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PREDICTION OF DEPRESSION IN PATIENTS BASED ON EEG TECHNIQUE

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***Abstract*— In the area of mental healthcare, where continuous and discrete monitoring is preferred, the electroencephalogram (EEG) is a critical component of e-healthcare systems. Data from EEG devices, which may show brain activity, can be used to represent various emotional states. Stress is a feeling of tension, either mentally or physically. Any situation or concept that makes you angry, irate, or anxious can set it off. Mental stress has become a social problem and may contribute to functional impairment at regular job. Electroencephalogram (EEG) signal analysis is successfully accomplished using a machine learning (ML) framework. This study examines the EEG-based classification of people with depression.**

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

I. INTRODUCTION

Most people understand stress as a condition when they are under excessive pressure to achieve more than they are capable of and are only just able to keep up with the demands. Both psychological and social needs may be present. People's emotional behaviour, job performance, and mental and physical health have all been shown to be negatively impacted by psychosocial stress, which is a common occurrence in daily life [1]. Numerous physiological illnesses are mostly brought on by psychosocial stress. For instance, it makes depression, stroke, heart attacks, and cardiac arrest more likely [4].

It is feasible to gather brain signals associated with various states from the scalp surface using the efficient electroencephalography (EEG) modality.

According to their frequency range,the various EEG wave types are categorised as follows: abnormal electrical discharge on the EEG may occur in the presence of a brain disease.

A demand or task causes your body to become stressed. When it keeps you safe or helps you meet a deadline, for example, stress can occasionally be helpful. Biological markers for chronic stress have been identified as the and beta bands, which demonstrate relative higher right anterior EEG data activity in people under stress.

The results of the experiment show that stable patterns are consistent across sessions, that positive emotions are associated with greater beta and gamma band activation than negative emotions, Positive emotions are linked to significantly larger delta responses at parietal and occipital sites as well as higher gamma responses at prefrontal sites, while neutral emotions are linked [1].

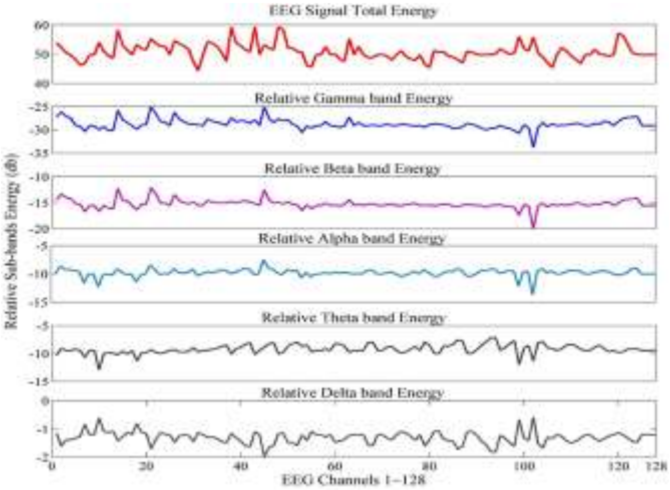

Figure 1: EEG Signal [1]

Human relationships are frequently facilitated by emotions, yet the wide range of emotional states among people has a detrimental influence on the accuracy of emotion recognition [6]. An emerging interdisciplinary subject of study in affective computing and sentiment analysis is multimodal emotion recognition. It tries to improve the accuracy of emotion identification systems by utilising the information carried by signals of various types. Utilising a potent multimodal fusion approach, this is accomplished [8].

Due to the variety of uses for facial expression recognition (FER) in the field of human-computer interaction, it is currently one of the most active study areas. The current success of automatic FER was made possible in large part by the development of deep learning methodologies. Due to the size of the majority of the FER data sets, It is still very challenging to train deep networks for FER. The performance of deep models is still below its maximum potential, despite the fact that transfer learning might partially resolve the problem, as deep features might contain redundant data from the pre-trained domain [10].

