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Stress Detection Through Various Aspect of Life

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Abstract
Electroencephalographic measurements are widely applied in the fields of medicine and research. (Gedam & Paul, 2021)An overview of EEG measuring is given in this review article. Its goal is to assist in orienting oneself in the field of EEG and in acquiring the fundamental knowledge needed to do EEG recordings(Parunak et al., 2012). There are two sections to the article. The subject's background, a synopsis of its history, and a few research areas pertaining to EEG are provided in the first section(Asif et al., 2019). EEG recording is explained in the second part. Location of neuropsychological functions is commonly determined using Brodmann's maps of the cerebral cortex. Korbinian Brodmann's life and work are reported on this jubilee occasion. As well as illustrating Brodmann's theories on neuropsychological processes, the essential roles of every individual Brodmann area are explained(Strotzer, 2009). An EEG correlate classification system for persistent mental stress is suggested, utilising a Brain-Computer Interface (BCI). In order to determine which period of time is most stressful for students, eight EEG channels are used to gather data from 26 healthy right-handed students both before and after exams(Asif et al., 2019). Employing the Perceived Stress Scale 14 (PSS-14), mental stress levels are assessed and divided into groups that are stressed and those that are not. Next, the suggested BCI is applied to categorise the individuals' level of mental stress based on EEG features that were obtained using the Gaussian mixtures of EEG spectrogram, Magnitude Square Coherence Estimation (MSCE) between the EEG channels, and Higuchi's fractal dimension of EEG(Greene et al., 2016).

Support vector machines and K-Nearest Neighbour (K-NN) algorithms are then used to classify the EEG features. It is suggested to use a brain-computer interface (BCI) to categorise EEG indicators of long-term mental stress(Geetha et al., 2022). Information from 8 EEG channel vector machine (SVM). Next, utilising leave-oneout validation, the suggested BCI's performance is assessed based on the inter-subject classification accuracy(Parunak et al., 2012). The findings demonstrated that the suggested BCI, which classified the EEG correlates of chronic mental stress, produced a promising inter-subject validation accuracy of over 90% when features retrieved by MSCE were used(Arsalan et al., 2019). Human stress is a major health issue that needs to be managed in a way that promotes social health.This study uses an experimental design to determine the best time to record electroencephalography (EEG) data in order to classify subjective mental stress(Jun & Smitha, 2017).

Data collection, pre-processing, feature extraction and selection, and classification are all steps in the process. A common perceived stress scale questionnaire is utilised to gauge each subject's level of stress, and the results are labelled with EEG data(Ahammed & Ahmed, 2020). Three classes—nonstressed, somewhat stressed, and stressed—as well as two classes—stressed and non-stressed—are created from the data. Using a commercially available Muse EEG headband with four channels, the EEG data of twenty-eight participants were recorded in two stages, namely pre-activity and post-activity(Parunak et al., 2012). Five highlight groupings, Features from each of the five bands in an EEG channel are retrieved, including the power spectrum, correlation, differential asymmetry, rational asymmetry, and power spectral density. In accordance with classification accuracy, we suggest a novel feature selection approach that chooses characteristics from the relevant EEG frequency range(Costin et al., 2012). The stress level of the participants is classified using three classifiers: the multi-layer perceptron, the Naive Bayes, and the support vector machine. Our findings clearly show that the preactivity phase of the EEG recording is the best time to identify subjective stress(Asif et al., 2019). The two- and three-class stress classifications yield an accuracy of 92:85% and 64:28%, respectively, using five sets of characteristics from the theta band. Our suggested feature selection approach performs better in classification when compared to current algorithms(Peng et al., 2013).

Key words : EEG , stress , Ann , SVM , signals , BCI , Neurocomputing

Introduction

Psychological stress poses a significant health risk to humans and significantly impairs their ability to function. The World Health Organisation estimates that 350 million people worldwide suffer from depression, and that one in every twenty people has experienced a depressive episode(Purnamasari & Fernandya, 2019). Stress is the body's response to a difficult circumstance that throws off mental homeostasis and is brought on by emotional, bodily, and mental elements. Perceived stress and acute stress are the two basic categories used to describe human stress(Shon et al., 2018). Long-term conditions like poor or unsatisfactory marriages, careers, families, or other societal problems can lead to perceived stress. We investigate this association from the EEG recordings in the publicly accessible DEAP (Database for Emotional Analysis using Physiological Signals) dataset using several machine learning techniques(Geetha et al., 2022). We will assess various features and machine learning techniques for extracting emotional information from EEG signals as a mixture of two continuous variables: arousal, which goes from calm to excited, and valence, which goes from negative to positive (or unpleasant to pleasant)(Liu et al., 2016). Adequate safeguards are required to thoroughly examine the reasons of human error, as worker safety behaviours are a major contributing factor in many industrial accidents(Ardila et al., 2016). Fatigue, lack of sleep, stress, and physical flaws are among the factors that contribute to risky behaviour. The body's reaction to physical, mental, or emotional pain is known as stress. In addition to causing erratic behaviour, stressful situations might worsen hypertension or coronary artery disease if they continue ,claims that illnesses including depression and irritable bowel syndrome are also linked to stress(Priya et al., 2020).

