Review of EEG-based Classification of Depression Patients

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ABSTRACT
The electroencephalogram, or EEG, plays a significant part in the operation of electronic healthcare systems, particularly in the field of mental healthcare, which places a premium on continuous monitoring that is as unobtrusive as possible. Signals on an EEG may be interpreted to indicate activity going on in a person's brain as well as distinct emotional states. A sensation of mental or bodily strain is what we refer to as stress. It might be anything—an experience or a thought—that provokes feelings of agitation, anger, or nervousness in you. Mental stress has emerged as a significant problem in modern society and has the potential to lead to functional incapacity in the workplace. The study of electroencephalogram (EEG) signals may benefit from the use of a machine learning (ML) framework. This article provides an overview of the categorization of depression patients based on EEG.

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

1. INTRODUCTION
Stress is a condition that is usually known as occurring when a person is expected to perform excessively under sheer strain and in a situation in which he or she can only minimally deal with the expectations placed upon them. These expectations could be of a psychological or societal nature. It is common knowledge that individuals experience psychosocial stress in their day-to-day lives, and this stress has been shown to lower people's quality of life by having an impact on their emotional behaviour at work as well as their mental and physical health [1]. Stress of a psychosocial nature is a major contributor to a variety of physiological conditions. For instance, it raises the risk of developing depression, having a stroke, having a heart attack, or going into cardiac arrest [4].

Electroencephalography, more often known as EEG, is a useful method that may be used to capture brain signals from the scalp surface area that correlate to a number of different states. The signal frequencies that fall within the range of 0.1 Hz to more than 100 Hz are the basis for the classification of these signals as delta, theta, alpha, beta, and gamma, respectively. It is a test that uses tiny metal discs (electrodes) that are connected to the scalp in order to determine whether or not there is electrical activity in the brain. The electroencephalogram (EEG) is a diagnostic tool that is used in clinical settings on a regular basis to assess alterations in brain activity that may be helpful in the diagnosis of brain illnesses, particularly epilepsy or another seizure condition.

It is possible to classify the different types of EEG waves [2,3] according to the frequency range in which they occur: delta waves occur between 0.1 and 3.5 Hz, theta waves occur between 4 and 7.5 Hz, alpha waves occur between 8 and 13 Hz, beta waves occur between 14 and 40 Hz, and gamma waves occur above 40 Hz. When anything is wrong with the brain, the electroencephalogram (EEG) could reveal an aberrant electrical discharge.

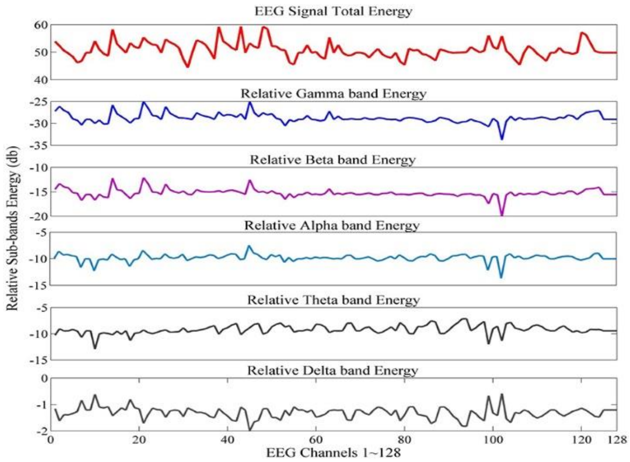

Figure 1: EEG Signal [1]

The response of your body to an adversity or a demand is what we call stress. Stress may be beneficial in small doses, such as when it alerts you to potential danger or motivates you to complete an important task in time. EEG nonlinear dynamics characteristics and frontal asymmetry of theta, alpha, and beta bands have been identified as biological markers for chronic stress. This has shown that persons who are stressed have relative larger right anterior EEG data activity.