II. LITERATURE SURVEY

Prior to feature extraction, C. Jiang et al.[1] present the spatial differences. Final thoughts and debate We successfully distinguished between positive and negative stimuli using the TCSP, with leave-one-subject-out cross-validation values of 84% and 85.7%, respectively. This is significantly higher (p 0.05) than the similar figures of 81.7% and 83.2% obtained without the TCSP. The gamma band contributed most, according to our assessment of the classification performance utilising a variety of frequency bands. We also looked at other classifiers, like logistic regression and k-nearest neighbour, which also showed similar tendencies in the improvement of classification when employing TCSP. The findings demonstrate that the accuracy of identifying depression patients is greatly improved by our suggested strategy, which makes use of geographical information.

W. Fang et al. [2] purpose of accounting for hardware resource constraints, we also proposed a multiphase CNN execution technique. The suggested architecture was validated using datasets of 32 participants from the DEAP database. The mean accuracies for valance binary classification and valance-arousal quaternary classification were 83.36% and 76.67%, respectively. The CNN chip's core area and overall power usage were 1.83 x 1.83 mm 2 and 76.61 mW, respectively. The ADVANTEST V93000 PS1600 was used to validate the chip operation. For each EEG image, the training process and real-time classification processing time took 0.12495 ms and 0.02634 ms, respectively. The suggested EEG-based real-time emotion detection system included a CNN chip platform, a feature extraction processor, a CNN headset with dry electrodes, and a graphical user interface. The carrying out.

The relating to the ongoing development of human-computer interaction technology is presented by X. Xu et al. in their article [3]. In the Internet of Things (IoT), the usage of emotional computing is slowly becoming more prevalent. A feature extraction technique is suggested. 16 people's emotions are brought on by visual stimulus. and the original signal is recorded using a Neuroscan device. Electromyography (EMG) and EEG data are then subtracted using band-pass filtering, and the signals for each frequency band are then reconstructed using DTCWT. Finally, with an accuracy of 90.61%, three separate emotions—calm, happy, and sad—are categorised using support vector machines (SVM). The obtained results show that the proposed method can effectively extract the feature vector and fix the problem of multiple class recognition's low accuracy.

By utilizing normalised mutual information (NMI), A channel selection strategy is provided by Z. Wang et al. [4] for picking the best subset of EEG channels. When compared to earlier methods, the proposed method solves the difficulty of achieving a higher recognition rate while substantially lowering EEG channels. EEG signals are first divided into fixed-length segments with a sliding window before being captured using a short-time Fourier transform. Channel reduction is then carried out utilising thresholding and connection matrix analysis after calculating the inter-channel connection matrix based on NMI. The widely-used emotion recognition database DEAP is the foundation for the studies. The experimental findings show that the suggested strategy can choose the best EEG channel subsets up to a specific number while still achieving good accuracy with SVMs of 74.41% for valence and 73.64% for arousal. According to later research, the distribution of the selected channels is consistent with cortical areas that are employed for general emotion tasks.

Affective computing is a multidisciplinary area of study that integrates computer science, psychology, and cognitive science, as demonstrated by P. J. Bota et al. in their [5] study. Applications for this technology could be found in various fields, such as automated driving assistance, healthcare, human-computer interaction, entertainment, marketing, and education. As a result, the discipline immediately attracted significant interest, resulting in an exponential rise in the quantity of papers written about the topic since its inception. A unique approach to extract shared characteristics for each class of emotional states is put forth by S. Wang et al. [6] and is capable of accurately representing human emotions. In order to extract the shared traits from ambiguous emotional states, the reverse cloud generator is utilised to integrate randomization and fuzziness. Finally, the proposed method for emotion recognition is validated using the Extended Cohn-Kanade (CK+) dataset and the Japanese female facial expression (JAFFE) dataset. The outcomes are satisfactory and show the potential utility of cloud models for machine learning and pattern recognition.

