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Literature survey on Different Technique used for Detection of Depression using EEG Signal

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Abstract-Electroencephalogram (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. Stress is a feeling of emotional or physical tension. It can come from any event or thought that makes you feel frustrated, angry, or nervous. Mental stress has become a social issue and could become a cause of functional disability during routine work. A machine learning (ML) framework is effective for electroencephalogram (EEG) signal analysis. This paper reviews of depression emotion recognition from EEG for e-healthcare applications.

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

I. INTRODUCTION

Stress is commonly recognized as a state in which an individual is expected to perform too much under sheer pressure and in which he/she can only marginally contend with the demands. These demands can be psychological or social. It is known that psychosocial stress exists in daily life, which has resulted in poor quality of life by affecting people's emotional behavior, job performance, mental and physical health [1]. Psychosocial stress is a leading cause of several physiological disorders. For example, it increases the likelihood of depression, stroke, heart attack and cardiac arrest [4].

Electroencephalography (EEG) is an efficient modality which helps to acquire brain signals corresponds to various states from the scalp surface area. These signals are generally categorized as delta, theta, alpha, beta and gamma based on signal frequencies ranges from 0.1 Hz to more than 100 Hz. It is a test that detects electrical activity in the brain using small, metal discs (electrodes) attached to the scalp. Routinely, EEG is used in clinical circumstances to determine changes in brain activity that might be useful in diagnosing brain disorders, especially epilepsy or another seizure disorder.

The types of EEG waves[2,3] are identified according to their frequency range – delta: below 3.5 Hz (0.1–3.5 Hz), theta: 4–7.5 Hz, alpha: 8–13 Hz, beta: 14–40 Hz, and gamma: above 40 Hz. The EEG may show unusual electrical discharge when some abnormality occurs in the brain.

Stress is your body's reaction to a challenge or demand. In short bursts, stress can be positive, such as when it helps you avoid danger or meet a deadline. EEG nonlinear dynamics features and frontal asymmetry of theta, alpha, and beta bands have been selected as biological indicators for chronic stress, showing relative greater right anterior EEG data activity in stressful individuals.

The experimental results 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 for negative emotions, the neural patterns have significant higher delta responses at parietal and occipital sites and higher gamma responses at prefrontal sites [1].

Emotions often facilitate interactions among human beings, but the big variation of human emotional states make a negative effect on the reliable emotion recognition [6]. Multimodal emotion recognition is an emerging interdisciplinary field of research in the area of affective computing and sentiment analysis. It aims at exploiting the information carried by signals of different nature to make emotion recognition systems more accurate. This is achieved by employing a powerful multimodal fusion method [8].

Facial expression recognition (FER) is currently one of the most active research topics due to its wide range of applications in the human-computer interaction field. An important part of the recent success of automatic FER was achieved thanks to the emergence of deep learning approaches. However, training deep networks for FER is still a very challenging task, since most of the available FER data sets are relatively small. Although transfer learning can partially alleviate the issue, the performance of deep models is still below of its full potential as deep features may contain redundant information from the pre-trained domain [10].

II.LITERATURE SURVEY

W. Zheng et al.,[1] presents the stable patterns of electroencephalogram (EEG) over time for emotion recognition using a machine learning approach. Up to now, various findings of activated patterns associated with different emotions have been reported. However, their stability over time has not been fully investigated yet. Researcg focus on identifying EEG stability in emotion recognition. We systematically evaluate the performance of various popular feature extraction, feature selection, feature smoothing and pattern classification methods with the DEAP dataset and a newly developed dataset called SEED for this study. Discriminative Graph regularized Extreme Learning Machine with differential entropy features achieves the best average accuracies of 69.67 and 91.07 percent on the DEAP and SEED datasets, respectively. The performance of our emotion recognition models shows that the neural patterns are relatively stable within and between sessions.

W. Fang et al.,[2] proposed an electroencephalogram (EEG)-based real-time emotion recognition hardware system architecture based on multiphase convolutional neural network (CNN) algorithm implemented on a 28-nm technology chip and on field programmable gate array (FPGA) for binary and quaternary classification. Sample entropy, differential asymmetry, short-time Fourier transform, and a channel reconstruction method were used for emotion feature extraction. In this work, six EEG channels were selected (FP1, FP2, F3, F4, F7, and F8), and EEG images were generated from spectrogram fusions. The complete CNN architecture included training and acceleration for efficient artificial intelligence (AI) edge application, and we proposed a multiphase CNN execution method to accommodate hardware resource constraints.

Datasets of 32 subjects from the DEAP database were used to validate the proposed design, exhibiting mean accuracies for valance binary classification and valance-arousal quaternary classification of 83.36% and 76.67%, respectively. The core area and total power consumption of the CNN chip were 1.83 x 1.83 mm^2, respectively, and 76.61 mW. The chip operation was validated using ADVANTEST V93000 PS1600, and the training process and real-time classification processing time took 0.12495 ms and 0.02634 ms for each EEG image, respectively. The proposed EEG-based realtime emotion recognition system included a dry electrode EEG headset, feature extraction processor, CNN chip platform, and graphical user interface, and the execution time costed 450 ms for each emotional state recognition.

