

# DEEP LEARNING TECHNIQUE FOR FEATURE CLASSIFICATION OF EEG TO ACCESS STUDENT'S MENTAL STATUS: A SURVEY

A. Syedali Fathima<sup>1</sup>, Dr. S. Mythili<sup>2</sup>

<sup>1</sup>PG scholar, Applied Electronics, PSNA CET, Dindigul, Tamil Nadu, India

<sup>2</sup>Professor, Department of ECE, PSNA CET, Dindigul, Tamil Nadu, India

\*\*\*

**ABSTRACT** - Emotions have an important role in daily life, not only in human interaction, but also in decision making processes, and in the perception of the world around us. Due to the recent interest shown by the research community in establishing emotional interactions between humans and computers, the identification of the emotional state of the former became a need. This can be achieved through multiple measures, such as subjective self reports, autonomic and neurophysiological measurements. In the last years, Electro Encephalo Graphy (EEG) received considerable attention from researchers, since it can provide a simple, cheap, portable, and ease to use solution for identifying emotions. In this review, presents a comprehensive overview of the existing works in emotion recognition using EEG signals. It focuses that analysis in the main aspects involved in the depression detection process and compare the works per them. From this analysis, proposes a set of good practice recommendations that researchers must follow to achieve reproducible, replicable, well validated and high quality results.

**KEYWORDS:** Emotion, Electroencephalogram, Classification.

## 1. INTRODUCTION

Electro Encephalo Graphy (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. It is typically non invasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used, as in electrocorticography. It is frequently used in the diagnosis of brain related diseases such as epilepsy, sleep disorders, mental disorders, and so on. EEG is a medical imaging technique that reads scalp electrical activity generated by brain structures, i.e., it measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. A typical adult EEG signal, when measured from the scalp, is about 10-100  $\mu$ V. These signals observed in the scalp are divided into specific ranges that are more prominent in certain states of mind, namely the delta (1-4 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (13-30Hz), and gamma (>30 Hz) bands

Alpha: Their frequency is 8-14 Hz, and their amplitude is approximately 20-100  $\mu$ V. Most of them appear in the back of the head (occipital, apical, and posterior temporal) under awake, quiet, and closed states. The

rhythm has the largest amplitude in the occipital region. Alpha waves disappear when one blinks, thinks or undergoes other stimuli, which is known as alpha wave blocking. Alpha waves mainly manifest when the cerebral cortex is in a closed and quiet state.

Beta: Beta waves have a frequency of > 13 Hz and a low amplitude of approximately 5~20  $\mu$ V, and are widely distributed. They are fast waves that occur during normal awake states. Beta waves are the main manifestation of electrical activity when the cerebral cortex is tense or excited.

Theta: Theta waves frequency is 4-7 Hz, their amplitude is 20-150  $\mu$ V, and they are closely related to the age and state of people. Normal adults generally have slower  $\theta$  waves during sleepiness, mainly in the frontal and central and  $\theta$  waves are common in infants and young children.  $\theta$  waves occur when the central nervous system is in a suppressed state.

Delta: Delta waves have a frequency <4 Hz, and an amplitude of 20-200 $\mu$ V. They almost never appear in normal adults when they are awake. The most common  $\delta$  waves appear during sleep, deep anesthesia, brain hypoxia or organic diseases.

Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on artificial neural networks. Learning can be supervised, semi-supervised or unsupervised. Deep learning is a class of machine learning algorithms that use multiple layers to progressively extract higher level features from raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify human meaningful items such as digits or letters or faces.

In recent years, deep learning architectures have achieved significant success in the areas of computer vision and natural language processing. However, very little progress has been made in neuroscience and biomedical domains due to the availability of few data. With rapid enhancement of available neurological data, there has been a significant improvement in the learning and diagnose of neural disorders including seizure, Alzheimer, Parkinson, epilepsy, Creutzfeldt Jakob,

depression, emotional states and other abnormality diseases.