The results of the experiments indicate that stable patterns exhibit consistency across sessions; the lateral temporal areas activate more for positive emotions than negative emotions in beta and gamma bands; the neural patterns of neutral emotions have higher alpha responses at parietal and occipital sites; and the neural patterns of negative emotions have significant higher delta responses at parietal and occipital sites and higher gamma responses at prefrontal sites [1]. [Note:

Yet, the wide range of human emotional states has a detrimental impact on the accuracy of emotion detection [6]. Emotions often serve as a medium via which human beings may communicate with one another. In the subfields of affective computing and sentiment analysis, multimodal emotion identification is a developing study topic that draws from a variety of academic perspectives. The purpose of this research is to improve the accuracy of emotion identification systems by using the information that is conveyed by signals of various types. This is accomplished by the use of an effective multimodal fusion approach [8].

Due to the vast number of applications that it has in the realm of human-computer interaction, facial expression recognition

(FER) is now one of the most active research subjects that is being investigated. The development of methods based on deep learning is largely responsible for the current success of automated FER, which has been accomplished in large part because to these methods. Nonetheless, because to the relatively small size of the majority of the accessible FER data sets, the process of training deep neural networks for FER is still considered to be one of the most difficult tasks. Although while transfer learning may help relieve the problem to some degree, the performance of deep models is still not up to its full potential since deep features could include duplicate information from the domain in which they were trained [10].

2. LITERATURE REVIEW

The spatial differences are shown by C. Jiang et al.,[1] before the feature extraction is performed. Outcomes and discussion of those results: With TCSP, we were able to reach a classification result of 84% and 85.7% for positive and negative stimuli, respectively. This is statistically substantially greater than the 81.7% and 83.2%, respectively, that we acquired without the use of TCSP (p 0.05). Also, we analysed the effectiveness of the categorization utilising each particular frequency band, and we discovered that the contribution made by the gamma band was the most significant. In addition, we tested a variety of classifiers, such as k-nearest neighbour and logistic regression, both of which shown comparable tendencies in the enhancement of classification brought about by the use of TCSP. The findings indicate that the classification of individuals suffering from depression using our suggested technique, which makes use of geographical information, leads in a considerable improvement in accuracy.

G. Zhao et al.,[2] Because of the consistent link between personality and EEG, it is possible to infer personality from mental activities. By the investigation of a person's thought waves when they are viewing emotionally engaging content, we are able to get insight into the individual's personality traits. The review was completed by 37 different members, and throughout it, they saw seven different video segments that were adjusted to reflect real joyful meetings and target seven different moods. The SVM classifier receives contributions in the form of highlights extracted from EEG data and emotional ratings. These contributions are used to anticipate five aspects of character features. Our model achieves better order execution for Extraversion (81.08 percent), Suitability (86.11 percent), and Reliability (80.56 percent) when optimistic feelings are inspired rather than negative ones; it achieves higher grouping correctnesses for Neuroticism (78.38-81.08 percent) when gloomy feelings, with the exception of loathing, are evoked than good feelings; and it achieves the most noteworthy arrangement precision for Receptiveness (83.78 percent) In addition, the presentation of highlights from abstract evaluations improves not only the grouping accuracy in each of the five character qualities (with increases ranging from 0.43 percent for uprightness to 6.3 percent for neuroticism), but also the discriminative power of the characterization correctnesses between the five character qualities in each category of feeling. These findings demonstrate the advantages of character derivation based on EEG data versus contemporary unambiguous behaviour indicators with regard to the accuracy of characterisation.

H. Kim et al.,[3] When it comes to articulating emotions, nothing beats the power of a well-taken photograph. Several researchers in the field of science have investigated the emotional content of images by focusing on various aspects that are distinct from photographs. In this body of work, we focus on two indisputable level aspects known as the article and the foundation, and we acknowledge that the semantic data included in photographs may serve as a reliable indicator of future emotions. Tests have shown that there is a strong association between the things and sentiments shown in photographs the majority of the time. One of the primary aspects that define a picture is its composition, and one of its primary components is an article. In point of fact, even when comparing articles that are quite similar, there may be subtle differences in emotion as a result of different foundations. We make use of the semantic data provided by the foundation in order to further refine the expectation execution. By combining the different degrees of highlights, we are able to construct an emotion-based feedforward deep brain network. This network is responsible for the creation of the feeling upsides of a particular image. Instead of relying on a small number of feeling categories to represent emotions, our method generates feeling values that are continuous characteristics in a two-layered space (valence and excitation), which is a more practical approach. The results of these tests demonstrate that our company is capable of predicting the emotions that are conveyed in photos.