X. Xu et al.,[3] presents the corresponding to the continual development of human-computer interaction technology, the use of emotional computing (EC) is gradually emerging in the Internet of Things (IoT). Emotion recognition is considered a highly valuable aspect of EC. Numerous studies have examined emotion recognition based on electroencephalogram (EEG) signals, but the recognition rate is unreliable. A feature extraction method is proposed that is based on double tree complex wavelet transform (DTCWT) and machine learning. The emotions of 16 subjects are induced under video stimulation, and the original signal is acquired using a Neuroscan device. Both EEG and electromyography (EMG) signal are then eliminated by band-pass filtering, and the reconstructed signal of each frequency band is obtained by DTCWT. Finally, support vector machine (SVM) is utilized to classify three kinds of emotions: calm, happy, and sad, obtaining a classification accuracy of 90.61%. Results show that the proposed algorithm can effectively extract the feature vector and improve the problem of low accuracy in multiple class recognition.

Z. Wang et al.,[4] proposes a channel selection method to select an optimal subset of EEG channels by using normalized mutual information (NMI). Compared with other methods, the proposed method solves the problem of obtaining a higher recognition rate while reducing EEG channels sharply. First, EEG signals are sliced into fixed-length pieces with a sliding window, and short-time Fourier transform is adopted to capture EEG spectrogram. Then inter-channel connection matrix is calculated based on NMI, and channel reduction is conducted by using thresholding and connection matrix analysis. The experiments are based on the widely-used emotion recognition database DEAP.

It can be derived from the experimental results that the proposed method can select optimal EEG channel subsets to a certain number while maintaining high accuracy of 74.41% for valence and 73.64% for arousal with support vector machines. Further analysis also reveals that the distribution of the selected channels is consistent with cortical areas for general emotion tasks.

P. J. Bota et al.,[5] shows the affective computing is a multidisciplinary field of research spanning the areas of computer science, psychology, and cognitive science. Potential applications include automated driver assistance, healthcare, human-computer interaction, entertainment, marketing, teaching and many others. Thus, quickly, the field acquired high interest, with an enormous growth of the number of s published on the topic since its inception. This aims to (1) Present an introduction to the field of affective computing though the description of key theoretical concepts; (2) Describe the current state-of-the-art of emotion recognition, tracing the developments that helped foster the growth of the field; and lastly, (3) point the literature take-home messages and conclusions, evidencing the main challenges and future opportunities that lie ahead, in particular for the development of novel machine learning (ML) algorithms in the context of emotion recognition using physiological signals.

S. Wang et al.,[6] propose a novel algorithm to extract common features for each type of emotional states which can reliably present human emotions. To uncover the common features from uncertain emotional states, the backward cloud generator is used to discover by integrating randomness and fuzziness. Finally, the proposed method for emotion recognition is verified on the common facial expression datasets, the Extended Cohn-Kanade (CK+) dataset and the Japanese female facial expression (JAFFE). The results are satisfactory, which shows cloud model is potentially useful in pattern recognition and machines learning.

R. A. Khalil et al.,[7] presents the emotion recognition from speech signals is an important but challenging component of Human-Computer Interaction (HCI). In the literature of speech emotion recognition (SER), many techniques have been utilized to extract emotions from signals, including many well-established speech analysis and classification techniques. Deep Learning techniques have been recently proposed as an alternative to traditional techniques in SER. This presents an overview of Deep Learning techniques and discusses some recent literature where these methods are utilized for speech-based emotion recognition. The review covers databases used, emotions extracted, contributions made toward speech emotion recognition and limitations related to it.

S. Nemati et al.,[8] presents a hybrid multimodal data fusion method is proposed in which the audio and visual modalities are fused using a latent space linear map and then, their projected features into the cross-modal space are fused with the textual modality using a Dempster-Shafer (DS) theory-based evidential fusion method. The evaluation of the proposed method on the videos of the DEAP dataset shows its superiority over both decision-level and non-latent space fusion methods. Furthermore, the results reveal that employing Marginal Fisher Analysis (MFA) for feature-level audio-visual fusion results in higher improvement in comparison to cross-modal factor analysis (CFA) and canonical correlation analysis (CCA). Also, the implementation results show that exploiting textual users' comments with the audiovisual content of movies improves the performance of the system.

H. Zhang et al.,[9] presents the complex process of explicit feature extraction in traditional facial expression recognition, a face expression recognition method based on a convolutional neural network (CNN) and an image edge detection is proposed. Firstly, the facial expression image is normalized, and the edge of each layer of the image is extracted in the convolution process. The extracted edge information is superimposed on each feature image to preserve the edge structure information of the texture image. Then, the dimensionality reduction of the extracted implicit features is processed by the maximum pooling method. Finally, the expression of the test sample image is classified and recognized by using a Softmax classifier. To verify the robustness of this method for facial expression recognition under a complex background, a simulation experiment is designed by scientifically mixing the Fer-2013 facial expression database with the LFW data set. The experimental results show that the proposed algorithm can achieve an average recognition rate of 88.56% with fewer iterations, and the training speed on the training set is about 1.5 times faster than that on the contrast algorithm.