Depression is a common mental illness that already affects more than 350 million people worldwide, and its main characteristics are persistent, pervasive and serious depressed mood or anhedonia. The patient has difficulty controlling his mood, has a lowered mood and has decreased interest or pleasure in all activities. The pathophysiology of depression remains unclear. Furthermore, it is estimated by the World Health Organization that depression will become the second leading cause of illness by 2020. Depression is the main cause of suicide, and up to 10% of people with depressive episodes will commit suicide if untreated. So that, there has been much research on the diagnosis of depression. The processing of EEG data generally includes pre-processing, feature extraction, feature selection and classification

## 2. FLOW DIAGRAM

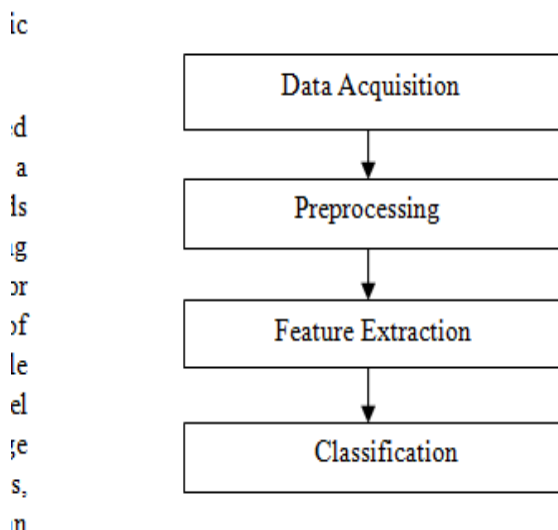


Fig.1.Flow diagram of EEG signal processing.

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer.

Pre-processing refers to the transformations applied to our data before feeding it to the algorithm. Data Preprocessing is a technique that is used to convert the raw data into a clean data set.

Feature extraction is a process of dimensionality reduction by which an initial set of raw data is reduced to more manageable groups for processing.

Classification is a supervised learning approach in which the computer program learns from the data input given to it and then uses this learning to classify new observation.

## 3. RELATED WORKS

Ahmad Rauf Subhani et al [1] presents an objective measure for identifying the levels of stress while considering the human brain could considerably improve the associated harmful effects. Machine learning (ML) framework involving Electro Encephalo Gram (EEG) signal analysis of stressed participants is proposed. The proposed ML framework involved EEG feature extraction, feature selection (receiver operating characteristic curve, t-test and the Bhattacharya distance), classification (logistic regression, support vector machine and naïve Bayes classifiers) and tenfold cross validation. The results showed that the proposed framework produced 94.6% accuracy for two level identification of stress and 83.4% accuracy for multiple level identification. The proposed method could help in developing a computer aided diagnostic tool for stress detection.

Bin Hu et al [2] proposed a method to evaluate the quality of EEG signals, based on which users can easily adjust the connection between electrodes and their skin. To apply an algorithm based on Discrete Wavelet Transformation (DWT) and Adaptive Noise Cancellation (ANC) which has been designed to remove Ocular Artifacts (OA) from the EEG signal. EEG sensor will be enhanced with a rule based system to interpret the data and to provide a diagnostic foundation for both pharmacological and Cognitive Behavioral Therapies (CBT) based preventative and intervening treatments.

Chin Teng Lin et al [3] presents the usefulness of the forehead EEG with advanced sensing technology and signal processing algorithms to support people with healthcare needs, such as monitoring sleep, predicting headaches, and treating depression. The depression treatment screening system can predict the efficiency of rapid antidepressant agents. The use of dry electrodes on the forehead allows for easy and rapid monitoring on an everyday basis. The proposed solutions are based on EEG patterns extracted from the forehead area using a wireless and dry EEG system. The basic principles of each method are introduced, and the feasibility of their use in real life applications is demonstrated.

Hong Peng et al [4] aims that to identify the altered EEG resting state functional connectivity patterns of depressed patients, which can be used to test the feasibility of distinguishing individuals with depression from healthy controls. The phase lag index was employed to construct functional connectivity matrices. The best classification results demonstrate that more than 92% of subjects were correctly classified by binary linear SVM through leave one out cross validation for the full frequency band, and the AUC was 0.98. This is only effective on the scalp, and it lacks more spatial information.

Hanshu Cai et al [5] Presents a case based reasoning model for identifying depression. Electroencephalography data were collected using a portable three electrode EEG device, and then processed to remove artifacts and extract features. The best performing K-Nearest Neighbour (KNN) was selected as the evaluation function to select the effective features which were then used to create the case base. The accuracy of optimal similarity identification of patients with depression was 91.25%, which was improved compared to the accuracy using KNN classifier (81.44%) or previously reported classifiers. It provides a novel pervasive and effective method for automatic detection of depression.

