two stages. First, CNN and 3D-CNN models pre-trained on corresponding large-scale image and video classification tasks are fine-tuned on emotion recognition tasks to learn audio and visual segment features, respectively. Second, the outputs of CNN and 3D- CNN models are combined into a fusion network built witha DBN model.

III. METHODOLOGY

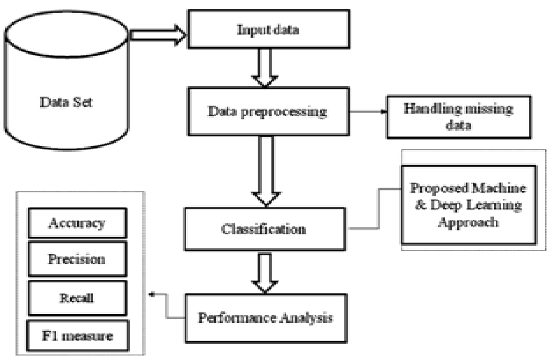


Fig 4. Flow Chart.

Firstly, download the EEG dataset from kaggle website, which is a large dataset provider and machine learning repository Provider Company for research. The EEG dataset have 2133 rows and CTA columns. The features of the dataset shows like # mean_0_a

mean_1_a mean_2_a mean_3_a
mean_4_a mean_d_0_a mean_d_1_a
mean_d_2_a mean_d_3_a etc

The sample dataset of selected dataset is taken formfft_0_b':'fft_749_b.

- Now apply the preprocessing of the data, here handingthe missing data, removal null values.
- Now extract the data features and evaluate in dependent and independent variable.
- Now apply the classification method based on the machine learning (KNN) and deep learning (LSTM) approach.

1. KNN:

KNN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories. It classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.

2. RNN- LSTM:

- Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning.
- It can process not only single data points (such as EEG signal o EEG images), but also entire sequences of data.
- The Long Short-Term Memory (LSTM) cell can process data sequentially and keep its hidden state through time.
- A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed or undirected graph along a temporal sequence.This allows it to exhibit temporal dynamic behavior.

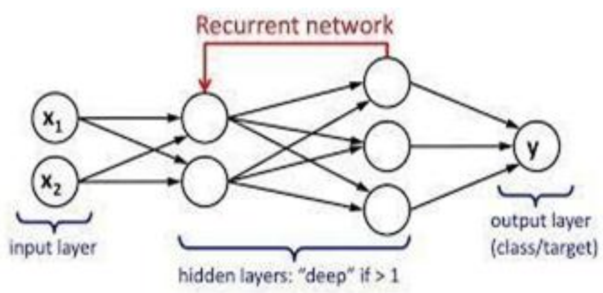


Fig 5. Basic RNN Architecture.

3. Recurrent Layer:

The Independently recurrent neural network addresses the gradient vanishing and exploding problems in the traditional fully connected RNN. Each neuron in one layer only receives its own past state as context information (instead of full connectivity to all other neurons in this layer) and thus neurons are independent of each other's history. The gradient back propagation can be regulated to avoid gradient vanishing and exploding in order to keep long or short-term memory. The cross-neuron information is explored in the next layers. IndRNN can be robustly trained with the non-saturated nonlinear functions such as ReLU. Using skip connections, deep networks can be trained.

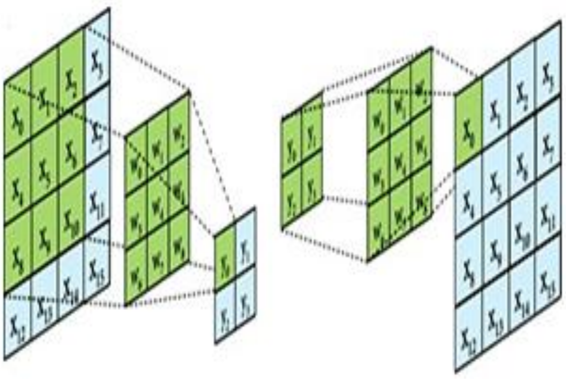


Fig 6. (a) Recurrent operation (b) Equivalent transposed recurrent operation.

Mathematically the Recurrent operation can be expressed as-

$$g(x,y)=w*f(x,y)$$

Where

g(x,y) =Image after filtering,

w = Filter kernel,

f(x,y)= Input image

Initially the computer vision experts were designing the filters which were applied to the images for the analysis of various features of the image. Now days during the training process the weights i.e the values in the filter are updated automatically, this is the innovation of using the recurrent layer in the neural network. During the training process the network learns which features it needs to be extracted from the image.

