MENTAL STRESS CLASSIFICATION AMONG HIGHER EDUCATION STUDENTS IN MALAYSIA FROM ELECTROENCEPHALOGRAM (EEG) USING CONVOLUTIONAL NEURAL NETWORK WITH MODIFIED STOCHASTIC GRADIENT DESCENT

NUR RAMIZAH BINTI RAMINO RASHID

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by

NUR RAMIZAH BINTI RAMINO RASHID

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Dear my late father, I apologize for the delay, this is for you Abah, Almarhum Haji Ramino Rashid bin Haji Abdul Jalil (1953-2021).

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
BCI	Brain-computer Interface
CNN	Convolution Neural Network
DEAP	Dataset for Emotion Analysis using Physiological Signals
DL	Deep Learning
EEG	Electroencephalogram
k-NN	k-Nearest Neighbours
RNN	Recurrent Neural Network
SEED	SJTU Emotion EEG Dataset
SGD	Stochastic Gradient Descent
SCWT	Stroop Colour and Word Test
SVM	Support Vector Machine
USM	Universiti Sains Malaysia

LIST OF APPENDICES

KLASIFIKASI TEKANAN MENTAL DALAM KALANGAN PELAJAR PENGAJIAN TINGGI DI MALAYSIA DARIPADA ELEKTROENSEFALOGRAM (EEG) MENGGUNAKAN KAEDAH PERLINGKARAN RANGKAIAN NEURAL DENGAN STOCHASTIC GRADIENT DESCENT TERUBAH

ABSTRAK

Kajian ini menyiasat pengkelasan tekanan mental dalam kalangan pelajar universiti di Malaysia menggunakan data Elektroensefalogram (EEG) dan rangkaian neural konvolusi 1D (1D-CNN) yang dioptimumkan dengan Pengurangan Kecerunan Stokastik (SGD) yang Terubah. Penyelidikan ini menangani jurang yang ketara dalam ketersediaan set data tempatan untuk pengesanan tekanan menggunakan isyarat EEG, kerana model dan set data sedia ada kebanyakannya memberi tumpuan kepada populasi lain dan tidak mengambil kira variasi serantau dalam faktor tekanan dan tindak balas. Selain itu, terdapat kekurangan pengoptimuman dalam model pengesanan tekanan, khususnya dalam menangani data EEG, yang boleh menjejaskan ketepatan model dan potensi aplikasi masa nyata. Untuk menangani cabaran ini, isyarat EEG dikumpulkan semasa ujian Stroop dan tahap tekanan yang dilaporkan sendiri diukur menggunakan Skala Tekanan yang Dirasai (PSS). Pendekatan prapemprosesan yang ketat, termasuk Analisis Komponen Bebas (ICA) untuk penyingkiran artifak, telah digunakan, diikuti dengan pengekstrakan ciri yang memberi tumpuan kepada metrik utama seperti tenaga, entropi, dan sisihan piawai daripada kedua-dua domain masa dan frekuensi. Algoritma yang dipilih, 1D-CNN, telah diubah menggunakan pengoptimum SGD yang disesuaikan yang menggabungkan momentum dan pengecilan kadar pembelajaran untuk meningkatkan konvergensi dan menangani cabaran seperti kecerunan lenyap. Pengubahsuaian ini penting untuk meningkatkan proses pembelajaran model, yang akhirnya membawa kepada prestasi pengkelasan tekanan yang lebih baik. Model 1D CNN yang dicadangkan, yang ditingkatkan dengan SGD yang Terubah, menunjukkan prestasi yang lebih baik berbanding model tradisional seperti Support Vector Machine (SVM), k-k-Nearest Neighbors (k-NN), dan seni bina yang lebih mendalam seperti CNN Standard dan Ale-