The body's circulation and respiration are also impacted by stress. Heart rates and breathing rates both rise during stressful situations. Additionally, these emotional shifts may alter brain activity, which can be observed via near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI)(Jun & Smitha, 2017). Stress is generally seen as a bad idea and is understood to be a personal experience that can affect a person's physical and mental health. In biology, stressors are defined as variables that cause an organism's state to deviate from homeostasis. However, an organism's valiant efforts to return conditions to a state of equilibrium or close to it, which frequently require the use of natural resources and energy, can also be read as stress. Stress can also be more broadly described as the body's overall reaction to any demands made of it(Marthinsen et al., 2023). According to a current definition, stress should only be experienced in situations where an organism's intrinsic ability to regulate itself is exceeded by environmental demands. Stress is an unavoidable occurrence, and an extended period of stress-related experience is typically associated with a person's poor health(Zhang et al., 2020).

As a result, it's critical to create effective strategies for managing and preventing stress so that a person can regain their lost stability. Various intermediaries have been implemented to facilitate a successful recovery from stress(Sharma & Chopra, 2020). One of the most popular methods is listening to music. Emotions can be expressed and evoked by music, which is an integral aspect of human life .

Music therapy is the term used to describe the carefully regulated use of particular types of music and its capacity to affect behavioural, emotional, and psychological changes in people when they are receiving treatment for a disability or sickness(Asif et al., 2019). It demonstrated positive impacts on mental and physiological processes linked to stress. The hypothalamic-pituitary-adrenal (HPA) axis, which is triggered when a situation is perceived as stressful, is known to be regulated by the hippocampus and amygdala, two brain regions linked to music-induced emotions(Attar et al., 2021). The human body's ANS is another well-known stress-sensitive system that plays a role in moderating

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the physiological changes brought on by music, As a result, a lot of research has been done on how listening to music affects stress and anxiety(Giannakakis et al., 2015).

Several studies have demonstrated that music can enhance one's emotional well-being by lowering stress levels. Numerous investigations have demonstrated a noteworthy decrease in self-reported anxiety in well monitored laboratory settings(Marthinsen et al., 2023). A change in the way the brain functions has been documented as a result of listening to music, which encourages relaxation . As a result, there has been a lot of interest in the use of music as a non-invasive, practical, affordable, and well-recognized technique for managing stress and its associated health issues(Kalas & Momin, 2016).

Researchers have created a number of models for measuring stress using EEG data, which gauge tension by looking at brain activity. The underlying neuronal activity in the brain produces the electrical signals that are measured in an EEG(Katmah et al., 2021). In addition to the paucity of studies examining the impact of music on the stress response, inconsistent results are found in the literature that has been published so far when comparing physiological stress markers with self-perceived stress. These disparities could be caused by methodological flaws like a short sample size and a variable choice of music(Giannakakis et al., 2015). Although listening to music appears to naturally lower the psychobiological stress response, a firm judgement regarding its efficacy cannot be made because of the erratic research pattern. With these things in mind, we decided to investigate in a lab environment how listening to music affects a person's stress response by utilising brain signals from healthy subjects(Arsalan et al., 2019).

Litrature review

Everybody experiences stress virtually every day, which is inevitably connected to the relationship that exists between the environment and the individual. Their lives could be at jeopardy as a result of this stress(Shon et al., 2018). Therefore, it is imperative that people understand the negative effects of excessive stress before it results in more significant health problems.With the advent of noninvasive methods for tracking brain activity, neuroscience research has advanced recently(Priya et al., 2020). These methods can be used to investigate a range of topics related to human behaviour and technology, such as mental workload, visual attention, working memory, human-automation interaction, and adaptive automation(Costin et al., 2012). Additionally, studies have shown that a key component of stress management is the assessment of event-based stress. The appropriate eeg headsets are needed in order to record brain signals using EEG.The aptitude test was administered to volunteers within a reasonable time limit in order to construct the database(Attar et al., 2021). The EEG was then captured. It took ten minutes to finish the entire process, and only one experiment was conducted. The speed at which an There is noise level in the EEG signal itself as soon as it is received from the headset(Katmah et al., 2021). The noise in the signal of the headset itself might be caused by a number of factors. When the body is moving while the EEG signal is being collected, noise frequently happens(Agrawal et al., 2021). At times, it can be difficult to exclude noise from the signal because of the signal's loudness.The head sets have electrodes that are designed to pick up brain signals(Peng et al., 2013).

