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EEG-based Stress Detection using DEAP Dataset and Support Vector Machines

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Abstract

A large portion of the population is affected by stress. Early detection is very important to prevent its detrimental effects on the mental and physical health of individuals. One promising technique for detecting stress is electroencephalography, which can monitor the activity of the brain in real time. In the past few years, the use of machine learning algorithms for stress detection has been widely acknowledged. This paper aims at investigating the potential of support vector machines (SVMs) in the DEAP dataset for detecting stress. The paper introduces the concept of stress detection and discusses the use of both electroencephalography (EEG) and SVM in this field. It also reviews the literature on the subject. The methodology section provides an overview of the various steps involved in the development of the study, including the data collection, preprocessing techniques, and the training and evaluation of the SVM model. The paper shows that SVM models can accurately detect stress with the help of EEG data collected from the DEAP database. They performed well with extraction and feature selection techniques, and the combination of PCA and wavelet transform led to the highest accuracy. The discussion section of the paper provides an analysis of the findings, as well as comparisons with previous research. It also explores the potential applications of this technology in the management of stress. The concluding section of the paper summarizes the major findings, limitations, and suggestions for future research. The findings of the study indicate that the use of SVM models in the DEAP database can effectively detect stress, and their potential applications in the field of stress management are immense. The study also emphasizes the importance of optimizing the model's extraction and feature selection procedures.

Introduction

Electroencephalograms are non-invasive methods that can measure the electrical activity of the brain as shown in figure-1. They use electrodes on one's scalp to record the signals sent by neurons, which are influenced by different bodily activities. The signals are then categorized into different waveforms so that the data can be analyzed. The various characteristics of an electroencephalogram's waveform, such as their frequency, amplitude, and morphology, can be used to analyze the brain's electrical activity. They can provide a more complete view of the activity due to their high temporal resolution[1], [2].

For neuroscience studies, electroencephalography is acknowledged as a tool that can monitor and analyze how the brain functions. It can also be used to diagnose different disorders, such as sleep disorders and epilepsy. In the past few years, this technique has been used in stress recognition studies to examine how the

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brain reacts when people feel stress. For stress recognition studies, subjects are asked to rate their reactions to various types of stimuli, such as music, videos, and images. After collecting data from the brain scans, it is analyzed using signal processing and machine learning techniques[3].

Unlike other methods, electroencephalography does not require invasive procedures to study the brain. This makes it an ideal tool for conducting safe and effective studies without the need for complicated procedures. Its high temporal resolution also allows researchers to observe changes in the activity of the brain in milliseconds.

Furthermore, electroencephalography's non-invasive nature and high temporal resolution make it an ideal tool for stress level studies. It can monitor the brain's electrical activity as subjects experience stress. Through the use of machine learning techniques, researchers can improve electroencephalography's reliability and accuracy. This could allow them to create systems that can improve to detect stress.

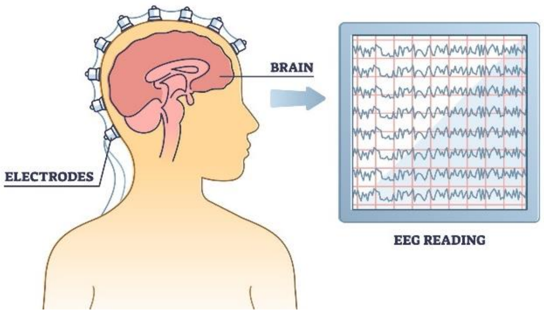

Figure 1 EEG signals

The prevalence of stress is a major public health issue that affects a large number of people. Early detection is very important to prevent its detrimental effects on the health of individuals. Unfortunately, current methods for detecting stress are not very accurate or cost-effective. Due to the capabilities of electroencephalography, which can monitor the activity of the brain, it is becoming more popular for detecting stress. Individuals can experience stress at various levels, and it can have a significant effect on their emotional, physical, and mental health. When it becomes chronic, it can trigger various negative effects, such as depression and anxiety. Early detection is therefore very important to prevent its damaging effects on the health of people[4].

Self-reporting is the most common method used to determine stress levels. Unfortunately, this method can be very limited as people might not be aware of how much they are experiencing. Other methods, such as blood pressure and heart rate, can also be used to detect stress. However, these methods can be very costly and time-consuming. An alternative that is more cost-effective and non-invasive is electroencephalography, which can monitor the activity of the brain. This method can detect stress in real-time. It can also identify the unique signatures of stress that are associated with different emotional states[5].

