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Analysis of Stress Using Electroencephalogram Data for Feature Extraction

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Abstract: Patient denial, insensitivity, subjective biases, and inaccuracy are only some of the issues that arise from relying solely on doctor-patient interaction and scale analysis when diagnosing Stress. The creation of an objective, computerized approach for predicting therapeutic outcomes is crucial for enhancing the precision of Stress diagnosis and treatment. In an effort to better detect Stress, this research modifies EEG data and use machine learning algorithms. Ten participants' EEGs were recorded using a Narosky system while they were exposed to various emotional face cues. Psychologists relied on the EEG signal as a diagnostic tool for Stress. Machine learning and deep learning were the methods that handled the feature processing. Using PCA, ICA, and EMD for BCI applications yields significant results. Using SVM, a programmer can reap many benefits: The stress and pressure can be detected by employing EEG signals, and PCA has great generalization properties. The effect of overtraining is particularly vulnerable to the curse-of-dimensionality when the signals are negative. The use of EEG signals for stress detection allowed for these benefits to be realized. The experimental study provides a somewhat comprehensive summary of the various methods, all of which rely on frequency domain analysis of 14 EEG data.

Keywords: *Human Stress, EEG signal, Feature extraction, BCI.*

1. Introduction

Stress is a mental illness that modern societies have been trying to address. For a depressed individual, this is a major obstacle. Impossible to go on living in this world. People gradually retreat from society and their surroundings due to negative emotions such as despair, emptiness, loss, impatience, pessimism, continual exhaustion, a sense of isolation, etc. Self-harm is a possible outcome of the disease, and the patient may struggle with suicidal ideation and behavior during the course of treatment. In order to save a person's life, a prompt diagnosis of Stress is essential.

The responses to a battery of questions from patients or other health studies help psychiatrists, psychologists, and doctors assess a patient's state of health and the degree of their depression or anxiety [1]. The naiveté of the doctors, the patient's irritation or unwillingness to answer questions, the mental battles between the patient and the doctor, the high cost of counselling sessions, etc., all contribute to the high error rate that characterizes these approaches. Therefore, researchers and doctors look for affordable, efficient, and trustworthy methods to diagnose Stress.

A different method of sickness detection is an electroencephalogram (EEG). The EEG is a great tool for learning about brain functioning because it analyses the brain's electrical activity, which occurs via electric waves [2]. Several illnesses have been identified by the analysis of EEG data.

Given the correlation between depression and changes in brain activity, and the fact that EEG readings track brain electrical activity, it stands to reason that EEG readings could be a useful biomarker for identifying Stress. Since this type of study relies on the expert knowledge of the psychiatrist, it is difficult and prone to humanoid error to conduct a graphical inquiry of long-term EEG data to distinguish between a normal and depressed patient [3]. In addition, evaluating and explaining EEG visually is time-consuming and taxing, and there is a high chance of error because it is a composite, nonlinear, and non-stationary indicator. To properly distinguish between typical and depressive EEG signs, a computer-aided diagnosis framework is sought.

2. Related Work

The potential of combining many channels of neurophysiological signal to decode human emotions is becoming more and more apparent. Emotion plays a crucial role in people's day-to-day activities. An individual's capacity for learning, memory, and basic leadership can all be affected by their level of enthusiasm, and groups of people can communicate more effectively when members are animated in their speech. As a result, there are many potential uses for detecting different emotional states across disciplines like education, medicine, AI frameworks, and human-computer cooperation. One of the most pressing challenges is emotion detection, which has recently gained wide acclaim among experts. Emotion Detection may be

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accomplished using extraneous highlights like facial emotions and speech pitch. Physiological flag changes, such as an electroencephalogram, can also be used for this purpose. Facial and vocal articulations, in contrast to physiological sign, are significantly influenced by the external environment, and the parameters effectively alter under a variety of circumstances. However, as physiological signs are hard to conceal, the EEG sign's emotion detection results are somewhat objective. As a result, studies examining the link between EEG activity and emotions have garnered a lot of interest. One of the major steps forward in emotion detection is isolating the emotion-related highlights from the multichannel EEG signals, which is essentially an example recognition task.

Although many methods exist for EEG emotion identification, the underlying goal of the test is always the same. The goal is, in part, to use a better characterization model to classify emotions and increase their precision by identifying relevant highlights through various explanatory methods. A further goal is to identify the most salient recurrence groups and brain regions for emotion detection practise, providing a solid physiological basis for EEG-based emotion Detection research.