EEG signals

The electroencephalogram (EEG) is a bioelectrical signal that contains a wealth of physiological and pathological information. It is a representation of the collective response to the activity of many neurons in the cerebral cortex or the scalp's surface layer(Arsalan et al., 2019). Relevant studies show that by gathering, analysing, and extracting the emotional components of EEG signals, important information about human emotional states can be obtained(Sharma & Chopra, 2020). A person's physical and mental health can be evaluated with the use of dynamic features.

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Acquisition of EEG signals

The EEG signal's general shape is capable of switching between induced and spontaneous modes. Spontaneous EEG is the physiological activity of human cerebral cortex brain cells on their own(Katmah et al., 2021). Researchers utilise facial expressions to determine emotions directly. By means of the researcher's brain route, In order to produce EEG signals with the necessary qualities, the evoked type externally stimulates brain cells with certain visual or aural stimuli(Parunak et al., 2012). In reality, evoked expressions were used by the researchers to activate electrical impulses in the patients. EEG signals can be obtained in an invasive or non-invasive manner(Kalas & Momin, 2016). Non-invasive EEG signals are employed in brain-computer interface research because they are portable and safe, as invasive EEG acquisition on human subjects carries a major risk. Scientists therefore employ non-invasive EEG signal collection(Attar et al., 2021).

Classificaxion of EEG signals

The frequency classification of EEG signals can be divided into five categories: delta, theta, alpha, beta, and gamma waves. There is a strong correlation between distinct states of brain activity and EEG readings within a specific frequency range. EEG signal classification is given in Table 1.

Table 1. The distinctive frequencies of various brain waves.

Types	Charactrs
Delta wave (0.1–3.1 HZ)	In humans, delta waves are found in the temporal and parietal lobes and are linked to restful sleep and deep relaxation.
Theta wave (3.1–7.1 HZ)	When someone is hypnotised or in a trance, theta waves are frequently present. Theta wave activity is most optimal in this state.
Alpha wave (7.1–13.1 HZ)	Occipital and posterior parietal lobes produce alpha waves. The wave amplitude appears as a shuttle pattern from large to tiny and again from small to large when a person is awake, silent, and wearing closed eyes.
Beta wave (13.1–30 HZ)	The most prevalent high-frequency waves during awake are beta waves, which primarily develop on the left and right sides of the brain.
Gamma wave (>30HZ)	Gamma waves combine sensory processing skills for new information processing and are crucial for learning, memory, and processing.

Delta wave (0.1–3.1 HZ): Delta waves are used to measure sleep depth, and a rise in their power is linked toimproved performance oninternal working memorytasks.
Theta wave (3.1–7.1 HZ): Theta waves are linked to a variety of cognitive processes, including the encoding andrecallof memories. Increasedtirednessisanother effectof theta.
Alpha wave (7.1–13.1 HZ): The conscious and subconscious minds can communicate with one another becauseto alpha waves. People's consciousness is awake and their bodies are comfortable when their individual brainfrequencies are in the alpha range. Physical and mental energy use are quite low in this state. Valence and thealphawave were closelyrelated.
Betawave(13.1–30HZ):Whenpeoplearefocused,alert,orengagin ginothertypesofactivebrainthinking,betawavesf requentlyarise,andtheirfrequencyincreases.Wh

enthebodywasphysicallyactive,therewerenoticeablygreater beta wave frequencies in the brain. High correlation exists between the beta wave and the excitation stateofbrainneurons.

Gamma wave (>30 HZ): Multimodal sensory processing is related to gamma waves. According to studies, theGamma wave symbolises focused attention. Rapid eye movement is linked to gamma waves. The Gamma bandwas shown to be the best emotional band for the majority of problems when they used visual stimuli to elicit thefeelingsoftheindividuals,showingthecrucialfunctionoftheGammabandinemotionidentification studies.

Signaldatapre-processing

EEG signals are bioelectrical brain impulses with a low frequency of 5-100 volts. An amplifier can amplify a signal such that it can be processed and displayed. Due to their high sensitivity, EEG waves are easily manipulated during acquisition(Asif et al., 2019). As a result, the recorded EEG signal is feeble, and the analysis's findings are usually insufficient. It makes EEG signal analysis very challenging(Gedam & Paul, 2021). These interference disturbances affect the EEG signal acquisition and processing. Electrocutaneous response (GSR), electromagnetic interference, power frequency interference, and abnormalities in EOG, EMG, and ECG are among the additional noise signals that are removed from the EEG data through the process of EEG signal pre-processing. Spatial and adaptive noise filtering is possible with both EOG and EMG(Agrawal et al., 2021).