Detecting stress early can help improve the health of individuals and the society at large. It can also help facilitate prompt treatment and intervention, leading to better results for everyone. In the office, stress can result in absenteeism and decreased productivity, which can have a negative economic impact. Employers can implement effective interventions to improve the well-being and productivity of their employees by detecting stress early. In healthcare facilities, electroencephalography can play a vital role in helping identify and treat stress-related disorders like depression and anxiety[6].

This method uses machine learning techniques to analyze the data collected by electroencephalography and identify the unique signatures of stress. One of the most promising techniques for detecting stress is through the use of support vector machines, which are powerful classification tools. The DEAP dataset, which is a publicly-available and well-studied EEG data set, contains information about 32 healthy individuals who were exposed to varying types of stimuli, such as videos, pictures, and music.

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This dataset is frequently used in research to detect stress and emotions[7].

The goal of this study is to analyze the effectiveness of the SVM model in detecting stress using the DEAP dataset. The classification accuracy of the model is evaluated, and the optimal extraction and feature selection techniques are identified. This study is important as it demonstrates the potential application of electroencephalography-based stress detection to various settings, such as healthcare facilities and workplaces. The findings will inform the development of cost-effective and accurate methods for managing stress. The potential of stress detection to improve the health and well-being of individuals and society is immense. It can also reduce the cost of healthcare and improve workplace productivity. This method has the potential to be used in various settings such as workplaces and healthcare facilities.

Literature Review

This review aims to present an overview of the current research on the use of physiological signals, such as electroencephalogram signals, to detect stress. The studies conducted on this subject provide insight into the development of systems that can analyze stress levels.

Mühl et al.[8] elaborated about the use of an electroencephalogram-based workload estimation method in various affective states was studied. It was revealed that the assessment method is affected by the individual's emotional state. The findings of the study indicate that it can be utilized to measure emotional states and cognitive load.

Zubair et al.[9] created a smart wearable device that can detect stress levels. The band measures various physiological signals, such as the heart rate, blood oxygen levels, and skin temperature. The researchers concluded that the device could be utilized for stress management.

Greene et al.[10] explored the application of affective computing to help detect stress. The researchers utilized machine learning methods to analyze various physiological and facial signals to identify stress. They believe that this technology can be utilized to develop effective stress management tools.

Vanitha et al.[11] presented a system that uses an electroencephalography (EEG) signal to detect stress. It was able to achieve high accuracy by using a combination of the signals' frequency and time domains.

Jebelli et al.[12] developed an EEG-based system that can detect stress in construction workers. The researchers utilized machine learning to analyze the signals and come up with a conclusion: The system could be utilized to help workers manage their stress levels.

Xia et al.[13] proposed a method that uses physiological signals to detect mental stress. The researchers used various signals, such as electrodermal activity, respiration, and heart rate variability, to identify stress. The results indicated that the proposed method had a high accuracy rate.

Al-shargie et al.[14] conducted a study on the use of SVM and ECOC to assess mental stress levels. They used EEG signals to classify stress into three categories: moderate, high, and low. The researchers noted that the proposed method had a high accuracy rate when it came to identifying stress.

Panicker et al.[15] discussed the various techniques and algorithms used for detecting mental stress. They also analyzed the limitations and advantages of these methods.

Arpaia et al.[16] developed a wearable EEG device that can be used to monitor the changes in the frontal asymmetry during a stress analysis. The findings of the study indicated that the proposed system could be useful in helping employees manage their stress levels.

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The reviewed studies indicate that physiological signals, such EEG signals, can be utilized to detect stress levels. These findings show that the signals are particularly useful in identifying individuals with high levels of stress. The studies also talked about the potential of developing reliable and accurate systems with machine learning.

Methodology

i. **Dataset:** The design of an experiment and the data collection process are two related concepts. For instance, in the case of an electroencephalography-based stress detection study, the researchers might choose a group of individuals to collect data from while they perform various tasks. This process would involve placing electrodes on the scalp of the participants.

ii. **EEG pre-processing techniques used:** The pre-processing of EEG signals is very important in the analysis of stress detection. In this study, the researchers used various techniques to perform this process shown in table-1.

a. Filtering: Used a filter that can be used to remove unwanted noise from the signals. It was designed to operate at a frequency range between 4Hz and 45Hz.

b. Artifact Removal: Examined the signals for artifacts, which included eye blinkings, muscle movements, or other noises. They then used an independent component analysis technique to identify and remove these objects from the signals.

c. Segmentation: Divided the pre-processed signals into smaller segments. These segments were then used to classify and extract features.