Jing Zhu et al [6] proposes a multimodal feature fusion method that can best discriminate between mild depression and normal control subjects as a step toward achieving our long term aim of developing an objective and effective multimodal system that assists doctors during diagnosis and monitoring of mild depression. Experimental results indicate that the EEG-EM synchronization acquisition network ensures that the recorded EM and EEG data require that both the data streams are synchronized with millisecond precision, and both fusion methods can improve the mild depression recognition accuracy, thus demonstrating the complementary nature of the modalities. The highest classification accuracy is 83.42%.

Michael Sokolovsky et al [7] designs a deep CNN architecture for automated sleep stage classification of human sleep EEG and EOG signals. The CNN proposed in this work to amply out performs recent work that uses a different CNN architecture over a single EEG channel version of the same dataset. It shows that the performance gains achieved by our network rely mainly on network depth, and not on the use of several signal channels. Performance of the approach is on par with human expert inter scorer agreement.

Mallikarjun et al [8] presents the Electro Encephalo Gram (EEG) signals are obtained from publicly available database are processed in MATLAB. This can be useful in classifying subjects with the disorders using classifier tools present in it. For this aim, the features are extracted from frequency bands (alpha, delta and theta). The results obtained from MATLAB are fed into neural network pattern recognition tool and ANFIS tool box which is integrated in MATLAB. These are powerful tool for data classification. Total 240 samples are trained in nprtool and classified for sleep disorders and 60 samples for classifying alcoholism with accuracy rate 88.32% & 91.7% respectively.

Nan Feng Jie et al [9] proposes a novel feature selection approach based on linear Support Vector Machine with a Forward Backward search strategy (SVM-FoBa) was developed and applied to structural and resting state

functional magnetic resonance imaging data collected from 21BD to 25MD Dand 23 healthy controls. Discriminative features were drawn from both data modalities, with which the classification of BD and MDD achieved an accuracy of 92.1% (1000 bootstrap re-samples). This work validated the advantages of multimodal joint analysis and the effectiveness of SVM-FoBa, which has potential for use in identifying possible biomarkers for several mental disorders.

Soraia M. Alarcao et al [10] presents a survey of the neurophysiological research performed to provide a comprehensive overview of the existing works in emotion recognition using EEG signals. Analysis focus on the main aspects involved in the recognition process (e.g., subjects, features extracted, classifiers). It is used to achieve reproducible, replicable, well validated and high quality results.

Yalin Li et al [11] proposed EEG based mild depressive detection using differential evolution. At present, the most commonly used method is the combination of feature selection and classification algorithm for detection. The classification accuracy needs to be further improved. The differential evolution is a population based adaptive global optimization algorithm. It is used to optimize the extracted features to achieve better result. Then the K Nearest Neighbor classification algorithm is used to classify patients with mild depression and normal people. It effectively improves the classification accuracy and efficiency, and is superior to other feature optimization methods.

#### 4. RESULT AND DISCUSSION

In this review, EEG signals are containing the number of samples obtained from the brain which is used for depression detection. Fig.8. shows that the output of a sample depression EEG signal

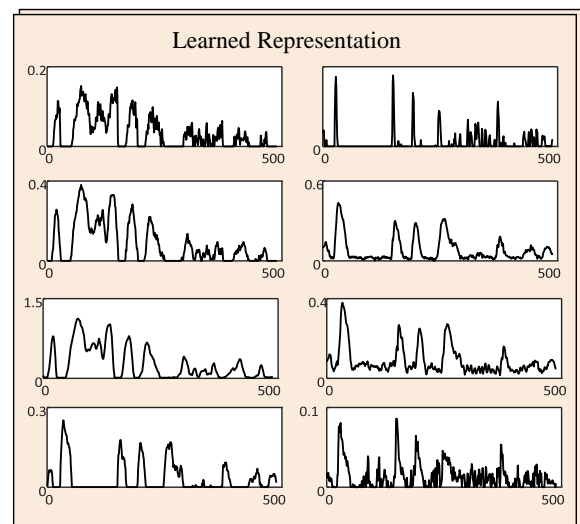


Fig.2.Features obtained at the output

These works employed neural network or machine learning classifiers using various preprocessing, feature extraction and classification techniques

## 5. CONCLUSION

In this survey, presents an analysis of the works, from 2014 to 2019, that propose novel methods for the detection of depression through EEG signals. Recently, the availability of large EEG data sets and advances in machine learning have both led to the deployment of deep learning architectures, especially in the analysis of EEG signals and the functionality of brain. In our proposed work, a novel computer model is to be developed for EEG-based screening of mental status of students using a deep neural network machine learning approach, known as Convolutional Neural Network (CNN). The proposed method, automatically learns from the input EEG signals to differentiate EEGs obtained from depressive and normal subjects.