P. M. Ferreira et al.,[10] we propose a novel end-to-end neural network architecture along with a well-designed loss function based on the strong prior knowledge that facial expressions are the result of the motions of some facial muscles and components. The loss function is defined to regularize the entire learning process so that the proposed neural network is able to explicitly learn expression-specific features. Experimental results demonstrate the effectiveness of the proposed model in both lab-controlled and wild environments. In particular, the proposed neural network provides quite promising results, outperforming in most cases the current state-of-the-art methods.

Y. Yang et al.,[11] proposes a hierarchical network structure with subnetwork nodes to discriminate three human emotions: 1) positive; 2) neutral; and 3) negative. Each subnetwork node embedded in the network that are formed by hundreds of hidden nodes, could be functional as an independent hidden layer for feature representation. The top layer of the hierarchical network, like the mammal cortex in the brain, combine such features generated from subnetwork nodes, but simultaneously, recast these features into a mapping space so that the network can be performed to produce more reliable cognition. The proposed method is compared with other state-of-the-art methods. The experimental results from two different EEG datasets show that a promising result is obtained when using the proposed method with both single and multiple modality.

S. Zhang et al.,[12] proposes to bridge the emotional gap by using a hybrid deep model, which first produces audio-visual segment features with Convolutional Neural Networks (CNNs) and 3D-CNN, then fuses audio-visual segment features in a Deep Belief Networks (DBNs). The proposed method is trained in two stages. First, CNN and 3D-CNN models pre-trained on corresponding large-scale image and video classification tasks are fine-tuned on emotion recognition tasks to learn audio and visual segment features, respectively. Second, the outputs of CNN and 3D-CNN models are combined into a fusion network built with a DBN model. The fusion network is trained to jointly learn a discriminative audio-visual segment feature representation. After average-pooling segment features learned by DBN to form a fixed-length global video feature, a linear Support Vector Machine is used for video emotion classification. Experimental results on three public audio-visual emotional databases, including the acted RML database, the acted eNTERFACE05 database, and the spontaneous BAUM-1s database, demonstrate the promising performance of the proposed method. To the best of our knowledge, this is an early work fusing audio and visual cues with CNN, 3D-CNN, and DBN for audio-visual emotion recognition.

III.STRESS DETECTION IN VARIOUS ENVIRONMENTS

1. Stress Detection in Different Driving Conditions
There can be many stressful events that may occur while driving like maintaining the speed limit, heavy traffic, and unsafe weather conditions, etc. Driving in such conditions may lead to violations of rules and possibly car accidents. Hence the identification of the stress level of a driver while driving is an important issue for safety, security, and health purpose. In such cases, wearable devices can be helpful by alerting the driver about the elevated stress levels and advising them to take necessary precautionary measures.

2.Stress Detection in Academic Environment
The study is one of the main sources of mental stress among adolescents especially students which generally comes from the excessive curriculum, preparation for exams, unsatisfactory academic performance, over expectations from parents, strict teachers, lack of interest in a particular subject, etc. These factors can affect the physical and mental health of students. Wearable sensors can be useful to detect stress and its level among students allowing them to perform better in their studies.

3. Stress Detection in Office-Like Working Environment
The office-like environments can create mental loads which can be responsible for health issues like anxiety, stress and depression of the employees. There can be many sources of stress like long working hours, tight deadlines, work overˇload, job insecurity in private sectors, working in teams, and peer pressure.

The identified challenges are described below-
Improperly worn devices and the unrestricted movement of the subjects are the main significant challenges. In controlled environments, the movements and the stressors are constrained and limited, thereby, giving an opportunity to researchers to intervene with the subjects to wear the device properly and to get precise results. But in a real-time environment, movements are unrestricted and unmonitored. Also, the subjects may incline to do more than one activity at a time, making the detection process more complicated and thereby could reduce the performance of stress detection systems.

Health issues such as those related to blood pressure, blood sugar, sleep patterns, alcohol or smoking habits, etc., are very likely to cause massive changes in subjects' physiology. Hence, it is vital to pay more attention to the said issues as they may affect the accuracy of the system.
 Collecting data in a real-time environment, removing artifacts and noise, and ensuring data accuracy are the most challenging aspects in developing any stress detection model.

To evaluate the performance of algorithms for stress from EEG detection problem, various evaluation metrics have been used. In this subsection, we review the most widely used metrics for detection. The machine learning approaches generate the confusion matrix and find the accuracy and other parameters through this.
- True Positive (TP)
- True Negative (TN)
- False Negative (FN)
- False Positive (FP)

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

IV.CONCLUSION

Stress is an escalated psycho-physiological state of the human body emerging in response to a challenging event or a demanding condition. Environmental factors that trigger stress are called stressors. This paper study the stress emotion detection approaches adopted in accordance with the sensory devices such as wearable sensors, Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), and also depending on various environments like during driving, studying, and working. The machine learning techniques is very effective to identify the types of emotion with high accuracy. The stressors, techniques, results, advantages, limitations, and issues for each study are highlighted and expected to provide a path for future research studies.

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