According to R. A. Khalil et al.'s [7] research, emotion identification from voice signals is a critical yet challenging component of human-computer interaction (HCI). In the literature on speech emotion recognition (SER), a variety of techniques, including many well-known speech analysis and classification techniques, have been employed to extract emotions from signals. Deep learning methodologies have recently been presented as a replacement to traditional SER procedures. This article offers a summary of deep learning methods and discusses a number of recent studies that employ these methods to identify speech-based emotions. The review goes over the databases used, the emotions that were pulled out, the improvements in speech emotion recognition, and any related limitations.

S. Nemati et al.[8] propose a hybrid multimodal data fusion method in which the textual modality is combined with the audio and visual modalities using a Dempster-Shafer (DS) theory-based evidential fusion method, and their projected features into the cross-modal space are combined with the visual and audio modalities using a latent space linear map. Using videos from the DEAP dataset, the proposed method's performance was compared against decision-level and non-latent space fusion techniques. Furthermore, the results demonstrate that marginal Fisher analysis (MFA) for feature-level audio-visual fusion outperforms cross-modal factor analysis (CFA) and canonical correlation analysis (CCA) in terms of improvement. The results of the implementation also show that mixing user comments in text with audiovisual components of movies improves the performance.

Based on the widely accepted theory that certain motions of certain facial muscles and components cause facial expressions, as stated by P. M. Ferreira et al. in their publication [10], we present a novel end-to-end neural network architecture. With the loss function, which is designed to regularise the entire learning process, the proposed neural network is able to explicitly learn attributes that are specific to an expression. Experimental results demonstrate that the proposed method performs satisfactorily in both lab-controlled and outside environments. Particularly, the suggested neural network offers rather encouraging results, frequently beating the most advanced techniques currently available.

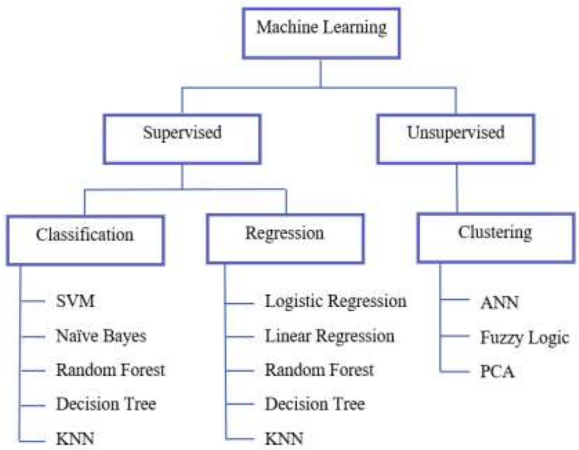

Figure 2: Machine learning Techniques [5]

In order to distinguish between the three categories of human emotions—positive, neutral, and negative—Y. Yang et al. [11] propose a hierarchical network structure with subnetwork nodes. In order to represent features, each embedded subnetwork node, which is composed of hundreds of hidden nodes, can function as a separate hidden layer. The top layer of a hierarchical network, like the animal cortex in the brain, collects data generated from subnetwork nodes and recasts these qualities into a mapping space, enabling the network to function and provide more reliable cognition.With other cutting-edge techniques, the suggested strategy is contrasted. Results of the experiment Both single modalities and multiple modalities can be used with the described technique, although a promising outcome is attained, as demonstrated by two separate EEG datasets.