## REFERENCES

1. Ahmad Rauf Subhani, Wajid Mumtaz, Mohamed Naufal Bin Mohamed Saad, Nidal Kamel, and Aamir Saeed Malik, **“Machine Learning Framework for the Detection of Mental Stress at Multiple Levels”** 2169-3536 2017 IEEE.
2. Bin Hu , Hong Peng, Qinglin Zhao, Bo Hu, Dennis Majoe, Fang Zheng, and Philip Moore, **“Chexnet: Radiologist-Level Pneumonia Detection On Chest X-Rays With Deep Learning”** IEEE Transactions On Nano bioscience, Vol. 14, No. 5, July 2015.
3. Chin Teng Lin, (Fellow, IEEE), Chun Hsiang Chuang (Member, IEEE), Zehong Cao, Avinash Kumar Singh, Chih Sheng Hung, Yi Hsin Yu, Mauro Nascimben, Yu Ting Liu, Jung Tai King, Tung Ping Su<sup>3</sup>, and Shuu Jiun Wang, **“Forehead EEG in Support of Future Feasible Personal Healthcare Solutions: Sleep Management, Headache Prevention, and Depression Treatment”** 2169-3536 2017 IEEE.
4. Hong Peng, (Member, IEEE), Chen Xia, Zihan Wang, Jing Zhu, Xin Zhang, Shuting Sun, Jianxiu Li, Xiaoning Huo, and Xiaowei Li, (Member, IEEE) **“Multivariate Pattern Analysis of EEG-Based Functional Connectivity: A Study on the Identification of Depression”**, 10.1109/ACCESS.2019.2927121.
5. Hanshu Cai, Xiangzi Zhang, Yanhao Zhang, Ziyang Wang, and Bin Hu, Member, IEEE, **“A Case-based Reasoning Model for Depression based on Three electrode EEG Data”**, 10.1109/TAFFC.2018.2801289, IEEE Transactions on Affective Computing.
6. Jing Zhu, Ying Wang, Rong La, Jiawei Zhan, Junhong Niu, Shuai Zeng, and Xiping Hu, **“Multimodal Mild Depression Recognition Based on EEG-EM Synchronization Acquisition Network”**, 10.1109/ACCESS.2019.2901950 2169-3536, 2019, IEEE.
7. Michael Sokolovsky, Francisco Guerrero, Sarun Paisarnsransom, Carolina Ruiz, Sergio A. Alvarez, **“Deep learning for automated feature discovery and classification of sleep stages”**, IEEE Transactions On Computational Biology And Bioinformatics, 2018.
8. Mallikarjun H M, Dr. H N Suresh, **“Depression Level Prediction Using EEG Signal Processing”**, 978-1-4799-6629-5/14/\$31.00, 2014, IEEE.
9. Nan Feng Jie, Mao Hu Zhu, Xiao Ying Ma, Elizabeth A Osuch, Michael Wammes, Jean Theberge, Huan Dong Li, Yu Zhang, Student Member, IEEE, Tian Zi Jiang, Senior Member, IEEE, Jing Sui, Senior Member, IEEE, and Vince D Calhoun, Fellow, IEEE, **“Discriminating Bipolar Disorder From Major Depression Based on SVM-FoBa: Efficient Feature Selection With Multimodal Brain Imaging Data”**, IEEE Transactions On Autonomous Mental Development, Vol. 7, No. 4, 1943-0604 © 2015, IEEE.
10. Soraia M. Alarcao, and Manuel J. Fonseca, Senior Member, IEEE, **“Emotions Recognition Using EEG Signals: A Survey”**, 10.1109/TAFFC.2017.2714671, IEEE Transactions on Affective Computing.
11. Yalin Li, Bin Hu, Xiangwei Zheng, and Xiaowei Li, **“EEG Based Mild Depressive Detection Using Differential Evolution”**, 10.1109/ACCESS.2018.2883480, 2169-3536, 2018, IEEE.