B. Xu et al.,[4] Feeling is a vital component in client produced video. In any case, it is hard to comprehend feelings passed in such recordings due on to the intricate and unstructured nature of client produced content and the sparsity of video outlines communicating feeling. In this work, interestingly, we propose a method for moving information from heterogeneous outside sources, including picture and literary information, to work with three related assignments in getting video feeling: feeling acknowledgment, feeling attribution and feeling focused outline. In particular, our system (1) gains a video encoding from an assistant enthusiastic picture dataset to further develop regulated video feeling acknowledgment, and (2) moves information from a helper literary corpora for zero-shot acknowledgment of feeling classes concealed during preparing. The proposed method for information move works with novel uses of feeling attribution and feeling focused outline. An exhaustive arrangement of investigations on numerous datasets show the adequacy of our system.

Z. Liu et al.,[5] A look feeling acknowledgment based human-robot connection (FEER-HRI) framework is proposed, for which a four-layer framework system is planned. The FEER-HRI framework empowers the robots not exclusively to perceive human feelings, yet additionally to create look for adjusting to human feelings. A facial feeling acknowledgment strategy in light of 2D-Gabor, uniform neighborhood paired design (LBP) administrator, and multiclass outrageous learning machine (ELM) classifier is introduced, which is applied to constant look acknowledgment for robots. Looks of robots are addressed by straightforward animation images and showed by a Drove screen prepared in the robots, which can be handily perceived by human. Four situations, i.e., directing, amusement, home assistance and scene recreation are acted in the human-robot connection try, in which smooth correspondence is acknowledged by look acknowledgment of people and look age of robots in 2 seconds or less. As a couple of imminent applications, the FEER-HRI framework can be applied in home assistance, savvy home, safe driving, etc.

P. Tzirakis et al.,[6] Programmed influence acknowledgment is a moving errand because of the different modalities feelings can be communicated with. Applications can be found in numerous areas including media recovery and human-PC association. Lately, profound brain networks have been utilized with incredible progress in deciding passionate states. Enlivened by this achievement, we propose a feeling acknowledgment framework utilizing hear-able and visual modalities. To catch the enthusiastic substance for different styles of talking, vigorous highlights should be extricated. To this reason, we use a convolutional brain organization (CNN) to separate elements from the discourse, while for the visual methodology a profound leftover organization of 50 layers is utilized. Notwithstanding the significance of component extraction, an AI calculation needs likewise to be obtuse toward exceptions while having the option to demonstrate the unique circumstance. To handle this issue, long momentary memory networks are used. The framework is then prepared in a start to finish design where-by likewise exploiting the relationships of every one of the streams-we figure out how to altogether beat, as far as concordance connection coefficient, customary methodologies in light of hear-able and visual carefully assembled highlights for the expectation of unconstrained and regular feelings on the RECOLA information base of the AVEC 2016 exploration challenge on feeling acknowledgment.

J. Hofmann et al.,[7] This study examined the elicitation of grinning and chuckling and the job of facial presentation guideline markers (e.g., down-directing of a grin or giggle) in sure feelings. In an organized gathering discussion setting, the recurrence and power of Duchenne and non-Duchenne grins and giggles while telling recollections of 16 positive feelings proposed by Ekman [1] were surveyed. Facial reactions were coded with the Facial Activity Coding Framework (FACS [2]) and chuckling vocalizations were evaluated. The outcomes show that grins and snickers happened in every one of the 16 positive feelings. Giggling happened most frequently in entertainment and fun at others' expense (chuckling happened in 72 and 71 percent of the reviewed feeling recollections individually). Likewise, the force of the grins and chuckles was higher in entertainment and fun at others' expense than in the other 14 positive feelings. Besides, down-managed shows (i.e., including facial markers checking the vertical activity of the zygomatic significant muscle) looked like Duchenne Showcases in their force. To sum up, more knowledge is acquired into the look of positive feelings, additionally featuring the job of chuckling. Likewise, the significance of surveying guideline markers in euphoria shows when individuals are in group environments is worried.