Rapid The stresses of daily life are becoming increasingly inescapable due to the rapid pace of technological and social change. The struggles we face in life, both emotionally and physically, are inherent. Different psychophysiological models have been used to observe the human response to stress. Hormones including adrenaline, immunoglobulin A (IgA), and cortisol are secreted in response to stress, whether the exam is psychological or physical. therefore, heart rate, blood pressure, and pulse rate all increase. The stresses of modern life pose real threats, which constantly agitate the mind. This stress reaction may not cause any immediate harm, but it might have undesirable long-term effects on a person's health. An ongoing state of stress results from the activation of the stress reaction during a visit. Hormones released in the body as a result of a prolonged stress response can have a profound effect on the immune system, reducing resistance to infection. Therefore, stress has become a major problem for human health, affecting people of all ages and sex in similar ways.

Psychosomatic symptoms of stress include mental and emotional turmoil as well as physical responses to the demands of daily life. Traditional definitions of stress explain it as a physiological reaction to a perceived emotional, mental, or physical threat. Although this definition appears circular at first glance, it contains some interesting concepts [1]. Emotional meaning assessment is a significant challenge in the study of feelings. Indeed, even experts have trouble agreeing on what counts as an emotion and how many different types of emotions there are. Previous research has investigated the application of psychophysiological and brain flag separately [3, 6, 7], but the relationships between these two signals have received very less attention. Analysing the effects of works that attempt to express emotion in their narratives is a particularly challenging task. When planning detection systems, it's important to think about how members' emotions are sparked and how many members there will be. This is especially true when trying to provide a client-autonomous system. Additionally, there was a more established link between negative emotions like tragedy, fear, and outrage and stress, and positive emotions like optimism, calm, and happiness and a lack of stress in one's mental health. These feelings are in charge of keeping the person calm and collected. According to the researchers' hypotheses, feeling calm and happy indicates that you are not under too much stress, whereas feeling sad and angry indicates that you are paying close attention. Four emotions, including Happy, Calm, Sad, and Angry, are targeted by the proposed human emotion recognition framework. When compared to other stress recognition frameworks, the proposed one has a more substantial level of presentation accuracy.

3. Proposed method

The primary function of a brain-computer interface (BCI) is to facilitate communication between patients and the outside world. Those who are unable to voluntarily restrain muscle growth are a primary target population for BCI applications, especially those who are classified as "secured." Most ebb and flow BCI studies, however, focus on figuring out how to persuade people with normal hearing to operate devices by thinking about doing so. Brain signals for a BCI can be collected directly from the brain's electrical activity or indirectly through a process known as hemodynamics. When a task or movement is carried out, the brain sends out electrical signals known as electroencephalography (EEG) that reflect the firing of neurons. Brain-computer interface diagram with signal collection, segmentation, highlight extraction, clustering, and device interfacing. The framework is complete after the user has placed an order for it. For practical applications, a normal order accuracy of 70% or higher is required. Despite the fact that emotion recognition technology is essential and highly sought after in a variety of settings, it continues to be an open problem. Human emotion recognition can be achieved by analyzing a person's facial image, voice, body shape, and so on. The human face is used more than any other part of the body to deduce emotional state. In particular, the frontal view of a person's face is often utilized to deduce their emotional state. Since extracting the proper component and detecting sensation necessitates complicated advancements, a feeling acknowledgment system isn't simple but complex. It is possible to do a number of calculations for emotion recognition using a frontal facial image. There are three main steps involved in the calculation: the image-preparation phase, the facial-component extraction phase, and the emotion-discovery organ. Fluffy shading channel, a digital face model, and a histogram analysis technique are used to isolate the face region and facial segment in the final image preparation step. In facial component extraction arrangement, the features responsible for emotion recognition are omitted.

3.1 Preprocessing

EEGs are used by doctors and scientists to detect and characterize mental activity like states of relaxation, tension, the presence or absence of seizure activity, and trance. Electrical activity around the anodes of the scalp is recorded by EEG. The EEG waves move and change over time. Eye and muscular movement can cause disruptions and obstructions in EEG readings. Furthermore, most AI algorithms are not practical for the basic information measure needed for grouping. Preprocessing the raw data is thus preferable as it reduces data volume and increases transparency. In the case of EEG data, preprocessing typically refers to noise removal to get closer to the actual neuronal sign. Preprocessing of EEG data is crucial for a number of reasons. Most critically, the signals obtained from the scalp do not accurately reflect the signals that originate in the mind because spatial information is lost in the translation. Additionally, EEG data will typically include a lot of noise, which might mask weaker EEG signals. Thus, EEG signals are pre-processed by converting them from the time domain to the frequency domain and cleaning them of any unwanted noise or artefacts. In order to complete the mission without compromising the quality of the collected EEG data sets.