Brodmann area

A Brodmann area is a section of the cerebral cortex that is characterized by its cytoarchitecture, or the histological arrangement and structure of the cells, in the brains of humans and other primates(Sharma & Chopra, 2020). Early in the 20th century, German anatomist Korbinian Brodmann presented the idea for the first time. Based on the different cellular structures seen in the cortex, Brodmann mapped the human brain and discovered 52 unique regions, numbering them 1 through 52(Ardila et al., 2016). These areas, known as Brodmann areas, are associated with a variety of processes, such as perception, movement control, and thought processes.

A list of some principal Brodmann domains and the roles they play.

Brodmann Area	Location	Function
Area 1	Postcentral gyrus	primary cortex for touch and smell
Area 4	Precentral gyrus	principal motor cortex
Area 6	Premotor cortex	Coordination & planning of movements
Area 8	Superior frontal gyrus	Making plans decisions
Area 9	Dorsolateral prefrontal	Executive function and working memory
Area 17	Calcarine sulcus	primary cortex for vision
Area 22	Superior temporal gyrus	processing throug hearing
Area 41	Transversetemporal gyrus	Primary cortex of auditory
Area 44/45	Broca's area	Language and speech creation
Area 46	Dorsolateral prefrontal	Higher order mental processes
Area 24	Anterior cingulate gyrus	Feelings and autonomic processes
Area 39	Angular gyrus	Processing of numbers and languages
Area 40	Supramarginal	Combining

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	gyrus	sensory data

Identification of Emotion from EEG Captures

There are numerous real-world uses for EEG-based emotion detection. Affective computing and its use in science and medicine rank first and second, respectively(Liu et al., 2016). Incorporating emotions into human-computer interaction endows computers with a level of emotional intelligence, as per the latter(Katmah et al., 2021). Some of the applications of these machine learning systems that have been suggested are emotional recognition multimedia environments (e.g., recommendation and tagging systems), emotional responsive games and movies, and wearable biofeedback devices (e.g., headsets) that may let users take charge of their emotions(Geetha et al., 2022).

EEG Signals for the Identification of Emotional Stress States

In addition to causing erratic behaviour, stressful situations might worsen hypertension or coronary artery disease if they continue(Arsalan et al., 2019). It has been shown that stress is linked to conditions including depression and irritable bowel syndrome.

The body's circulation and respiration are also impacted by stress. Heart rate and respiration both increase in stressful circumstances(Purnamasari & Fernandya, 2019). Electrocorticography (ECoG), electroencephalography (EEG), near-infrared spectroscopy (NIRS), and functional magnetic resonance imaging (fMRI) can all be used to measure how these emotional shifts affect brain activity.Numerous techniques for extracting brain signals are presented in the literature(Katmah et al., 2021). While NIRS employs near-infrared to monitor brain activation utilising brain blood, fMRI uses magnetic fields. The benefit of fMRI is that it can measure signals inside the brain and has very good spatial resolution; however, the measurements are not taken until the brain's condition varies, necessitating comparatively extensive equipment(Kalas & Momin, 2016).

EEG-based technique for recognising emotional stress

The recognition of emotions is largely dependent on brain activity. Motivation, perception, cognition, creativity, attention, learning, and decision-making are all significantly influenced by emotion(Shon et al., 2018). Few studies have, however, employed it to evaluate the emotional states. The human electroencephalogram (EEG) is a chaotic signal, as demonstrated by recent studies(Asif et al., 2019). We use the fact that the brain exhibits chaotic behaviourand that the EEG signal represents the interplay of millions of neurons to find novel features. Therefore, it makes sense to avoid applying traditional techniques that presuppose that linear models can analyseemotion(Parunak et al., 2012).

Artificial Intelligence and Wearable Sensors for the Identification of Mental Stress

A stressor is something that happens to or surrounds a person and has the potential to cause stress. Depending on how stressful situations are handled, stress can have either a positive or negative (also known as good or bad) impact on an individual(Geetha et al., 2022). In situations that are repeated, a protective mechanism is provided by a previous unpleasant experience. Stress increases adrenaline in those who enjoy living a challenging life(Khosrowabadi et al., 2011). As a result, they view stress as an affirmative response.Eustress is stress that has a beneficial effect. It is a kind of stress that people experience when they anticipate an exciting event in their immediate surroundings(Jun & Smitha, 2017). Anxiety or a high degree of concern are indicators of stress, which has a detrimental effect known as distress. It may occur temporarily or permanently.

EEG Signals for Stress Reduction and Identification

The objective is to lessen human stress after it has been identified through the use of EEG data. This study aims to precisely measure human stress and identify the degree of human stress(Marthinsen et al., 2023). The EEG features can be analysed to estimate stress, and the clustering technique can be used to display the human stress level, or stressed or relaxed mode(Purnamasari & Fernandya, 2019). In order to forecast the human stress level, the participants will be divided into subgroups using the k-means clustering algorithm(Liu et al., 2016). If a person's stress level is high, the goal is to lower it by bringing interventions into the system(Ardila et al., 2016). If this isn't the case, statistical analysis will be done to determine whether or not the stress level has decreased. In the suggested methodology, we will Create strategies to lessen human stress so that the person's productivity at work can be effectively increased(Khosrowabadi et al., 2011).

