International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Stress Analysis using Feature Extraction Approach Using EEG Signal

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Submitted: 20/09/2023 **Revised**: 25/10/2023 **Accepted**: 11/11/2023

Abstract: Individuals experience stress in every society. Work-related concerns, disappointments, poor working conditions, etc., are prevalent worldwide sources of stress. Stress can be useful in the short term. However, chronic stress has serious consequences for health, including an increased risk of cardiovascular problems like heart disease, hypertension, and stroke. Mood and personality disorders including depression and anxiety are also possible outcomes. Therefore, the ability to recognise stress is useful for managing the health problems stress might cause. Stress can be measured and evaluated dependant on perceptual, behaviour and physiological reactions. Using feature extraction and classification methods, a few scholars have developed alternative approaches. It is based on that some of these procedures are intricate in their applicability and they produce less precise findings in human stress analysis. Therefore, a trustworthy and exact system is required. The goal of this study is to use Electroencephalography (EEG) signals to identify stress in real time, with the ultimate goal of creating a more accurate and trustworthy system. Stress can be reliably measured in a noninvasive manner with the help of EEG signals. To improve the accuracy of classification in stress detection, in this study, have been employed for feature extraction to extract significant time-frequency features. Accurate classification relies heavily on the selection of the best suitable feature extraction method. Equipment for acquiring EEG signals is used to validate the designed system.

Keywords: *Signal processing, Brain-Computer Interface (BCI), Electroencephalography (EEG), Stress detection.*

I. Introduction

According to the field of psychology, "stress" refers to a "strain and pressure" combination. Stress can be helpful and even beneficial in little doses. High blood pressure, cardiovascular disease, heart attack, and stroke are only some of the health problems that can be triggered by stress in excess. Mental health is also affected, including anxiety, depression, and personality disorders. Psychological, physiological, occupational, and biomechanical indicators all provide unique insights into the effects of stress. Electroencephalogram (EEG) signal analysis for the diagnosis of stress is a valuable medical diagnostic tool. Electroencephalogram (EEG) readings quantify the relationship between brain activity and physiological responses in the brain's major organ, the brain. EEG has been utilised for decades in the study of human stress regulation and treatment in the field of neuroscience. Based on the literature, we can infer that more specialised expertise in the BCI sector is necessary for putting into practise brain-computer interaction systems. When analysing an EEG signal, a ratio of the spectral power to the spectral centroid is chosen as a feature for a K-nearest neighbour classifier. The author examines stress detection using physiological signals and demonstrates how HCI might be improved as a result. It has described the link of brain signals with stress detection model by classifying human stresses. The international affective pictures and system (IAPS) [3] was used to show the subjects in the stress detection procedure audio and visual stresss stimuli. To classify the data, the authors of [4] use a multi-layer perceptron (MLP) after using the kernel density estimation (KDE) method to extract features from the signals. There are four main types of stress that can be identified: sadness, fear, happiness, and serenity. Researchers have utilised a variety of machine learning and deep learning methods to analyse EEG signals and identify features useful for classifying types of stress.

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Various feature extraction and classification algorithms are applied to EEG signals in order to determine a person's stress level through the monitoring of neurological functioning.

II. Literature Review

In 2022, Asghar et al. [1] have provided an first extracted a subset of eigenmode functions from the raw EEG signal, which we refer to as Intrinsic Mode Functions (IMF). To compile data from the time and frequency domains, a Spatio-temporal analysis was carried out using a Complex Continuous Wavelet Transform (CCWT). Using three separate Deep Neural Networks (DNNs), a combined feature vector was extracted using the multiple model extraction technique. To get over the computational curse, they proposed using differential entropy and mutual information to pick high-quality features and pool the k-means results to generate smaller dimensional qualitative feature vectors, thus further reducing feature size. Despite appearances, testing and validating real-time applications with acceptable categorization performance was swift after the network was trained with this model. Two freely available data sets, SEED and DEAP, have verified the efficacy of the suggested strategy for selecting features for benchmarking. This approach offered real-time sentiment analysis, high classification accuracy, and a lower computational cost than state-of-the-art sentiment recognition algorithms.

Nijhawan et al. [2] want to broaden sentiment and emotion analysis in 2022 to identify a person's stress level from his or her social media posts and comments. The researchers use machine learning methods and a deep learning model, BERT for sentiment classification, to do sentiment analysis on massive Twitter datasets. In addition, they used Latent Dirichlet Allocation, an unsupervised machine learning approach to document clustering, pattern recognition, and the extraction of illustrative word clusters and phrase clusters. This allows us to deduce which theme pertained to the underlying textual information. They have used these models to determine how internet users are feeling. Furthermore, these feelings might be utilised in the analysis of stress and depression. In conclusion, a BERT model and machine learning models both perform exceptionally well in terms of detection.

