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Detection of Depression of EEG Signal Using Machine and Deep Learning Technique :- A Review

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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.

***Keywords*—Electroencephalogram (EEG), Cross-Validation(CV), Leave-One-Subject-Out(LOSO), Dempster-Shafer (DS),etc …**

I. INTRODUCTION

Depression, as a common illness worldwide, is classified as a mood disorder and described as feelings of sadness or anger that interfere with a person's everyday activities. According to the World Health Organization, it is likely to be the leading global disease by 2030. Depression disorder is a pathological process that causes many symptoms, resulting in limited mental and physical functionality. It is often accompanied by cognitive impairments, which may increase the risk of Alzheimer's disease and suicide and accelerate cognitive decline. The earlier depression is detected, the easier it is to treat. As a low-cost, non-invasive acquisition, and high temporal resolution technique, electroencephalography is widely used in neural systems and rehabilitation engineering. This work is focused on the experimental paradigm, emotion feature extraction, feature selection, machine learning, and the dataset for training and testing, particularly on spatial information feature extraction and selection. This focus was chosen because many studies have shown that subjects with depression exhibit different spatial responses in neuro physiological signals compared to healthy controls, when they are exposed to stimulation.

PREVALENCE PER 100,000

DEPRESSIVE DISORDERS	
Tamil Nadu	4,796
Andhra Pradesh	4,563
Telangana	4,356
Odisha	4,159
Kerala	3,897

CONDUCT DISORDERS	
Jharkhand	983
Bihar	974
Meghalaya	961
Uttar Pradesh	927
Nagaland	924

ANXIETY DISORDERS	
Kerala	4,035
Manipur	3,760
West Bengal	3,480
Himachal Pradesh	3,471
Andhra Pradesh	3,462

IDIOPATHIC DEVELOPMENTAL INTELLECTUAL DISABILITY	
Bihar	6,339
Uttar Pradesh	5,503
Madhya Pradesh	5,216
Assam	5,121
Jharkhand	4,940

Fig. 1: Mental health data (Indian health report)

A. EEG Signals

EEG signals are non-stationary and nonlinear signals, similar to many other physiological signals. To analyze these signals, linear and nonlinear features are typically used, such as the power spectrum density, Lempel-Ziv complexity, variance, mobility, fluctuations, Higuchi fractal, approximate entropy, Kolmogorov entropy, correlation dimension, Lyapunov exponent, and permutation entropy. To analyze our hypothesis effectively, it was necessary to select optimal features, as some dimension features may mislead the classifiers.

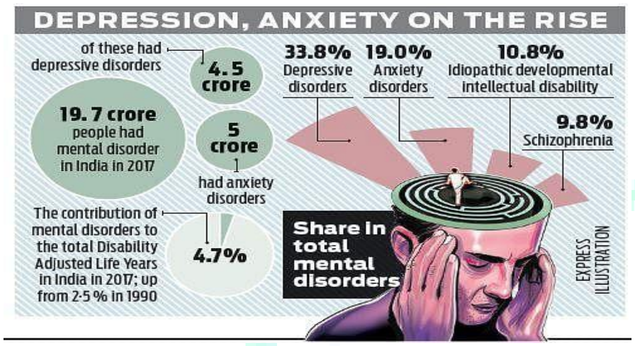

Fig. 2: Depression statics (WHO report)

Subject-independent k-fold cross-validation (CV) and leave-one-subject-out (LOSO) CV are two widely used EEG classification strategies. In fact, when k = 1, the LOSO method is a special case of the k-fold technique. As the LOSO approach can enjoy more training data and adjust super-parameters on each subject, it will always achieve better results compared with the k-fold method. When detecting a potential depression patient, we chose the LOSO strategy to evaluate the model for detecting depression patients in this study, to make the best use of the existing data.

B. EEG SIGNAL

The Electroencephalography (EEG) is a method to record an electro gram of the electrical activity on the scalp that has been shown to represent the macroscopic activity of the surface layer of the brain underneath. It is typically non-invasive, with the electrodes placed along the scalp. Electro cortico graphy, involving invasive electrodes, is sometimes called "intracranial EEG". EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain.[1] Clinically, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp.[1]