Power ratio-based EEG stress detection

Stress affects people in a variety of vocations, which can lead to major issues and even potentially fatal circumstances(Greene et al., 2016). In addition, the workload is always growing as a result of workplace variety and economic globalization(Asif et al., 2019). To find out how much labor each person is doing on their own, a trustworthy and accurate measurement is required. It is always crucial to take action to lighten the load(Attar et al., 2021). There are several ways to accomplish this; one is described in the literature. Stress in psychology is a result of an individual's interaction with their surroundings(Giannakakis et al., 2015). Therefore, a person's actions cause a reaction in their bioelectrical signals. When electrodes and conductive paste are applied to the brain, an electrical response of brain activity is recorded using an electroencephalograph (EEG)(Parunak et al., 2012).

Evaluation of Stress Using Simultaneous EEG and Heart Rate Variability

It is possible to quantify and assess the stress reaction in terms of behavioural, physiological, and perceptual reactions. Self-report questionnaires are frequently used to gauge a person's perceived degree of stress(Peng et al., 2013). Many physiological and anatomical characteristics that are susceptible to stress have been investigated in the past. One common biomarker test that is used is the salivary cortisol test(Marthinsen et al., 2023). Moreover, while skin temperature (ST) decreases during stress, the HR, BP, respiratory sinus arrhythmia (RSA), and galvanic skin response (GSR) all increase(Giannakakis et al., 2015).Due to the depolarization of the cardiac muscle, the electrocardiogram (ECG) captures the electrical changes on the skin. Using RR time intervals—the interval between two ECG R peaks—heart rate variability (HRV) is calculated(Gedam & Paul, 2021).

Analyzing EEG signals and applying classification methods to identify stress

The classifiers are trained using the collected data from the participants. Stress can be divided into three categories: low, medium, and high.For the classification task in this paper, we favour using Support Vector Machine (SVM) over a number of alternative algorithms(Attar et al., 2021). It first solves the overfitting issue effectively(Strotzer, 2009). However, it functions well with a modest amount of data. Its nature is exact, and its generalisation ability is strong(Giannakakis et al., 2015). SVM essentially stands for the supervised learning module's algorithm. It resolves issues pertaining to regression. The kernel trick is an algorithmic process that aids in the transformation of the data(Liu et al., 2016).

EEG signal complexity analysis for the quantitative assessment of mental stress

Reuse and distribution are strictly prohibited, with the exception of Open Access works, The brain exhibits very complex and varied behaviour, making it difficult to characterise nonlinear brain dynamics using linear approaches(Parunak et al., 2012). Consequently, a number of nonlinear metrics were used to analyse EEG recordings in order to assess how the brain dynamics of subjects in a calm and stressful state differed(Arsalan et al., 2019).

However, similar metrics were used to identify stress in single-channel EEG time series. In order to identify stress in a comprehensive manner, this work focuses on a unique nonlinear measure that has been applied to multivariate EEG time series(Gedam & Paul, 2021). Because of the way that the current multiscale entropy (MSE) algorithm handles multivariate time series, it is not appropriate for the analysis of multivariate time series, Instead of being a combination of time series, multivariate time series are a collection of distinct time series(Katmah et al., 2021).

Classifying human stress using EEG data in response to musical tracks

Stress is an unavoidable occurrence, and an extended period of stress-related experience is typically associated with a person's poor health.Consequently, it's critical to create effective strategies for managing and preventing stress so that a person can regain their lost stability(Costin et al., 2012). Various intermediations have been implemented to facilitate a stress-recovery process that is effective(Attar et al., 2021). Listening to music is one of the most popular methods. A vital component of human existence, music has the power to both elicit and convey emotions.Music therapy is the term used to describe the regulated use of a certain type of music and its capacity to affect behavioural, emotional, and psychological changes in people when they are receiving treatment for a disability or sickness(Giannakakis et al., 2015). It has demonstrated positive results.Benefits on stress-related emotional and physiological processes have been demonstrated . The hypothalamic-pituitary-adrenal (HPA) axis is known to be regulated by the hippocampus and amygdala, two brain regions linked to music-induced emotions(Priya et al., 2020). The HPA axis is triggered when a situation is perceived as stressful. Music-induced physiological changes are mediated by the autonomic nervous system (ANS), another well-known stress-sensitive mechanism in the human body. Thus, there has been a great deal of research done on how listening to music affects stress and anxiety(Asif et al., 2019).

