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An Adaptive Technique based on Machine and Deep Learning for Prediction of Depression using EEG

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Abstract : 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. 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 machine and 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.

***IndexTerms* –** EEG, Emotion, Stress, Deep Learning, Machine Learning, E-healthcare.

I. Introduction

WHO gauges that the weight of psychological wellness issues in India is 2443 incapacity changed life years (DALYs) per 100 00 populace; the age-changed self destruction rate per 100 000 populace is 21.1. The financial misfortune because of emotional well-being conditions, between 2012-2030, is assessed at USD 1.03 trillion.

Stress is generally perceived as a state wherein an individual is relied upon to perform a lot under sheer tension and in which he/she can imperceptibly battle with the requests. These requests can be mental or social. It is known that psychosocial stress exists in day to day existence, which has brought about low quality of life by influencing individuals' passionate way of behaving, position execution, mental and actual wellbeing [1].

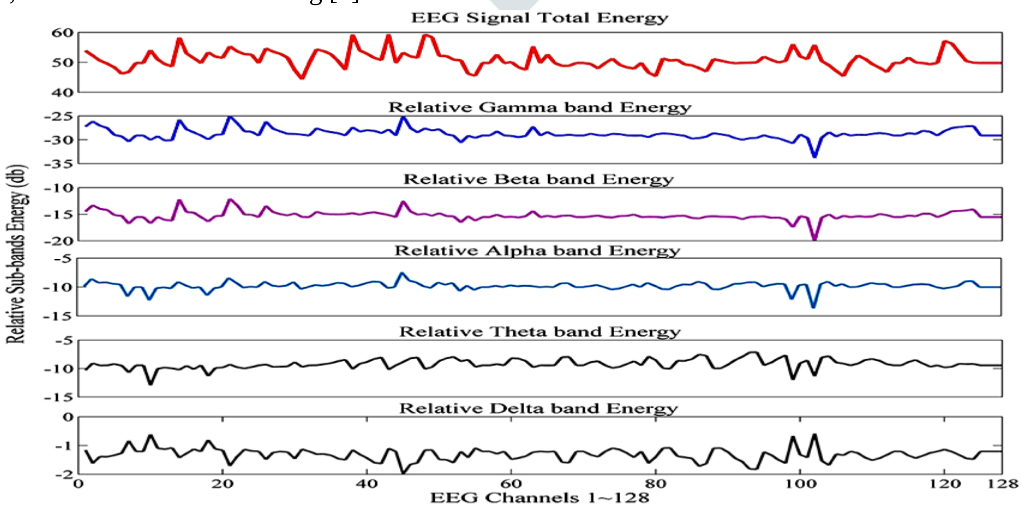


Figure 1: EEG Signal [1]

Psychosocial stress is a main source of a few physiological problems. For instance, it improves the probability of wretchedness, stroke, cardiovascular failure and heart failure [4].

Electroencephalography (EEG) is a proficient methodology which assists with procuring mind cues compares to different states from the scalp surface region. These signs are by and large arranged as delta, theta, alpha, beta and gamma in view of sign frequencies goes from 0.1 Hz to in excess of 100 Hz. A test recognizes electrical movement in the cerebrum utilizing little, metal circles (anodes) joined to the scalp.

The sorts of EEG waves[2,3] are distinguished by their recurrence range - delta: underneath 3.5 Hz (0.1-3.5 Hz), theta: 4-7.5 Hz, alpha: 8-13 Hz, beta: 14-40 Hz, and gamma: over 40 Hz. The EEG might show uncommon electrical release when some irregularity happens in the cerebrum.

Stress is your body's response to a test or interest. In short explodes, stress can be positive, for example, when it assists you with staying away from risk or fulfill a time constraint. EEG nonlinear elements and front facing deviation of theta, alpha, and beta groups have been chosen as organic markers for ongoing pressure, showing relative more noteworthy right foremost EEG information movement in upsetting people.