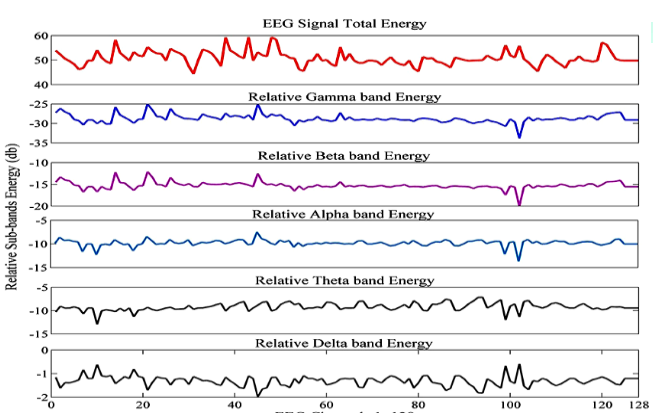

Fig.3: EEG Signal

Diagnostic applications generally focus either on event-related potentials or on the spectral content of EEG. The former investigates potential fluctuations time locked to an event, such as 'stimulus onset' or 'button press'. The latter analyses the type of neural oscillations (popularly called "brain waves") that can be observed in EEG signals in the frequency domain.

C. EEG Wave Pattern

Delta Waves are the frequency range up to 4 Hz. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow-wave sleep. It is also seen normally in babies. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions. It is usually most prominent frontally in adults (e.g. FIRDA – frontal intermittent rhythmic delta) and posteriorly in children (e.g. OIRDA – occipital intermittent rhythmic delta).

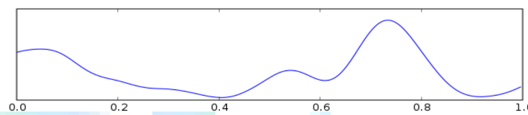

Fig. 4 : Delta waves

Theta is the frequency range from 4 Hz to 7 Hz. Theta is seen normally in young children. It may be seen in drowsiness or arousal in older children and adults; it can also be seen in meditation. Excess theta for age represents abnormal activity. It can be seen as a focal disturbance in focal subcortical lesions; it can be seen in generalized distribution in diffuse disorder or metabolic encephalopathy or deep midline disorders or some instances of hydrocephalus. On the contrary this range has been associated with reports of relaxed, meditative, and creative states.

II. LITERATURE REVIEW

A. Seal et al.,[1] present Depr Net in two investigations, specifically, the record wise split and the subject wise split, is introduced in this review. The outcomes accomplished by Depr Net have an exactness of 0.9937, and the region under the recipient working trademark bend (AUC) of 0.999 is accomplished when record wise split information are thought of. Then again, a precision of 0.914 and the AUC of 0.956 are acquired, while subject wise split information are utilized. These outcomes propose that CNN prepared on record wise split information gets over trained on EEG information with few subjects. The exhibition of Depr Net is astounding contrasted and the other eight gauge models. Besides, on picturing the last CNN layer, it is observed that the upsides of right terminals are unmistakable for discouraged subjects, while, for ordinary subjects, the upsides of left cathodes are conspicuous.

S. Sun et al.,[2] This Electroencephalography (EEG)-based research is to investigate the viable biomarkers for wretchedness acknowledgment. Resting-state EEG information were gathered from 24 significant burdensome patients (MDD) and 29 typical controls utilizing 128-anode geodesic sensor net. To more readily recognize despondency, we separated multi-kind of EEG highlights including straight elements (L), nonlinear elements (NL), useful availability highlights stage slacking list (PLI) and organization measures (NM) to thoroughly portray the EEG signals in patients with MDD. Also, AI calculations and factual examination were utilized to assess the EEG highlights. Consolidated multi-types includes.

W. Zheng et al.,[3] presents explore stable examples of electroencephalogram (EEG) over the long haul for feeling acknowledgment utilizing an AI approach. Up to now, different discoveries of initiated designs related with various feelings have been accounted for. In any case, their strength over the long run has not been completely examined at this point. In this work, we center around distinguishing EEG strength in feeling acknowledgment. We efficiently assess the presentation of different well known include extraction, highlight choice, highlight smoothing and design characterization techniques with the DEAP dataset and a recently evolved dataset called SEED for this review.

W. Tooth et al.,[4] This review proposed an electroencephalogram (EEG)- based ongoing feeling acknowledgment equipment framework engineering in view of multiphase convolutional brain organization (CNN) calculation carried out on a 28-nm innovation chip and on field programmable entryway cluster (FPGA) for double and quaternary characterization. Test entropy, differential unevenness, brief time frame Fourier change, and a channel reproduction technique were utilized for feeling highlight extraction. In this work, six EEG channels were chosen (FP1, FP2, F3, F4, F7, and F8), and EEG pictures were produced from spectrogram combinations. The total CNN design included preparing and speed increase for productive man-made reasoning (artificial intelligence) edge application, and we proposed a multiphase CNN execution strategy to oblige equipment asset limitations.