Using a stacking-ensemble based classification technique that increases accuracy, Chatterjee and Byun [3] in 2022 detected positive, negative, and neutral emotional states in EEG signals. Using different classifier approaches. Each base classifier's output was used in the training of the Meta classifier's first level to produce the final predictions. Improved classification accuracy is one of the benefits of the proposed ensemble model. The proposed method also beat the baseline classifiers when comparing performance indices. In terms of emotion classification, the proposed stacking strategy shows promising results when compared to state-of-the-art methods.

Dai et al. [4] suggested a proposed approach We ran 4500 samples through 4 different sets of tests to ensure the accuracy of the model. The model's three-layer features were extracted using feature visualization technologies and analysed using a scatterplot at the same time. The suggested model outperformed the other models in terms of accuracy, and the extracted features showed the highest levels of separation. They discovered that unnecessary layers added to the model did not increase its performance, and that excluding data from some channels had little impact on the model's ability to classify. Based on these findings, it appears that the suggested model enabled emotion recognition at a greater accuracy and speed than reported in earlier models. They think this method might be used in a range of contexts where rapid and reliable emotion recognition is crucial.

By presenting a method to detect stress in textual data and assessing it using different public English datasets, Muoz and Iglesias [5] hope to advance the state of the art in 2022. To improve classification accuracy, the suggested method fused lexicon-based characteristics with distributional representations. We present a lexicon-based feature framework for stress detection in text that makes use of emotional, syntactic, social, and topical aspects. In addition, we looked at three distinct word embedding methods for using distributional representation. Three machine learning models were used to apply this strategy, and their performance was assessed across a number of experiments. Three publicly available English datasets were used in this evaluation, which established a benchmark for future studies. Based on the data, the best performing model is found to be one that combines Fast Text embeddings with certain lexicon-based features.

2.1 Problem Definition

Patients' mental and physical health can be negatively impacted by stress, which is sometimes referred to as the "pensive issue." Long-term stress exposure causes serious health problems, thus early diagnosis is essential. The identification of mental stress is complicated by the need to boost dependability and detection accuracy. Therefore, numerous stress and emotion detection models based on deep and machine learning are constructed, with the benefits and drawbacks of each scheme shown in Table 1. DNN [1] is more cost-effective and works well in real-time settings. Furthermore, it offers very precise classification. However, in order to improve sentiment analysis and train the network, decomposition procedures are required. On the other hand, the training time required to be lowered for analysing huge dimensional data. When assessing a patient's mental health, the BERT [2] has a high rate of detection. In addition, it yields effective results for determining emotional state through interpersonal interactions. However, it fails to differentiate between spam and legitimate tweets. For analysis of depression, for instance, sentiment word detection algorithms are required. Recall, F-measure, ROC, accuracy, and precision are all improved by RF [3]. The computational complexity is also reduced. Despite this, it can handle just a limited dataset. In addition, it does not offer sufficient system dependability when compared to other open datasets. CNN [4] has strong interpretability, and it solves the problem of incomplete feature detection findings. As a result, it is able to process information quickly, thoroughly, and reliably. However, the model's performance is subpar. Next, it must take out the characteristics of the lower, middle, and upper levels. The stress detection capabilities of the Ensemble model [5] are based on the use of syntactic, emotional, social, and topic-related information. It also delivers quicker diagnostic results and finds the stress earlier. However, word embedding methods are required to boost the accuracy of the mental state classification. The system dependability and accuracy are both enhanced by SVM [6]. On the other hand, it efficiently learns the mental abilities. However, a long period of operation is needed. In addition, there is a significant amount of processing overhead. Artificial neural networks [7] guarantee the model's higher reliability. However, the computational cost and complexity are much reduced. Unfortunately, we cannot do emotion classification using the information at hand. BiLSTM-GRU [8] improves classification results by eliminating EEG's non-linearity and non-stationarity. And additionally, it delicately handles the long-term dependencies and it boosts the system feasibility. The enormous number of parameters, however, must be reduced before the system can be deployed to edge devices. Prediction in big EEG datasets also requires automatic feature extraction methods. Thus, a novel stress and emotion detection model is built with the aid of deep structure technology to address these concerns.