Look acknowledgment (FER) is presently perhaps the most dynamic examination subject because of its wide scope of uses in the human-PC connection field. A significant piece of the new outcome of programmed FER was accomplished on account of the rise of profound learning draws near.

II. BACKGROUND

A. Seal et al.,[1] propose that CNN prepared on recordwise split information gets overtrained on EEG information with few subjects. The presentation of DeprNet is astounding contrasted and the other eight gauge models. Moreover, on envisioning the last CNN layer, it is observed that the upsides of right anodes are unmistakable for discouraged subjects, while, for typical subjects, the upsides of left terminals are noticeable.

S. Sun et al.,[2] presents consolidated multi-types includes (All: L+ NL + PLI + NM) beat single-type highlights for arranging gloom. Examining the ideal elements set we observed that contrasted with other sort highlights, PLI involved the biggest extent of which practical associations in intra-side of the equator were considerably more than that of in between half of the globe.

W. Zheng et al.,[3] research stable examples of electroencephalogram (EEG) over the long haul for feeling acknowledgment utilizing an AI approach. Up to now, different discoveries of enacted designs related with various feelings have been accounted for. Notwithstanding, their solidness over the long haul has not been completely examined at this point. In this paper, we center around recognizing EEG steadiness in feeling acknowledgment.

W. Tooth et al.,[4] presents the activity was approved utilizing ADVANTEST V93000 PS1600, and the preparation interaction and continuous characterization handling time took 0.12495 ms and 0.02634 ms for every EEG picture, individually. The proposed EEG-based realtime feeling acknowledgment framework incorporated a dry terminal EEG headset, highlight extraction processor, CNN chip stage, and graphical UI, and the execution time cost 450 ms for each passionate state acknowledgment.

P. J. Bota et al.,[5] shows the emotional figuring is a multidisciplinary field of exploration crossing the areas of software engineering, brain research, and mental science. Potential applications incorporate mechanized driver help, medical care, human-PC association, diversion, showcasing, educating and numerous others.

S. Wang et al.,[6] the proposed technique for feeling acknowledgment is checked on the normal look datasets, the Drawn out Cohn-Kanade (CK+) dataset and the Japanese female look (JAFFE). The outcomes are palatable, which shows cloud model is possibly valuable in design acknowledgment and machines learning.

R. A. Khalil et al.,[7] presents the feeling acknowledgment from discourse signals is a significant however testing part of Human-PC Connection (HCI). Profound Learning methods have been as of late proposed as an option in contrast to conventional strategies in SER.

III. METHODOLOGY

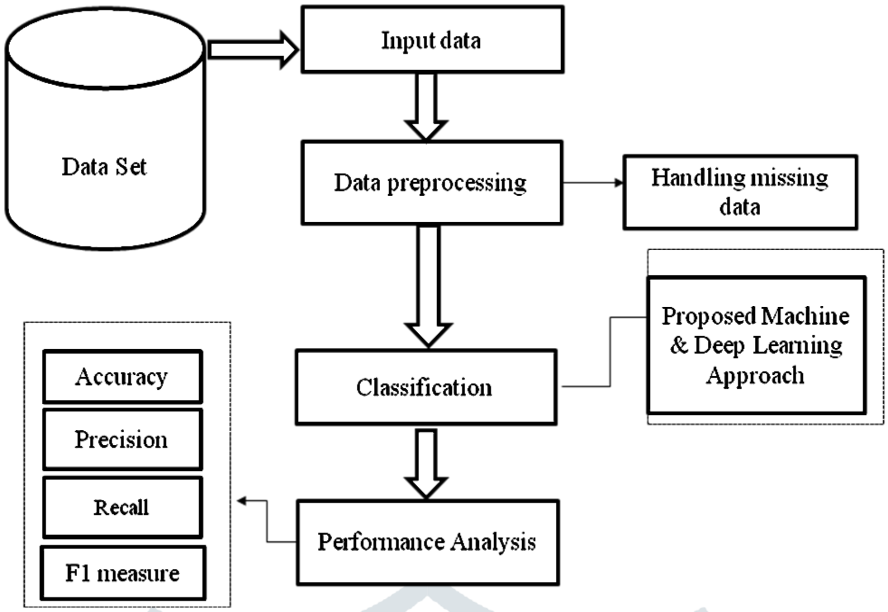


Figure 2: Flow Chart

- 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 form fft_0_b':'fft_749_b.
- Now apply the preprocessing of the data, here handing the 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.