P. J. Bota et al.,[5] The original work on Full of feeling Processing in 1995 by Picard set the base for registering that connects with, emerges from, or impacts feelings. Emotional processing is a multidisciplinary field of examination traversing the areas of software engineering, brain research, and mental science. Potential applications incorporate computerized driver help, medical care, human-PC connection, amusement, promoting, instructing and numerous others. In this way, rapidly, the field gained exorbitant interest, with a colossal development of the quantity of works distributed on the theme since its commencement.

S. Wang et al.,[6] Feelings frequently work with associations among individuals, yet the huge variety of human passionate states make a pessimistic impact on the solid feeling acknowledgment. We propose a clever calculation to extricate normal highlights for each sort of passionate states which can dependably introduce human feelings. To uncover the normal elements from questionable passionate states, the regressive cloud generator is utilized to find { Ex , En , He } by coordinating haphazardness and fluffiness. At long last, the proposed technique for feeling acknowledgment is confirmed 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 helpful in design acknowledgment and machines learning.

R. A. Khalil et al.,[7] Feeling acknowledgment from discourse signals is a significant yet testing part of Human-PC Cooperation (HCI). In the writing of discourse feeling acknowledgment (SER), numerous strategies have been used to separate feelings from signals, including some deep rooted discourse investigation and arrangement procedures. Profound Learning strategies have been as of late proposed as an option in contrast to customary procedures in SER. This work presents an outline of Profound Learning strategies and talks about some new writing where these techniques are used for discourse based feeling acknowledgment. The survey covers data sets utilized, feelings removed, commitments made toward discourse feeling acknowledgment and restrictions connected with it.

S. Nemati et al.,[8] Multimodal feeling acknowledgment is an arising interdisciplinary field of exploration in the space of emotional registering and opinion investigation. It targets taking advantage of the data conveyed by signs of various nature to make feeling acknowledgment frameworks more exact. This is accomplished by utilizing a strong multimodal combination technique. In this review, a crossover multimodal information combination strategy is proposed in which the sound and visual modalities are intertwined utilizing an inert space straight guide and afterward, their extended highlights into the cross-modular space are melded with the literary methodology utilizing a Dempster-Shafer (DS) hypothesis based evidential combination technique.

H. Zhang et al.,[9] To keep away from the complicated course of unequivocal element extraction in conventional look acknowledgment, a face appearance acknowledgment strategy in light of a convolutional brain organization (CNN) and a picture edge identification is proposed. Initially, the look picture is standardized, and the edge of each layer of the picture is removed in the convolution interaction. The extricated edge data is superimposed on each element picture to protect the edge structure data of the surface picture. Then, the dimensionality decrease of the separated certain highlights is handled by the most extreme pooling strategy. At last, the declaration of the test picture is characterized and perceived by utilizing a Softmax classifier. To check the power of this strategy for look acknowledgment under a mind boggling foundation, a reenactment explore is planned by experimentally blending the Fer-2013 look information base with the LFW informational collection. The test results show that the proposed calculation can accomplish a normal acknowledgment pace of 88.56% with less emphasess, and the preparation speed on the preparation set is around 1.5 times quicker than that on the differentiation calculation.

P. M. Ferreira et al.,[10] Look acknowledgment (FER) is right now quite possibly the most dynamic examination point because of its wide scope of uses in the human-PC association field. A significant piece of the new progress of programmed FER was accomplished on account of the rise of profound learning draws near. Notwithstanding, preparing profound organizations for FER is as yet an exceptionally difficult assignment, since the majority of the accessible FER informational indexes are moderately little. Despite the fact that move learning can to some extent reduce the issue, the exhibition of profound models is still underneath of its maximum capacity as profound elements might contain repetitive data from the pre-prepared space. All things considered, we propose a clever start to finish brain network engineering alongside an all around planned misfortune work in light of the solid earlier information that looks are the consequence of the movements of a few facial muscles and parts.

III. CONCLUSION AND FUTURE WORK

As a mood disease, depression is affecting an increasing number of people. As a face-in-the-crowd task stimulus experiment based on frequency information filtering, time information feature extraction, and spatial information feature selection, we developed an improved EEG-based feature classification method employing spatial information, which is useful for the detection of patients with depression. By employing the classification performance was significantly improved, which indicates that can enhance the spatial differences before feature extraction; however, we should be aware of the limitation of the datasets. Depression as a mental disorder with clinical manifestations such as significant depression and slow thinking is always accompanied by abnormal brain activity and obvious emotional alternation. Therefore, as a method tracking the brain functions, EEG can detect these abnormal activities.

This dissertation presents machine and deep learning techniques for detecting depression using EEG. Simulation is performed using python sypder 3.7software.

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