Table 1: Features and challenges of traditional stress detection models using deep learning

Author [citation]	Methodology	Features	Challenges
Asghar *et al.* [1]	DNN	• It is less expensive and it is suited for real time applications. • It provides high classification accuracy.	• It needs decomposition steps to enhance the sentiment analysis to train the network. • The training time needed to be reduced for analyzing large dimensional data.
Nijhawan *et al.* [2]	BERT	• It provides very good detection rate during the analysis of mental health of patients. • It provides efficient outcome over the detection of emotion	• It does not detect the spam and non-spam tweets. • It needs sentiment word identification algorithms for analyzing the depression.

		status based on the social interactions.	
Chatterjee and Byun [3]	RF	• It provides higher recall, F-measure, ROC, accuracy and precision. • It decreases the computational complexity.	• It only processes small amount of dataset. • It does not provide effective system reliability among open datasets.

Individuals experience stress in every society. Work-related concerns, disappointments, poor working conditions, etc., are prevalent worldwide sources of stress. The majority of the world's population experiences stress because of their jobs.

Video of face appearance and stress acknowledgment strategies was studied by the writers of [5]. They argue that outward and interior events trigger different face expressions and tensions in people.

For instance, a stressed-out driver in traffic can benefit from stress recognition technology in the real world. It also analyses traits like facial discovery and articulations to determine areas of physical weakness. They use videos to demonstrate a variety of strategies based on external appearance and to acknowledge emotions. It demonstrates how similar examination can be used to analyse and comprehend stresses, illuminating the approach of feature extraction and characterization used in face appearance. The relative evaluation is performed with consideration for precision, utilisation tool, focal points, and impediments.

The feature extraction approaches have been applied for investigation of EEG data like Fast Fourier transform (FFT), Principal Component Analysis (PCA), GA, Wavelet Transformations (WT) and Wavelet Packet Decomposition (WPD). FFT, ICA, AR, WT, WPD, and PCA are all named as other widely used methods in the growing field of stress detection. Before feeding data into a classifier, feature extraction is performed using the aforementioned techniques, which are discussed in [6].

Table 2: Survey on Feature extraction methods for identifying influential features

Journal	Title	Year	Techniques/ Method	Observations	Identified Issues
https://pubmed.ncbi.nlm.nih.gov/30400575/	Emotional Stress State Detection Using Genetic Algorithm-Based Feature Selection on EEG Signals	2018	Genetic Algorithm (GA)	Showcased GA as an optimization tool applicable to the large data set. These features are then given to Neural network classifier.	Working on dynamic data sets is difficult.
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5472660/	**Independent Component Analysis and Source Localization on Mobile**	2017	Independent Component Analysis (ICA)	It is an efficient methodology with high performance on the broad decomposed data	More computations are encompassed in decomposing signals.

	EEG Data Can Identify Increased Levels of Acute Stress				
https://www.researchgate.net/publication/342991809_Feature_Extraction_based_on_Wavelet_Transform_for_Classification_of_Stress_Level	Feature Extraction Based on Wavelet Transform for Classification of Stress Level	2020	Wavelet Transform (WT)	Able to assess signals both in time and frequency domains. Can take out energy, distance or clusters.	Heisenberg Uncertainty limits performance.

III. Methodology

Worries about the future are an inevitable byproduct of the lightning-fast pace at which technology and society are evolving. There's a good chance that this definition is circular [16]. Nonetheless, it does offer some really important suggestions. The evaluation of stress's significance is an important topic in stress detection research. Experts disagree on what qualifies as stress and how many different kinds of stress there actually are. As a result of these challenges, EEG signal analysis, feature extraction, and classification are widely practised methods for recognising human stress. It is acknowledged that the methodologies centre on signal capture, pre-processing, and feature extraction in light of the current stress identification system situations. Multiple EEG channels and bands have been used in existing research for EEG signal processing, which increases the complexity of signal processing and, in turn, reduces classification accuracy [20].

To address and solve these problems, a standard automated method for analysing, extracting features from, and classifying EEG signals is being developed. The EEG sensor is used in the brain movement estimation or sign procurement phase to record mental activity. Pre-processing signals is the next step after the signal collection phase. Planning ahead will allow for a revision of upcoming caretaking procedures, enhancing signal quality while preserving essential data. The recorded signal is prepared to clean and eject raucous data. Basic features are taken from the mind workouts signal after the noise-free signals have been obtained during the pre-processing stage. In the process of feature extraction, unique characteristics of the recorded personality signals are recognised. It is a dynamic process to safeguard vital information from loss and, at the same time, reduce the size of the feature vector measurement in order to sidestep computational unpredictability. In light of the foregoing, it is clear that selecting appropriate discriminative highlights is crucial for achieving a useful characterization result that is in line with the client's objectives [21]. The organised signal is then transformed in the control interface stage into useful information for devices such as a wheelchair, discourse synthesiser, or personal computer. All of these efforts proved the value of feature extraction for stress recognition, and they also highlighted the need for more advanced methods that can boost classification precision. This is essential in order to locate the best frequencies and channels for stress detection. Thus, [22] an automated framework is developed.