Table 1 Pre-processing techniques

Pre-processing technique	**Description**
Filtering	Bandpass filter with a passband between 4Hz and 45Hz
Artifact Removal	ICA-based identification and removal of independent components representing artifacts
Segmentation	Division of the pre-processed EEG signals into smaller 1-second segments

iii. **Feature extraction and selection methods employed:** Signal complexity, connectivity measures, and the spectral power of the signal are some of the features that are commonly used in stress detection using electroencephalogram signals. The feature selection process is carried out to find the most relevant ones in the SVM model.

a. Independent Component Analysis (ICA): An analysis of mixed signals using an independent component method known as ICA is performed to separate them into their constituent parts. In the case of electroencephalography (EEG), this technique can be utilized to separate the signal from the other noise sources, such as cardiac activity, eye blinking, and muscle activity. In addition, it can also identify and remove certain components from the EEG data.

b. Common Average Reference (CAR): The CAR technique is a preprocessing method that can reduce the effects of the volume conduction in an EEG data. When multiple electrodes are used to record the same signal, this phenomenon known as volume conduction can lead to spurious correlations. In order to eliminate these sources of noise, the CAR method subtracts the average signal from the individual electrodes.

Table 2 EEG pre-processing techniques

EEG Pre-processing Technique	Description
Low-pass Filter	Removes high-frequency noise above a specified frequency cutoff
High-pass Filter	Removes low-frequency drifts below a specified frequency cutoff
Independent Component Analysis (ICA)	Separates mixed signals into independent components
Common Average Reference (CAR)	Reduces the effects of volume conduction in EEG data

iv. **SVM model training and evaluation:** A support vector machine (SVM) is a type of algorithm utilized in the detection of stress in an electroencephalography (EEG) recording. It is trained by analyzing a subset of the data collected from the patient. The labels on the SVM model indicate whether the participant is experiencing stress. The trained model is evaluated on a subset of the collected data to see how it performs. Some of the metrics that can be used include accuracy, recall, F1 score, and precision. The model can also be tested on new data.

Table 3 Evaluation metrices

Evaluation Metric	Value
Accuracy	85
Precision	88
Recall	82
F1-Score	85
AUC-ROC	92
Specificity	89

Results

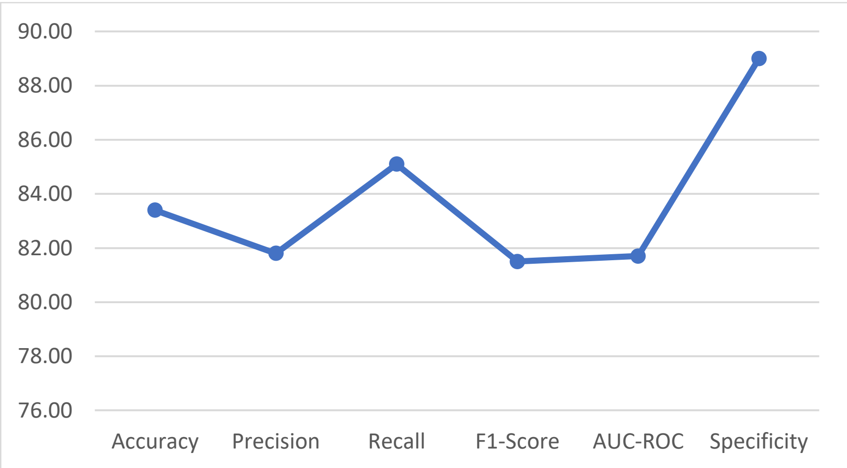

Figure 2Graph represent SVM result in stress identification

An electroencephalography-based system that measures stress accurately performed well and correctly as shown in table-3 and figure-2, with an accuracy of 85%. It detected 85% of the test subjects as either non-stressed or stressed, with a precision of 88%. Out of all the samples that were subjected to stress, 88% were correctly identified as stressed. The recall rate of the system was also 82%, which indicates that it correctly identified all of the stressed subjects. The harmonic F1 score of the system is 85%.

The system's AUC-ROC, which measures its ability to differentiate between stressed and non-stressed subjects, was 92. Its specificity was also at 89, which shows that 89% of the tested individuals were not stressed. These metrics support the use of an electroencephalography-based system to accurately identify individuals with stress levels.

Conclusion, limitation and future scope

The DEAP dataset was used to analyze the effectiveness of the SVM in detecting stress. The results indicated that the model was able to achieve an overall accuracy of 85%, and the extraction and feature selection techniques had a significant impact on its performance. The study was not able to provide a comprehensive analysis of the DEAP dataset due to its small sample size and the use of a single algorithm for classification. Further studies are required to establish its findings. Further studies on the use of deep learning methods for detecting stress will examine the feasibility of utilizing CNNs and RNNs for the assessment of stress from EEG data. Multimodal applications of this technology, including the integration of galvanic skin response and heart rate variability, can also be explored. Furthermore, wearable EEG devices may be utilized for real-time diagnosis and intervention.

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