M. S. Hossain et al.,[8] Feeling mindful portable applications have been expanding because of their shrewd highlights and client agreeableness. To acknowledge such an application, a feeling acknowledgment framework ought to be progressively and profoundly exact. As a cell phone has restricted handling power, the calculation in the feeling acknowledgment framework ought to be carried out utilizing less calculation. In this work, we propose a feeling acknowledgment with elite execution for portable applications. In the proposed framework, facial video is caught by an installed camera of an advanced mobile phone. A few delegate outlines are separated from the video, and a face recognition module is applied to remove the face districts in the edges. The Bandlet change is acknowledged on the face districts, and the resultant subband is separated into non-covering blocks. Neighborhood paired examples' histograms are determined for each square, and afterward are connected over every one of the squares. The Kruskal-Wallis include determination is applied to choose the most prevailing containers of the connected histograms. The prevailing receptacles are then taken care of into a Gaussian blend model-based classifier to arrange the inclination. Test results show that the proposed framework accomplishes high acknowledgment precision in a sensible time.

Y. Zhang et al.,[9] Feeling acknowledgment addresses the position and movement of facial muscles. It contributes essentially in many fields. Current methodologies have not gotten great outcomes. This work expected to propose another feeling acknowledgment framework in view of look pictures. We enlisted 20 subjects and let each subject posture seven unique feelings: blissful, misery, shock, outrage, nausea, dread, and impartial. Thereafter, we utilized biorthogonal wavelet entropy to extricate multiscale includes, and utilized fluffy multiclass support vector machine to be the classifier. The defined cross approval was utilized as a severe approval model. The factual investigation showed our strategy accomplished a general exactness of 96.77±0.10%. Furthermore, our technique is better than three cutting edge strategies. On the whole, this proposed technique is productive.

W. Zheng et al.,[10] To explore basic recurrence groups and channels, this work presents profound conviction organizations (DBNs) to developing EEG-based feeling acknowledgment models for three feelings: good, impartial and pessimistic. We foster an EEG dataset gained from 15 subjects. Each subject plays out the investigations two times at the time period few days. DBNs are prepared with differential entropy highlights extricated from multichannel EEG information. We analyze the loads of the prepared DBNs and explore the basic recurrence groups and channels. Four unique profiles of 4, 6, 9, and 12 channels are chosen. The acknowledgment exactnesses of these four profiles are somewhat steady with the best precision of 86.65%, which is far better than that of the first 62 channels. The basic recurrence groups still up in the air by utilizing the loads of prepared DBNs are reliable with the current perceptions. Likewise, our analysis results show that brain marks related with various feelings really do exist and they share shared characteristic across meetings and people. We contrast the exhibition of profound models and shallow models. The normal exactnesses of DBN, SVM, LR, and KNN are 86.08%, 83.99%, 82.70%, and 72.60%, separately.

M. Fairhurst et al.,[11]Handwriting biometrics has a long history, particularly when the transcribed mark is the objective, however it has additionally demonstrated conceivable to involve penmanship as a reason for the expectation of different non-interesting yet forensically helpful qualities of the essayist, by and large viewed as instances of alleged 'delicate biometrics'. Most normally, these are attributes like the age or orientation of the author, yet the prescient capacities emerging in penmanship offer more extensive open doors for quality forecast. This study presents a fundamental examination of the utilization of penmanship to anticipate data about the author relating explicitly to more significant level attributes like enthusiastic state. The creators present an underlying review to exhibit that this is conceivable, and investigate various factors especially applicable to the utilization of such an ability in areas of criminological examination.