The approach involves analyzing EEG readings using a DEAP data set. A 32-channel dataset was generated utilizing a 10-20 electrode placement technique. The 32 subjects have viewed 40 distinct videos designed to elicit emotional responses. Preprocessing and down sampling to 128 Hz have been applied to the dataset. The table below provides a detailed overview of the data set.

Table 01: Dataset Summary

Online subjective annotation	
Number of videos	120
Video duration	1 minute
Selection method	60 via last.fm affective tags, 60 manually selected
No. of ratings per video	14 - 16
Rating scales	Arousal Valence Dominance
Rating values	Discrete scale of 1 - 9
Physiological Experiment	
Number of participants	32
Number of videos	40
Selection method	Subset of videos with emotion assessment interface
Rating scales	Arousal, Valence, Dominance Liking (how much do you like the video?) Familiarity (how well do you know the video?)
Rating values	Familiarity: discrete scale of 1 - 5 Others: continuous scale of 1 - 9
Recorded signals	32-channel 512Hz EEG Peripheral physiological signals Face video (for 22 participants)

Table 02: Real-Time Analysis Comparison

Feature Extraction Algorithm	Band	Happy (20)	Angry (20)	% Accuracy Happy n Angry	% Precision Happy	% Precision Angry	TPR Happy	TPR Angry
Proposed approach	Alpha	17	11	70	65.38	78.57	0.85	0.6
	Beta	15	18	82.5	88.24	78.26	0.75	0.9
KDE	Alpha	12	17	72.5	80	68	0.6	0.9
	Beta	13	15	70	72.2	68.18	0.65	0.8
RER	Alpha	14	14	70	70	70	0.7	0.7
	Beta	14	14	70	70	70	0.7	0.7
ELC	Alpha	17	17	85	85	85	0.85	0.9
	Beta	17	18	87.5	89.47	85.71	0.85	0.9

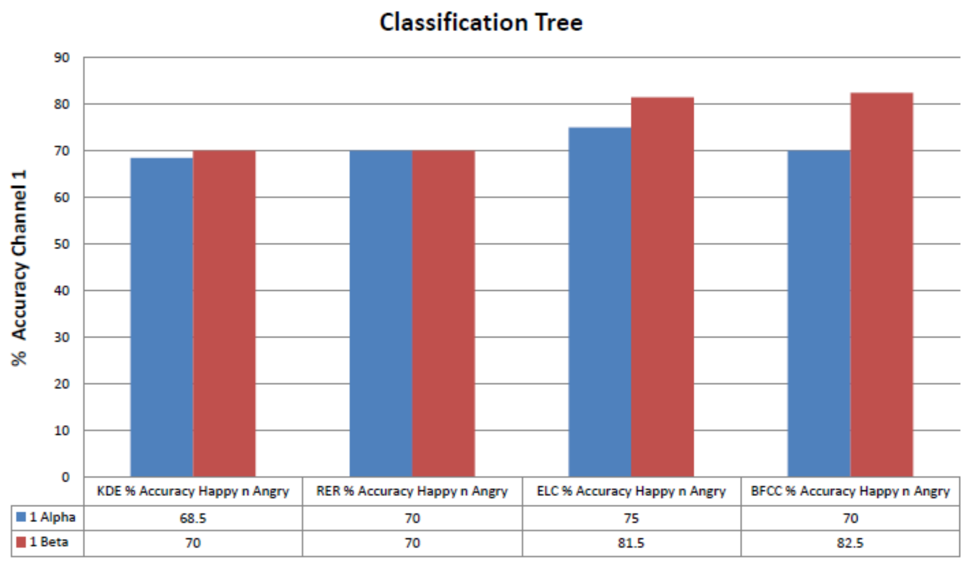

Fig 1: classification accuracy of channel 1 for happy and angry emotions

4. Conclusion

The goal of this study is to create a user-independent human emotion identification system based on EEG signals. In this study, we offer many feature extraction methods to help us locate the most effective and relevant characteristics for human emotion recognition. This study is the first to use geometrical features of the EEG signal data to distinguish between healthy and depressed subjects. This study is the first to analyse and contrast the presentation of optimisation methods for classifying normal and depressed EEG data using feature vector range reduction. We found that SVM classifiers are more effective than other feature choosing procedures and classifiers at condensing feature vector presentations and making accurate sadness detection predictions. We have compared the presence of the proposed framework in 9 healthy individuals and 9 individuals suffering from depression. The proposed method successfully classified normal and depressed EEG signals with an ACC of 98 percent.