xNet. Khususnya, 1D CNN mencapai ketepatan 92.64%, mengatasi SVM (84.5%), k-NN (76.6%), CNN Standard (91.3%), RNN (90.04%) dan AlexNet (91.65%). Model 1D CNN juga menunjukkan sensitiviti dan kekhususan yang tinggi, menjadikannya penyelesaian yang kukuh untuk pengesanan tekanan berasaskan EEG. Penemuan utama menunjukkan bahawa model 1D-CNN yang ditingkatkan bukan sahaja lebih berkesan tetapi juga menawarkan kerangka kerja yang dipertingkat dan boleh dipercayai untuk pengkelasan tekanan mental. Kajian ini memberikan sumbangan yang ketara kepada bidang ini, menawarkan metodologi yang kukuh untuk pengesanan tekanan berasaskan EEG. Kerja masa depan dicadangkan untuk mengembangkan set data, menggabungkan input multimodal, dan meneroka teknik pembelajaran mendalam lanjutan untuk aplikasi pemantauan tekanan masa nyata.

MENTAL STRESS CLASSIFICATION AMONG HIGHER EDUCATION STUDENTS IN MALAYSIA FROM ELECTROENCEPHALOGRAM (EEG) USING CONVOLUTIONAL NEURAL NETWORK WITH MODIFIED STOCHASTIC GRADIENT DESCENT

ABSTRACT

This study investigates the classification of mental stress among Malaysian university students using Electroencephalogram (EEG) data and a 1D-Convolutional Neural Network (1D-CNN) optimized with Modified Stochastic Gradient Descent (SGD). The research addresses a significant gap in the availability of localized datasets for stress detection using EEG signals, as existing models and datasets predominantly focus on other populations and do not account for regional variations in stressors and responses. Moreover, there is a lack of optimization in stress detection models, specifically in handling EEG data, which can affect the models' accuracy and real-time application potential. To address these challenges, EEG signals were collected during Stroop tests and self-reported stress levels were measured using the Perceived Stress Scale (PSS). A rigorous preprocessing approach, including Independent Component Analysis (ICA) for artifact removal, was applied, followed by feature extraction focusing on key metrics such as energy, entropy, and standard deviation from both time and frequency domains. The chosen algorithm, 1D-CNN, was modified using a tailored SGD optimizer that incorporates momentum and learning rate decay to improve convergence and address challenges like vanishing gradients. This modification was essential for enhancing the model's learning process, ultimately leading to better stress classification performance. The proposed 1D CNN model, enhanced with Modified SGD, demonstrated superior performance compared to traditional models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and deeper architectures like Standard CNN and AlexNet. Specifically, the 1D CNN achieved an accuracy of 92.64%, outperforming SVM (84.5%), k-NN (76.6%), Standard CNN (91.3%), RNN (90.04%) and AlexNet (91.65%). The 1D CNN model also demonstrated high sensitivity and specificity, making it a robust solution for EEG-based stress detection. Key findings indicate that

the refined 1D CNN model is not only more effective but also offers an enhanced and reliable framework for mental stress classification. This research provides a significant contribution to the field, offering a robust methodology for EEG-based stress detection. Future work is suggested on expanding datasets, incorporating multi-modal inputs, and exploring advanced deep learning techniques for real-time stress monitoring applications.

CHAPTER 1

INTRODUCTION

1.1 Reasearch Background

The mental stress experienced by university students in Malaysia represents a multifactorial issue, underpinned by various socio-economic, academic, and psychological determinants (Shahabudin, 2014). Extensive research has consistently highlighted the high prevalence of mental health disorders, particularly depression, anxiety, and stress (DAS), among this demographic (Beiter et al., 2015). Epidemiological studies reveal that a substantial proportion of Malaysian university students are affected by these conditions, with prevalence rates as high as 34.8% for depression, 42.2% for anxiety, and 33.5% for stress in some cohorts (Maung et al., 2023). Another study further exacerbates the concern by reporting that 68.9% of students experience moderate to high levels of psychological distress, with 72.7% suffering from anxiety and 60.6% from depression (Hassan et al., 2022). These statistics underscore the critical need for effective mental health monitoring and intervention strategies within academic institutions (Rusli et al., 2023).