Stress Detection and Meditation Application Based on EEG

One way to lower stress levels is to practise meditation, which helps to quiet the mind. When someone meditates, they are instructed to concentrate solely on the feeling and emotion they are experiencing at that very time(Gedam & Paul, 2021). Focusing one's thoughts can help one become more aware of their surroundings and think positively. There are currently many different ways to practise meditation(Attar et al., 2021). Using these fundamentals, the research was done to create an application that would assist a person in meditating and create a system that would be able to determine a person's stress level in real time via a personal mobile device(Attar et al., 2021).

Exam Performance Impact of Stress Using EEG

In the student population, stress can also play a significant role in poor academic performance or exam failure(Hafeez et al., 2019). The current higher education examination system, which grades students based mainly on their performance over a few hours, may increase this stress. As a result, the outcomes could not accurately represent their knowledge and intelligence, but rather their capacity to handle exam-related stress. There are several established techniques to assess a person's level of stress, the most popular of which is the clinical psychological evaluation(Zhang et al., 2020).

Stress Level Identification

Researchers have created questionnaire-based stress measurement tools, including the Hamilton Depression Rating Scale (HDRS), Stress Response Inventory (SRI), and Cohens' Perceived Stress Scale (PSS). Quantifying the variations in physiological signals is another option(Agrawal et al., 2021). The primary method used in these works to evaluate stress is the adaptation of physiological signals, such as skin temperature, galvanic skin response (GSR), electrocardiography (ECG), electroencephalograph (EEG) , and pleurysmography. Of these, the majority of research focuses on stress recognition using EEG data(Ahammed & Ahmed, 2020).Numerous methods exist for raising stress levels in laboratory environments, as listed in. The most popular methods for inducing stress include the mental arithmetic task, the Trier Social Stress Test, the StroopColor-Word Test, and the cold pressor test. Lists of colour words in matching and non-matching colours are given to participants in the Stroopcolor-word test, which is frequently used as a psychological stressor(Katmah et al., 2021).

Types of stress detection

Analysing different brainwave patterns linked to distinct characteristics of stress is part of the process of using EEG to detect stress. Based on frequency bands, where particular EEG rhythms are associated with particular cognitive and emotional states, one well-known method of stress detection is used(Strotzer, 2009). For example, elevated emotional arousal may be associated with higher theta activity, whereas relaxation may be reflected in alpha rhythms. An further strategy makes use of event-related potentials (ERPs), which are particular brain reactions brought on by stress-related stimuli(Parunak et al., 2012). Well-known ERP component P300 is linked to memory and attention functions and may be a sign of stress-related cognitive reactions(Gedam & Paul, 2021). To further capture the changing character of stress over time, time-domain analysis looks at variations in the temporal dynamics of EEG signals during stressful tasks(Priya et al., 2020). Combining these methods enables a deeper comprehension of stress that will allow for the creation of sophisticated and precise detection techniques(Jun & Smitha, 2017). The integration of these various forms of stress detection by EEG is expected to improve stress assessment accuracy and dependability as this field of study develops, leading to more potent stress management techniques(Agrawal et al., 2021).

Stress Mode	Description
Acute Stress	Immediate response to a specific event or situation, often short-term and activating the "fight or flight" response.
chronic Stress	Prolonged and continuous stress over an extended period, potentially leading to adverse health effects.
Physical stress	Stress resulting from physical exertion, injury, or illness.
Emotional Stress	Stress triggered by emotional experiences, such as grief, anxiety, or interpersonal conflicts
Financial Stress	Stress induced by financial difficulties, insecurity, or debt.
Traumatic Stress	Severe stress resulting from exposure to traumatic events, often leading to long-term psychological consequences
Social Stress	Stress originating from social interactions, peer pressure, or societal expectations.

Methodology

We utilise a methodical technique to examine brainwave patterns suggestive of stress. Initially, non-invasive electrodes are applied to the scalp to collect EEG data(Khosrowabadi et al., 2011). Preprocessing of signals includes feature extraction and noise reduction with an emphasis on theta, alpha, beta, and gamma frequency regions(Asif et al., 2019). Then, using a labelled dataset, machine learning algorithms—such as classifiers and pattern recognition models—are taught to identify unique EEG patterns linked to

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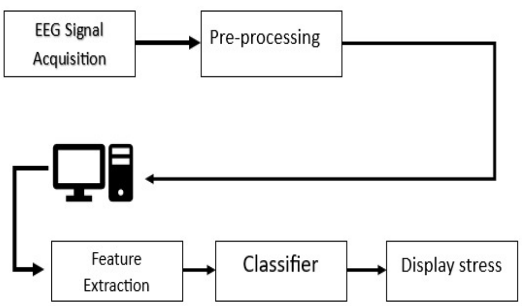
stress(Arsalan et al., 2019). Continuous assessment is made possible via real-time monitoring, and the system sounds an alarm when it notices patterns linked to stress(Priya et al., 2020). By comparing with self-reported stress levels and physiological markers, validation is carried out(Shon et al., 2018). With the help of this all-encompassing methodology, which makes use of EEG technology, stress may be accurately and promptly detected, leading to a more proactive and individualised approach to stress management(Geetha et al., 2022).