An automated system is created to monitor EEG signals for signs of stress in humans and help them cope with the condition. The framework can look into the channel(s) and band(s) to help with stress recognition. In addition, studies on stress recognition and detection using single-channel EEG analysis.

The best methods for feature extraction are determined by quantitative measurements of EEG band characteristics. EEG band features such as the centroid, crest, flatness, flux, kurtosis, Shannon entropy, standard deviation, variance, mean, frequency cepstral coefficient, energy logistic coefficient, and band relative energy are extracted to determine the best features for stress recognition [23]. In order to correctly determine a person's stress, a feature selection method is used to pick the most important factors. Stress-appropriate feature extraction methods are also identified via various categorization methods. Classifiers like KNN, SVM, NN, and CT are used to distinguish between a person's tense and relaxed states [24].

3.1 Feature Extraction

A feature is a meaningful subset of data from an EEG signal that allows for in-depth insight into that signal. EEG features are quantifiable properties of EEG signals in a given dataset. These signals exist in both the time domain and the frequency domain as discrete time series. Various metrics, including spectrum property, statistical property, and Signal coefficient property, are used to define the features. Feature extractions rely heavily on the aforementioned three characteristics of EEG signals. With the use of the Signal coefficient property, pertinent features are extracted, allowing the intended task to be carried out. To narrow down the extracted characteristics from the EEG signal and zero in on the most important ones. Some fundamentals are outlined below. [25].

Time domain features

In a time-domain signal, the study is centred on statistical information, for example, the mean and standard deviation. After this is done, the data sample's distribution, or histogram, can be calculated. Also calculated are kurtosis and skewness. More complex aspects are also extracted, such as the long-term memory of a time series's fractal measurement (i.e., the Hurst Exponent) or the Signal-based evaluation of the measure of consistency and the unconventionality of variations across a time series study [26].

Limitations of Existing feature extraction techniques

One, there aren't enough effective feature extraction methods for dealing with superfluous details.

High dimensional information is present in existing feature extraction approaches, which causes issues for classification algorithms due to their high computational cost and memory utilisation [27].

Third, there aren't enough feature selection algorithms to pick the best feature to improve classification accuracy [28].

There is not currently an EEG-based stress recognition system or model.

The rise in computational complexity has rendered some feature extraction techniques incapable of producing satisfactory results.

Sixth, the absence of a simple, low-cost, single-channel technology for stress detection.

It is recommended that a unified framework for feature extraction and classification be developed to address and solve these problems [29].

IV. Proposed Feature Extraction Approach

- The band frequency cepstral coefficients vector ('BFCC') generated in the prior section is now stored in a patterns database. Feature extraction methods and their process are depicted in Figure 02.
- Band of frequencies recently found Algorithms that place a premium on the cepstral coefficient include:
- As a feature vector, it: excludes the basic frequency and associated harmonics to try to reduce the stressed/stress features that are dependent on humans; • • represents the dynamic character of the EEG signal;
- decreases the size of the feature vector; and
- aids dimensionality reduction.

V. Result analysis

This diagram illustrates how an automated framework based on EEG readings and sentiment analysis may detect signs of stress in humans and help them cope with the condition. After careful analysis, different electrical frequencies in EEG can be connected to distinct behaviors and mental states.

Thus, EEG displays a varied abundance that is subject to both intrinsic drive and individual changes in mental attitude. The procedure for differentiating between a person's anxious and relaxed states is represented in fig 01 and consists of pre-processing, EEG band separation, EEG band selection, EEG feature extraction, and emotion detection with sentiment analysis.

The goal of this study is to create a system for automatically detecting stress in humans using EEG readings. Finding the most useful characteristics of sentiment analysis for human emotion identification and stress screening.