Academic stress is a predominant factor contributing to the high incidence of mental health issues among Malaysian students (Saleem et al., 2013). The competitive academic environment, coupled with the cultural and societal emphasis on academic excellence, exerts significant pressure on students to perform at exceptionally high standards. This pressure is often compounded by external stressors, such as financial constraints, which are particularly prevalent among students from lower-income backgrounds (Thomas, 2022). Financial burdens can necessitate part-time employment, further exacerbating stress by diminishing the time available for academic pursuits and social interaction (Hossain et al., 2023). Social and familial expectations also play a crucial role, as students navigate the challenges of adapting to university life while managing the expectations of success imposed by their families and society (Kassim &

Hanafi, 2020).

The intersection of these stressors creates a complex and challenging mental health landscape for Malaysian university students. Despite the recognition of these issues, current methodologies for detecting and addressing mental stress remain inadequate. Traditional approaches predominantly rely on self-reported data, which is inherently subjective and may not accurately reflect the true mental state of the individual. Moreover, these methods are reactive, often identifying issues only once they have escalated to severe levels (Yusoff et al., 2017). This reactive approach limits the potential for early intervention, which is critical for preventing the progression of stress into more severe mental health conditions.

Given the complexities of mental stress and its potential escalation into more severe mental health issues, the development of an automated system for measuring and monitoring mental stress could be crucial in preventing such outcomes. This growing recognition has fueled interest in the detection of various mental states, including stress, drowsiness, and fatigue, making it a prominent area of research. Several studies have successfully demonstrated the feasibility of using Electroencephalogram (EEG) data to measure mental stress in experiments that employ stimuli or visual monitoring (Giannakakis et al., 2019; Giannakakis et al., 2017; Panicker & Gayathri, 2019). However, developing or adapting signal processing methods to accurately extract relevant information from EEG signals for stress detection presents several challenges.

Current research on mental stress detection using EEG data has predominantly focused on the development and optimization of various signal processing methodologies and classification algorithms. Numerous studies have substantiated the efficacy of EEG-based systems in monitoring neurophysiological states such as stress, drowsiness, and fatigue within controlled experimental settings. These studies have leveraged advanced machine learning techniques to classify different mental states with varying degrees of accuracy (Badr et al., 2024; Mhaouch et al., 2024; Sahithi et al., 2024). However, several critical limitations persist within the existing body of work, which continue to challenge the broader applicability and generalizability of these findings.

One of the primary limitations in EEG-based stress detection studies lies in the nature of the datasets commonly used. Many of these datasets are restricted in access, limiting their availability to the broader research community, which hinders collaborative efforts and the validation of findings across different studies (X. Hu et al., 2019). Additionally, a significant number of these datasets focus on neurocognitive states that, while related, do not accurately reflect the unique neural signatures of mental stress. For instance, datasets designed to capture neural correlates of cognitive fatigue or workload, though relevant, may not directly correspond to the specific patterns associated with stress (Mhaouch et al., 2024). This overlap between related but distinct mental states can lead to inaccuracies in model training and testing, ultimately affecting the reliability of stress detection algorithms (Bahameish et al., 2024).

The challenge of limited dataset access is further exacerbated by issues related to privacy, ethics, and the high costs associated with EEG data collection (Fidas & Lyras, 2023). Data sharing in EEG research is complex, involving technical, ethical, and legal challenges, particularly given the sensitive nature of EEG data, which can reveal personal cognitive and emotional information (X. Hu et al., 2019). As a result, many datasets are kept confidential or are only available under strict access agreements, limiting their use for broader research purposes (Rashid et al., 2020). This restricted access not only impedes the validation of results across multiple studies but also introduces potential biases and reduces the reproducibility of research findings.

Moreover, there is a significant inconsistency in the documentation and standardization of the stress-inducing protocols employed during data acquisition(Giannakakis et al., 2019; Masri et al., 2023). The lack of uniformity in how stressors are administered, such as the type, duration, and intensity of the stimuli used to evoke stress responses, introduces variability that complicates the interpretation of EEG data. This variability undermines the replicability of findings across studies and presents challenges in the generalization of models developed under specific experimental conditions to real-world applications. The heterogeneity in stressor documentation also impedes the ability to perform meta-analyses or comparative studies, further limiting the cumulative advancement of the field.