In order to close the emotional gap, S. Zhang et al. [12] suggest employing a hybrid deep model that first uses convolutional neural networks and 3D-CNNs to build the audio-visual segment characteristics before combining those features in Deep Belief Networks (DBNs). Twice training is done on the specified way. To learn audio and visual segment features, respectively, CNN and 3D-CNN models are first fine-tuned on emotion detection tasks after being pre-trained on comparable large-scale picture and video classification tasks. Second, a fusion network constructed using a DBN model combines the outputs of the CNN and 3D-CNN models. To jointly learn a discriminative audio-visual segment feature representation, the fusion network is trained. A linear Support Vector Machine is utilised for video emotion classification after average-pooling segment features learned by DBN to create a fixed-length global video feature. the performed RML database, as well as experimental findings from three public audio-visual emotional databases, The performing eNTERFACE05 database and the spontaneous BAUM-1s database demonstrate the promising performance of the suggested technique. To the best of our knowledge, this is a pioneering attempt at identifying audio-visual emotions using CNN, 3D-CNN, and DBN.

III. STRESS DETECTION IN VARIOUS ENVIRONMENTS

1) Stress Detection in Different Driving Conditions

Driving can be stressful for a variety of reasons, including following the speed limit, dealing with traffic congestion, driving in hazardous weather, etc. Driving in such circumstances may result in breaking the law and even auto accidents. Therefore, determining a driver's stress level while driving is crucial for reasons of safety, security, and health. Wearable technology can be useful in these situations by warning the motorist about their elevated stress levels and encouraging them to take the appropriate safety precautions.

2) Stress Detection in Academic Environment

One of the primary causes of mental stress in teenagers, particularly in students, is the study, which typically results from an overly demanding curriculum, exam preparation, subpar academic performance, unreasonably high expectations from parents and stern teachers, an absence of interest in a particular topic, etc. These elements may have an impact on pupils' physical and emotional wellbeing. Wearable sensors can help students increase their academic performance by identifying their level of stress and helping them manage it.

3) Stress Detection in Office-Like Working Environment

Office environments can strain the mind, which can result in health issues including anxiety, stress, and depression among workers. There are many different sources of stress, such as extended work hours, severe deadlines, task overload, job uncertainty in the private sector, teamwork, and peer pressure.

The identified challenges are described below-

- The two biggest significant challenges are the subjects' freedom of mobility and improperly worn gadgets.

- In controlled situations, the subjects' movements and stressors are restricted and limited, providing researchers the chance to intervene and instruct the individuals on how to correctly wear the device and obtain accurate findings. Movements, however, are uncontrolled and unobserved in a real-time setting. Additionally, because people tend to do multiple things at once, stress detection systems may function less well as a result of the complexity of the detection process.

- Massive changes in subjects' physiology are extremely likely to be caused by health conditions including those involving blood pressure, blood sugar, sleep patterns, drinking or smoking habits, etc. It is crucial to pay closer attention to the aforementioned difficulties as they could impact the system's accuracy.

- The most difficult parts of creating any stress detection model are gathering data in a real-time setting, eliminating artefacts and noise, and guaranteeing data correctness.

Various evaluation criteria have been employed to assess the effectiveness of algorithms for the problem of stress from EEG detection. We discuss the most popular detection metrics in this subsection. The confusion matrix is produced using machine learning techniques, which are then used to determine accuracy and other criteria.

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

By formulating this as a clarification problem, we can define following metrics,

$$\begin{aligned} Precision &= \frac{|TP|}{|TP| + |FP|} \\ Recall &= \frac{|TP|}{|TP| + |FN|} \\ F1 &= 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \\ Accuracy &= \frac{|TP| + |TN|}{|TP| + |TN| + |FP| + |FN|} \end{aligned}$$

IV. CONCLUSION

Stress is a heightened psycho-physiological condition of the body that occurs in response to a demanding circumstance or difficult event. Stress is brought on by environmental factors known as stressors. This study examines the methods for identifying stress emotions that are used in conjunction with sensory devices like wearable sensors, electrocardiograms (ECG), electroencephalograms (EEG), and photoplethysmograms (PPG), as well as in various settings like while driving, studying, and working. Different types of emotions can be accurately and effectively recognised by machine learning algorithms. It is anticipated that future research investigations will adhere to the stresses, methodologies, results, advantages, limitations, and concerns for each study.

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