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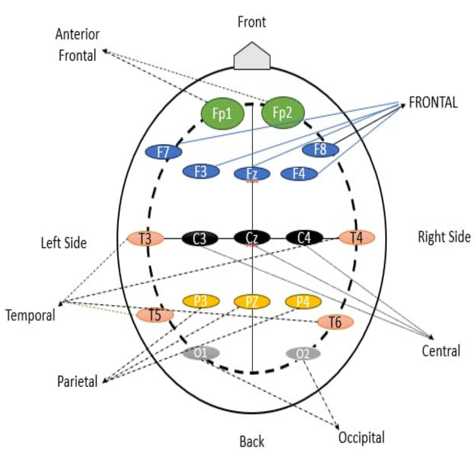

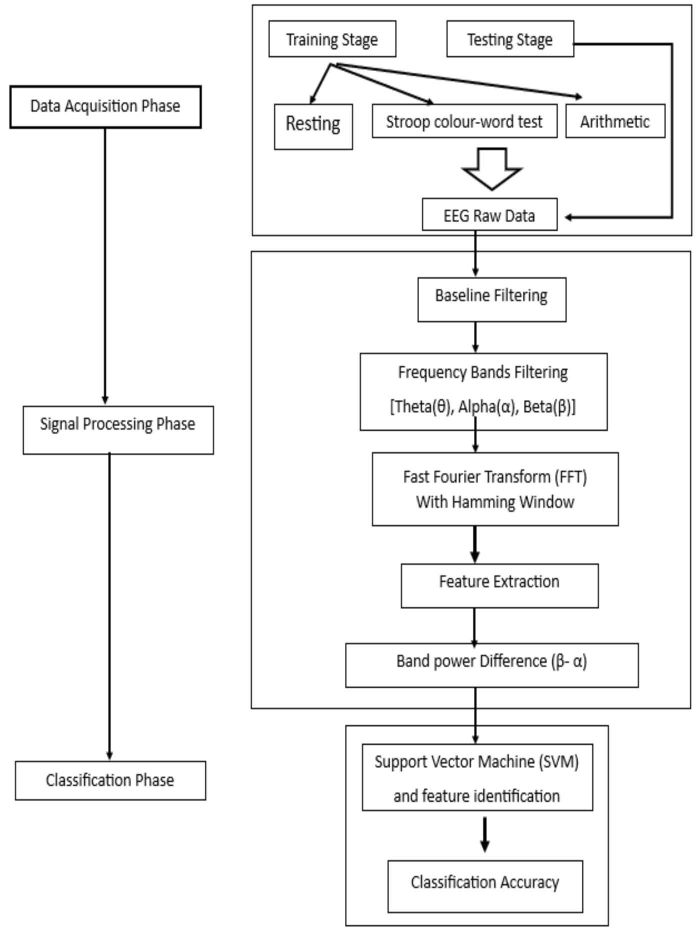

Discussion

The use of EEG to identify stress has great potential and offers a convincing way to improve our knowledge of and ability to manage stress(Katmah et al., 2021). EEG offers a window into the brain's reaction to stressors by collecting complex neural patterns, which enables a sophisticated investigation of cognitive and affective processes(Liu et al., 2016). This methodology's potential applications in a range of fields, such as healthcare, workplace well-being, and personal stress management, are discussed(Katmah et al., 2021). Although significant progress has been achieved in precisely identifying stress from EEG patterns, it is important to take into account the ethical ramifications, including privacy issues and the appropriate use of neurotechnology. Further studies ought to tackle the difficulties brought forth by individual differences and the dynamic character of stress reactions(Marthinsen et al., 2023). As we examine the incorporation of EEG-based.The discourse on electroencephalogram (EEG) stress detection explores the complicated link between neural activity and the physiological expression of stress, providing a thorough understanding of the cognitive and affective aspects of this multifaceted phenomenon(Agrawal et al., 2021). EEG is a non-invasive technique that records brain activity in real time and offers a dynamic picture of the neurological mechanisms behind stress. Theta, alpha, beta, and gamma frequencies are among the primary indications that allow researchers and practitioners to recognise unique patterns associated with stress conditions(Sharma & Chopra, 2020). But issues like individual differences and the complex structure of stress reactions demand a sophisticated knowledge and ongoing improvement of analytic methods. The conversation also heavily emphasises the requirement of ethical issues, such as consent and privacy(Purnamasari & Fernandya, 2019).

Computation

When processing and analyzing the electrical activity of the brain that has been recorded, an electroencephalogram (EEG) calculation usually consists of multiple phases.