U. Tariq et al.,[12] This work subtleties the creators' endeavors to push the benchmark of feeling acknowledgment execution on the Geneva Multimodal Feeling Depictions (GEMEP) Look Acknowledgment and Investigation information base. Both subject-reliant and subject-free feeling acknowledgment situations are tended to in this work. The methodology toward tackling this issue includes face recognition, trailed by central issue distinguishing proof, then highlight age, and afterward, at long last, characterization. A group of highlights comprising of progressive Gaussianization, scale-invariant component change, and some coarse movement highlights have been utilized. In the characterization stage, we utilized help vector machines. The order task has been separated into individual explicit and individual free feeling acknowledgments utilizing face acknowledgment with either manual marks or programmed calculations. We accomplish 100 percent execution for the individual explicit one, 66% presentation for the individual free one, and 80% execution for in general outcomes, as far as grouping rate, for feeling acknowledgment with manual ID of subjects.

3. STRESS DETECTION IN VARIOUS ENVIRONMENTS

1) Stress Detection in Different Driving Conditions

While you're behind the wheel, you could face a number of stressful situations, such as adhering to the set speed limit, dealing with heavy traffic, or facing potentially hazardous weather conditions. Driving in these circumstances poses a risk of rule breaches as well as potential collisions with other vehicles. Because of this, determining a driver's level of stress when they are behind the wheel is a significant problem for the sake of health, safety, and security. Wearable technology has the potential to be beneficial in situations like these by warning the motorist about their increased stress levels and urging them to take the required preventative actions.

2) Stress Detection in Academic Environment

One of the primary causes of mental stress among adolescents, particularly students, is schoolwork. This type of stress can generally be traced back to factors such as an excessive curriculum, the preparation for exams, unsatisfactory academic performance, excessive expectations from parents and teachers, a lack of interest in a particular subject, and other similar factors. These elements have the potential to have an impact on the kids' physical and mental health. Students might benefit academically from the usage of wearable sensors that monitor their levels of stress in order to help them perform better in their classes.

3) Stress Detection in Office-Like Working Environment

Employees who work in settings that are reminiscent of offices may be more likely to experience mental pressures such as anxiety, stress, and depression as a result of their working conditions. There are many different things that might cause stress, such as having to work long hours, having strict deadlines, having an excessive amount of work, working in teams, and being under the pressure of peers.

The identified challenges are described below-

- The most important problems come in the form of improperly worn equipment as well as unfettered mobility on the part of the individuals.
- In controlled settings, the subjects' motions and the stresses that they are exposed to are restrained and limited. As a consequence, researchers have the chance to work with the subjects to ensure that they wear the device correctly so that they can get accurate data. On the other hand, in a setting that operates in real time, mobility is neither controlled nor regulated. Also, the individuals may have a tendency to participate in more than one activity at the same time, which may make the identification process more difficult and, as a result, may impair the effectiveness of stress detection systems.
- Massive alterations in a subject's physiology are quite likely to be brought on by health problems such as those relating to blood pressure, blood sugar, sleep patterns, drinking or smoking habits, and so on and so forth. So, it is essential to pay greater attention to the aforementioned difficulties since there is a possibility that they may damage the precision of the system.
- The most difficult components of designing any kind of stress detection model are probably going to be collecting data in a real-time setting, getting rid of artefacts and noise, and making sure the data are accurate.

There are a variety of assessment measures that have been used in order to evaluate the effectiveness of algorithms for the stress from EEG detection issue. In this part, we will discuss the detection metrics that are used the most often. The methodologies used for machine learning first build the confusion matrix, and then use this to determine the accuracy as well as other metrics.

- True Positive (TP)
- True Negative (TN)
- False Negative (FN)
- False Positive (FP)

4. CONCLUSION

The human body goes into a state of heightened psychophysiological arousal in reaction to a demanding situation or an event that presents a challenge. Stressors are defined as environmental conditions that bring on feelings of anxiety or tension. The purpose of this paper is to investigate the techniques for detecting stressful emotions that have been implemented in accordance with sensor devices like wearable sensors, electrocardiograms (ECG), electroencephalograms (EEG), and photoplethysmography (PPG), as well as in accordance with different environments like while driving, studying, and working. The methods of machine learning are particularly efficient and effective in determining the sorts of emotions with a high level of accuracy. Each study's stresses, methodologies, findings, benefits, limits, and difficulties are discussed here, and it is anticipated that this will give a roadmap for future research investigations.

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