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.

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.

- 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

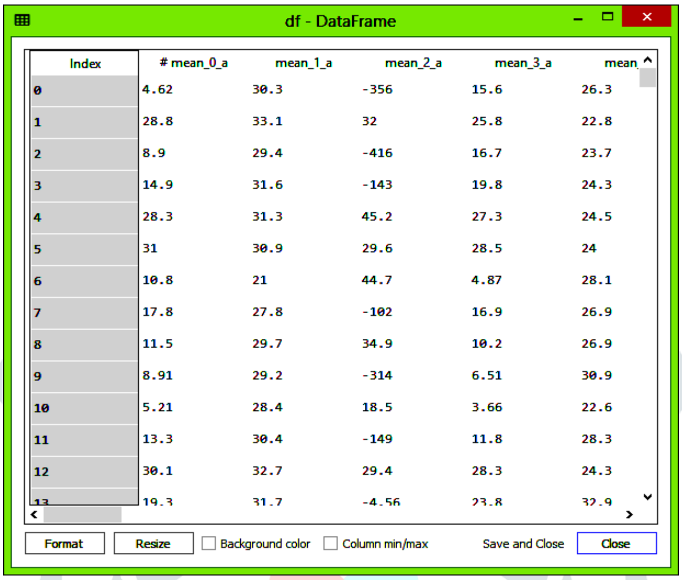
$$\text{F1\_Score} = \frac{2\text{x (Precision x Recall)}}{\text{Precision} + \text{Recall}}$$

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

Classification Error = 100- Accuracy

IV. SIMULATION AND RESULTS

The simulation is performed using python spyder 3.7 software.



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	23.8	32.9

Figure 3: dataset

Figure 3 is showing the dataset of this research. The dataset is taken from the kaggle website.

	0	1	2
0	0	1	0
1	1	0	0
2	1	0	0
3	0	1	0
4	0	1	0
5	0	0	1
6	1	0	0
7	0	1	0
8	1	0	0
9	0	1	0
10	0	0	1
11	1	0	0
12	1	0	0

Figure 4: Train dataset

Figure 4 is showing the training dataset which is used to train the model.

Figure 5: Test dataset

Figure 5 is showing the test dataset which is used to test the proposed model.

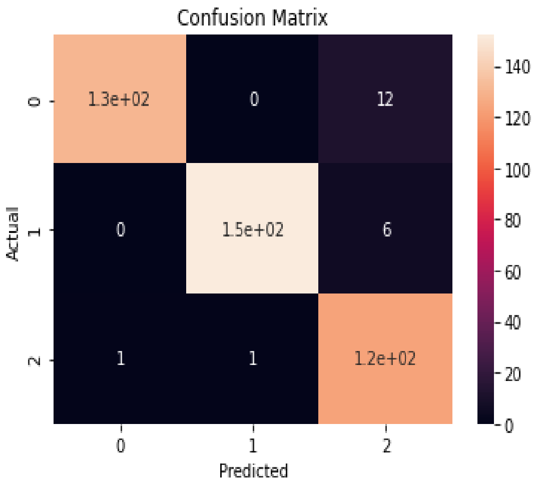


Figure 6: Confusion matrix

Figure 6 is showing the confusion matrix of the proposed model.

Table 1: Result Comparison

Sr. No.	Parameters	Accuracy	Classification Error
1	Work [1]	91%	9 %
2	KNN	94.14%	5.86 %
3	LSTM (Proposed Work)	96.48 %	3.52 %

V. CONCLUSION

This research proposed adaptive technique based on the machine learning and deep learning technique to identify the prediction from given dataset. The python spyder IDE 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.