Machine Learning :

In order to convert raw EEG signals into features appropriate for training and assessing machine learning models, a sequence of procedures must be followed during the computation of EEG in machine learning.(Peng et al., 2013) The first preprocessing processes are normalization for uniform scaling, filtering to identify particular frequency bands, and eliminating artifacts like eye blinks with techniques like Independent Component Analysis (ICA).(Mcguire, n.d.) Next, elements including time domain statistics, frequency domain characteristics, and time-frequency representations are retrieved from the EEG data, which has been divided into epochs centered around consequential events.(Arsalan et al., 2019) After feature extraction, pertinent features are chosen for additional analysis using dimensionality reduction techniques like principal component analysis (PCA).(Giannakakis et al., 2015) Training and testing sets are made easier by labeling EEG epochs according to experimental circumstances.(Zhang et al., 2020) AUC-ROC, accuracy, precision, recall, and other metrics are measured when machine learning models—which can range from Support Vector Machines to Neural Networks—are chosen, trained on the labeled EEG data, and then assessed using cross-validation procedures.(Agrawal et al., 2021)

Artificial Intelligence

Artificial intelligence computation of EEG data requires advanced processing methods to extract the complex patterns from brain signals. First, preprocessing techniques like filtering are used to concentrate on particular frequency ranges,(Greene et al., 2016) and techniques for removing artifacts like Independent Component Analysis (ICA) guarantee the extraction of real brain signals.(Liu et al., 2016) The EEG data is further standardized by normalization to ensure uniform feature scaling. By dividing the EEG

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signals into distinct epochs, pertinent temporal events may be isolated, which facilitates the process of feature extraction. The dynamic aspect of brain activity is captured by time-frequency representations, frequency domain features derived from Fourier or wavelet transforms, and time domain statistics combined.(Geetha et al., 2022) Principal component analysis and other dimensionality reduction techniques can be used to simplify the dataset after feature extraction.(Shon et al., 2018)

Image processing

Electroencephalogram signals are converted into visually comprehensible representations during the EEG computation process in image processing, which makes it easier to retrieve relevant data regarding brain activity.(Costin et al., 2012) The first preprocessing processes include filtering to separate out pertinent frequency bands and eliminating artifacts, like those from twitches of the eyes or contractions of the muscles.(Asif et al., 2019) Following processing, these EEG signals are transformed into structures that resemble images and are frequently referred to as spectrograms or time-frequency representations.(Purnamasari & Fernandya, 2019) Electroencephalogram signals are converted into visually comprehensible representations during the EEG computation process in image processing, which makes it easier to retrieve relevant data regarding brain activity.(Parunak et al., 2012) The first preprocessing processes include filtering to separate out pertinent frequency bands and eliminating artifacts, like those from twitches of the eyes or contractions of the muscles. Following processing, these EEG signals are transformed into structures that resemble images and are frequently referred to as spectrograms or time-frequency representations.(Ardila et al., 2016)

Future Scope

The field of EEG-based stress detection has enormous promise for revolutionary developments in both theory and real-world applications. We believe that as technology develops further, more complex algorithms that are able to identify individualised and nuanced patterns in EEG data will be refined and developed, improving the precision and dependability of stress identification(Jun & Smitha, 2017). Connectivity with wearable technology and smartphone apps may open the door to real-time tracking and prompt feedback, enabling people to take charge of their stress management. Furthermore, there are a lot of intriguing opportunities for immersive and customised stress intervention techniques at the nexus of EEG and other cutting-edge technologies like virtual reality and artificial intelligence(Parunak et al., 2012). Beyond stress detection, EEG's future applications could include neurofeedback and insights into a range of cognitive and emotional states.including brain-computer connections and training. The combination of neuroscience, engineering, and data science is set to spark revolutionary breakthroughs and usher in a new era of comprehending and improving human cognition and well-being as multidisciplinary collaboration blossoms(Geetha et al., 2022).

Conclusion

Finally, using EEG to identify stress turns out to be a game-changing technique with far-reaching effects on a variety of aspects of life. The knowledge gained from EEG data has the potential to completely change how we manage stress in a variety of contexts, including healthcare, the workplace, and personal wellbeing(Costin et al., 2012). Proactive approaches to mental health are encouraged by the possibility of early therapies made possible by the non-invasive real-time stress detection(Jun & Smitha, 2017). It is essential to address privacy issues and ethical issues as this

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technology develops to ensure responsible deployment. Future-gazing, the incorporation of EEG into wearable technology and its combination with cutting-edge innovations point to a time when people will be able to easily track and reduce stress in their daily lives(Purnamasari & Fernandya, 2019). The secret lies at the nexus of personalised healthcare, technology, and neuroscience, to opening the door to a society that is more adaptable and robust, where our comprehension of stress is not only expanded but also actively translated into real advancements in the ways we manage the challenges of contemporary living(Strotzer, 2009).

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