The computer-assisted screening method we proposed for Stress was both accurate and healthful. As an example of the power of binary classification, the proposed framework achieves high MCC values of 0.95 and 0.98 when classifying normal and depressive EEG indications for the left and right hemispheres, respectively.

Any participation test indication with distinct samples was preprocessed, processed, and categorised in around 0.03 seconds using the proposed outline because to the simplicity of the RPS matrix and feature removal computation and the minimal number of feature vector displays.

More work needs to be done to investigate the stress connection between EEG signal analysis and various human emotions. Biomedical applications also allow for the clinically-based problem to be taken for diagnosis.

References:

[1] Marcel Trotzek , Sven Koitka , and Christoph M. Friedrich, "Utilizing Neural Networks and Linguistic Metadata for Early Detection of Stress Indications in Text Sequences", IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, VOL. 32, NO. 3, MARCH 2020.

[2] Systems, C., " EEG-Based stress detection system using human emotions", (2018), 10,2360–2370.

[3] Thi, T., Pham, D., Kim, S., Lu, Y., Jung, S., Won, C., "Facial Action Units-Based Image Retrieval for Facial Expression Recognition", IEEE Access, 7, 5200–5207.https://doi.org/10.1109/ACCESS.2018.2889852 , (2019).

[4] N.d. ,"shocking statistics of workplace stress you never knew - harish saras." accessed february 1, 2019. Https://www.harishsaras.com/stress-management/shocking-statistics-of-workplace-stress/.

[5] Viegas, carla, and roymaxion , "towards independent stress detection: a dependent model using facial action units." 2018 international conference on content-based multimedia indexing (cbmi), 1–6.

[6] Woo, seong-woo, "classification of stress and non-stress condition using functional near-infrared spectroscopy." 2018 18th international conference on control, automation and systems (iccas), no. Iccas: 1147–51.

[7] Wan-Young Chung, Teak-Wei Chong, and Boon-Giin Lee ," METHODS TO DETECT AND REDUCE DRIVER STRESS: A REVIEW," International Journal of Automotive Technology, Vol. 20, No. 5, pp. 1051-1063 (2019) DOI 10.1007/s12239-019-0099-3.

[8] "Shocking Statistics of Workplace Stress You Never Knew - Harish Saras." n.d. Accessed February 1, 2019. https://www.harishsaras.com/stress-management/shocking-statistics-of-workplace-stress/.

[9] M. Tarun Kumar, R. Sandeep Kumar, K. Praveen Kumar, S. Prasanna, G. Shiva," Health Monitoring and Stress Detection System," an International Research Journal of Engineering and Technology (IRJET) Volume: 06 Issue: 03 | Mar 2019.

[10] Luis G. Hernández , Oscar Martinez Mozos, José M. Ferrández and Javier M. Antelis," EEG-Based Detection of Braking Intention Under Different Car Driving Conditions," Frontiers in Neuroinformatics, vol. 12, May 2018.

[11] Khalid masood and mohammed a. Alghamdi," modeling mental Stress Using a Deep Learning Framework," IEEE Access Vol.7 , 2019.

[12] Patil, A. ., & Govindaraj, S. K. . (2023). ADL-BSDF: A Deep Learning Framework for Brain Stroke Detection from MRI Scans towards an Automated Clinical Decision Support System. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3), 11–23. https://doi.org/10.17762/ijritcc.v11i3.6195

[13] Dhabliya, D. (2021). Feature Selection Intrusion Detection System for The Attack Classification with Data Summarization. Machine Learning Applications in Engineering Education and Management, 1(1), 20–25. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/8

[14] Juneja, V., Singh, S., Jain, V., Pandey, K. K., Dhabliya, D., Gupta, A., & Pandey, D. (2023). Optimization-based data science for an IoT service applicable in smart cities. Handbook of research on data-driven mathematical modeling in smart cities (pp. 300-321) doi:10.4018/978-1-6684-6408-3.ch016 Retrieved from www.scopus.com