REFERENCES

1. A. Seal, R. Bajpai, J. Agnihotri, A. Yazidi, E. Herrera-Viedma and O. Krejcar, "DeprNet: A Deep Convolution Neural Network Framework for Detecting Depression Using EEG," in IEEE Transactions on

Instrumentation and Measurement, vol. 70, pp. 1-13, 2021, Art no. 2505413, doi: 10.1109/TIM.2021.3053999.

2. S. Sun, H. Chen, X. Shao, L. Liu, X. Li and B. Hu, "EEG Based Depression Recognition by Combining Functional Brain Network and Traditional Biomarkers," 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2020, pp. 2074-2081, doi: 10.1109/BIBM49941.2020.9313270.
3. W. Zheng, J. Zhu and B. Lu, "Identifying Stable Patterns over Time for Emotion Recognition from EEG," in IEEE Transactions on Affective Computing, vol. 10, no. 3, pp. 417-429, 1 July-Sept. 2019, doi: 10.1109/TAFFC.2017.2712143.
4. W. Fang, K. Wang, N. Fahier, Y. Ho and Y. Huang, "Development and Validation of an EEG-Based Real-Time Emotion Recognition System Using Edge AI Computing Platform With Convolutional Neural Network System-on-Chip Design," in IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 9, no. 4, pp. 645-657, Dec. 2019, doi: 10.1109/JETCAS.2019.2951232.
5. P. J. Bota, C. Wang, A. L. N. Fred and H. Plácido Da Silva, "A Review, Current Challenges, and Future Possibilities on Emotion Recognition Using Machine Learning and Physiological Signals," in IEEE Access, vol. 7, pp. 140990-141020, 2019, doi: 10.1109/ACCESS.2019.2944001.
6. S. Wang, H. Chi, Z. Yuan and J. Geng, "Emotion Recognition Using Cloud Model," in Chinese Journal of Electronics, vol. 28, no. 3, pp. 470-474, 5 2019, doi: 10.1049/cje.2018.09.020.
7. R. A. Khalil, E. Jones, M. I. Babar, T. Jan, M. H. Zafar and T. Alhussain, "Speech Emotion Recognition Using Deep Learning Techniques: A Review," in IEEE Access, vol. 7, pp. 117327-117345, 2019, doi: 10.1109/ACCESS.2019.2936124.
8. S. Nemati, R. Rohani, M. E. Basiri, M. Abdar, N. Y. Yen and V. Makarenkov, "A Hybrid Latent Space Data Fusion Method for Multimodal Emotion Recognition," in IEEE Access, vol. 7, pp. 172948-172964, 2019, doi: 10.1109/ACCESS.2019.2955637.
9. H. Zhang, A. Jolfaei and M. Alazab, "A Face Emotion Recognition Method Using Convolutional Neural Network and Image Edge Computing," in IEEE Access, vol. 7, pp. 159081-159089, 2019, doi: 10.1109/ACCESS.2019.2949741.
10. P. M. Ferreira, F. Marques, J. S. Cardoso and A. Rebelo, "Physiological Inspired Deep Neural Networks for Emotion Recognition," in IEEE Access, vol. 6, pp. 53930-53943, 2018, doi: 10.1109/ACCESS.2018.2870063.
11. Y. Yang, Q. M. J. Wu, W. Zheng and B. Lu, "EEG-Based Emotion Recognition Using Hierarchical Network With Subnetwork Nodes," in IEEE Transactions on Cognitive and Developmental Systems, vol. 10, no. 2, pp. 408-419, June 2018, doi: 10.1109/TCDS.2017.2685338.
12. S. Zhang, S. Zhang, T. Huang, W. Gao and Q. Tian, "Learning Affective Features With a Hybrid Deep Model for Audio–Visual Emotion Recognition," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 28, no. 10, pp. 3030-3043, Oct. 2018, doi: 10.1109/TCSVT.2017.2719043.