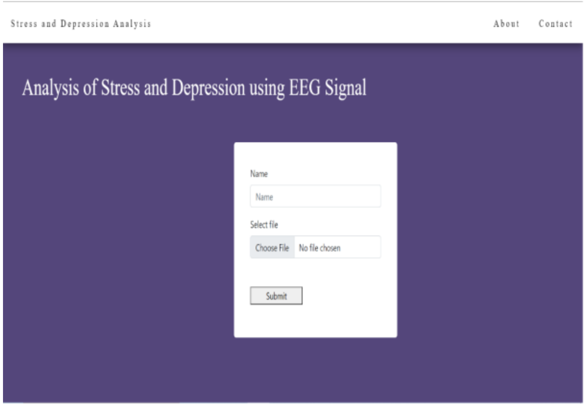

Fig 01: home screen for CSV file selection

This section provides a thorough explanation of the present feature extraction algorithm. Using PCA, ICA, and EMD for BCI applications yields significant results. There are numerous advantages for the programmer when using SVM: Principal component analysis (PCA) has outstanding generalization properties and can be used to determine stress and pressure using EEG signals, however overtraining is afflicted by the curse of dimensionality. These advantages were possible because of the application of EEG signals to the detection of stress and pressure. Methods that utilize frequency domain analysis of 14-channel EEG data are summarized in the following figures (Figures 03–05).,

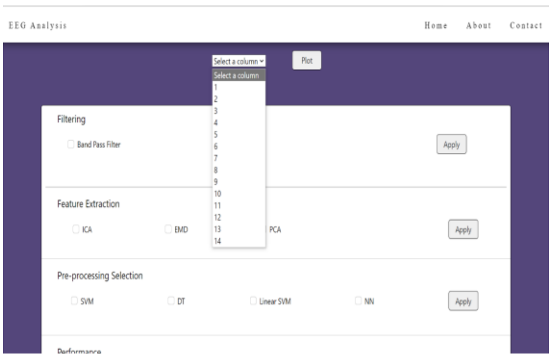

Fig 02: 14 brain signal analysis

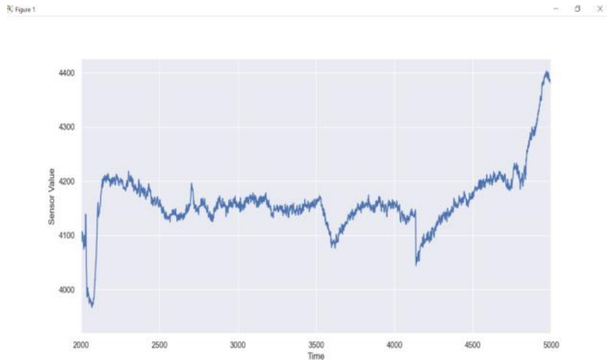

Fig 03: single wave for finding signal value against the specific period

Preprocessing outcome on selected brain signal

Fig 04: SVM pre-processing analysis using different parameter

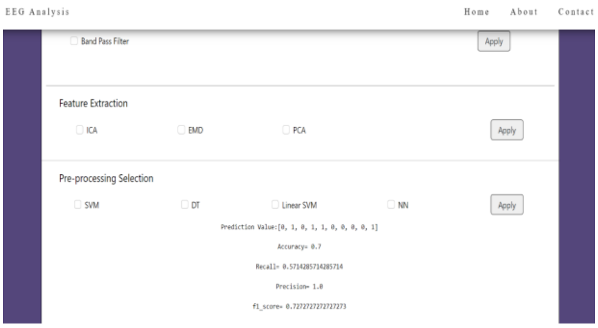

Fig 05: SVM classifier with accuracy and recall

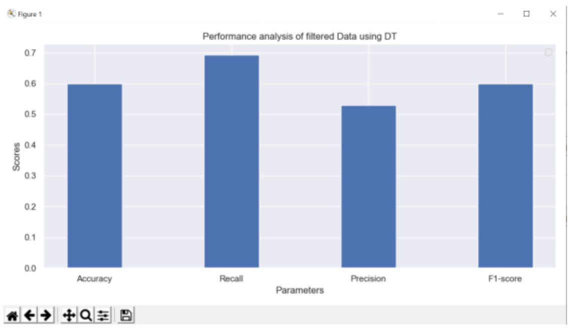

Fig 06: Result analysis using basic classification approaches.

Above figure 06 given the detail overview of classification approaches using different parameter.

VI. Conclusion

The purpose of this work is to construct a user-independent human stress detection system based on EEG signals. Finding the most useful and efficient characteristics for human stress identification. We assess the usefulness of currently utilised algorithms (PCA, ICA, and EMD parameters) and conclude that these methods do not give dependable results. Further study is required to establish the relevance of EEG signal analysis to the proposed technique. It is also possible to use biomedical apps for clinical diagnosis.

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