- Now generate confusion matrix and show all predicted class like true positive, false positive, true negative and false negative.
- Now calculate the performance parameters by using the standard formulas in terms of the precision, recall, F_measure, accuracy and error rate.
- Precision is a measure of the accuracy, provided that a class label has been predicted. It is defined by:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

- Recall is the true positive rate:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

- F1 Score is needed to a balance between Precision and Recall

$$\text{F1\_Score} = \frac{2\text{x (Precision x Recall)}}{\text{Precision} + \text{Recall}}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

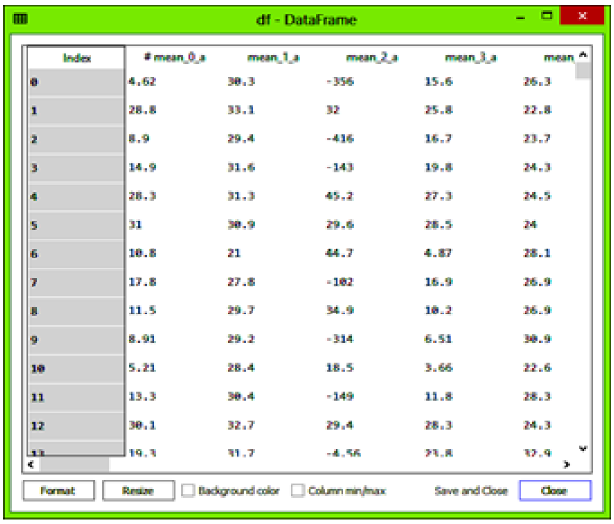
Classification Error = 100- Accuracy

IV. SIMULATION RESULTS

The simulation is performed using python spyder software.

Table 2. Specification of the system.

Sr. No	Parameter	Value
1	Windows	7
2	RAM	8GB
3	CPU	Intel
4	Processor	Core i3
5	GraphicsMemory	2 GB
6	Software	Python
7	IDE	Sypder
8	Version	3.7



df - DataFrame

Index	# mean_0_a	mean_1_a	mean_2_a	mean_3_a	mean
0	4.62	30.3	-356	15.6	26.3
1	28.8	33.1	32	25.8	22.8
2	8.9	29.4	-416	16.7	23.7
3	14.9	31.6	-143	19.8	24.3
4	28.3	31.3	45.2	27.3	24.5
5	31	30.9	29.6	28.5	24
6	10.8	21	44.7	4.87	28.1
7	17.8	27.8	-102	16.9	26.9
8	11.5	29.7	34.9	10.2	26.9
9	8.91	29.2	-314	6.51	30.9
10	5.21	28.4	18.5	3.66	22.6
11	13.3	30.4	-149	11.8	28.3
12	30.1	32.7	29.4	28.3	24.3
13	19.3	31.7	-4.56	21.8	32.9

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Fig 7. Dataset.

Figure 7 is showing the dataset of this research. The dataset is taken from the kaggle website.

Fig 8. Train dataset.

Figure 8 is showing the training dataset which is used to train the model.

Fig 9. Test dataset

Figure 9 is showing the test dataset which is used to test the proposed model.

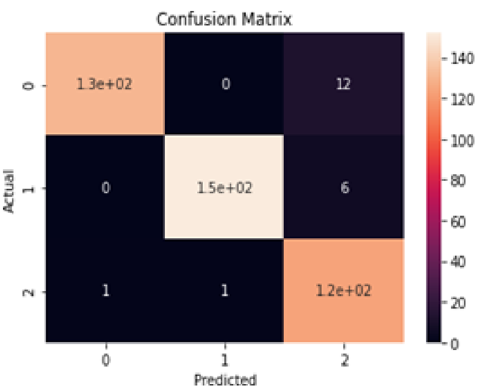

Fig 10. Confusion matrix.

Figure 10 is showing the confusion matrix of the proposed model.

Table 3. Simulation Results of KNN.

Sr. No.	Parameters	Proposed Approach
1	Accuracy	94.14%
2	Classification error	5.86 %
3	Precision	97%
4	Recall	94%
5	F-measure	95%

Table 4. Simulation Results of LSTM.

Sr. No.	Parameters	Proposed Approach
1	Accuracy	96.48 %
2	Classification error	3.52 %
3	Precision	99%
4	Recall	94%
5	F-measure	97%

Table 5. Result Comparison.

Sr. No.	Parameters	Accuracy	Classification error
1	Work [1]	91%	9 %
2	Work [3]	91.07%	8.93%
3	Work [9]	88.56%	11.44%
4	Proposed Work	96.48 %	3.52 %

V. CONCLUSION

This research proposed the machine learning and deep learning technique to identify the prediction from given dataset. The python spyder ISE 14.7 software is used to simulate the work. Machine learning KNN classifier approach is achieved 94% accuracy while deep learning LSTM classifier approach is achieved 96% accuracy. Therefore the simulation results shows that the proposed approach gives significant better results than existing work. In future the other set can be taken and apply more classification and the regression methods and predict various other parameters.

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