1.2 Problem Statement

The mental stress experienced by university students in Malaysia is a multifaceted issue driven by various socio-economic, academic, and psychological factors. Despite the high prevalence of stress-related disorders among this demographic, current approaches to mental health monitoring within academic settings remain inadequate (Badr et al., 2024; Katmah et al., 2021; Mueller et al., 2022). Traditional methods, which primarily rely on self-reported data, are inherently subjective and reactive, often failing to detect stress until it has escalated into more severe mental health issues. The growing interest in using EEG data to objectively measure mental stress offers a promising avenue for more accurate and early detection (Katmah et al., 2021; Yao et al., 2023). However, significant challenges impede the advancement of EEG-based stress detection systems.

A critical limitation in this field is the scarcity of publicly accessible EEG datasets that accurately capture the neural signatures of mental stress, particularly within the context of Malaysian university students. Most existing datasets are either restricted in access, limiting their use for validation and generalization, or they focus on related but distinct neurocognitive states such as cognitive fatigue or workload (Badr et al., 2024; Katmah et al., 2021), which do not directly correspond to stress. This misalignment hampers the development of robust machine learning models specifically tailored for stress detection.

Furthermore, the process of data cleaning and feature extraction in EEG research presents additional challenges. EEG signals are inherently noisy, and the presence of artifacts can significantly distort the data, leading to inaccuracies in analysis (Fu et al., 2022; Kit et al., 2023; Mueller et al., 2022). Effective artifact removal and the extraction of features that truly represent mental stress are crucial for developing reliable stress detection models (Halim & Rehan, 2020). Moreover, the lack of consistency in the documentation and standardization of stress-inducing protocols across studies introduces variability that complicates the interpretation of EEG data, further limiting the replicability and generalizability of findings (Arroyo-Araujo et al., 2022; Kabbara et al., 2023; Katmah et al., 2021).

Addressing these challenges is essential to advancing the field of EEG-based mental stress detection. This research aims to develop a comprehensive EEG dataset specifically focused on capturing mental stress among Malaysian university students. To achieve this, the study will implement rigorous data collection protocols, ensuring the accurate and consistent application of stress-inducing stimuli. Additionally, advanced signal processing techniques will be employed for data cleaning and feature extraction, facilitating the development of a machine learning model optimized for stress detection. By bridging these gaps, this research will pave the way for the development of more precise and scalable methodologies for mental stress detection (Giannakakis et al., 2019; Masri et al., 2023). The outcomes of this study have the potential to facilitate timely interventions, ultimately enhancing the mental well-being and academic success of university students in Malaysia.

1.3 Research Questions

The study is guided by the following questions:

1. How can EEG data be effectively constructed and processed to reflect the stress levels of Malaysian university students?

2. What are the most suitable features for accurately classifying mental stress based on EEG signal?

3. How can the proposed model be optimized to enhance its accuracy and reliability in classifying mental stress?

1.4 Research Objectives

The primary objectives of this thesis are as follows:

1. To construct a robust EEG dataset from participants within Malaysia, ensuring the data reflects the unique environmental and demographic characteristics of the local population for stress detection research.

2. To enhance the dataset's suitability for stress classification by removing noise and artifacts, followed by extracting key time-domain and frequency-domain features.

3. To refine and evaluate a One Dimensional Convolutional Neural Network (1D-CNN) model with Modified Stochastic Gradient Descent (SGD) to enhance the performance of stress classification, ensuring improved accuracy and reliability based on the preprocessed EEG data.

1.5 Methodology Overview

The research will involve the collection of EEG data from university students in Malaysia, under conditions designed to simulate typical academic stressors. This data will be meticulously preprocessed to remove noise and artifacts, followed by feature extraction (Aggarwal & Chugh, 2019; Boonyakitanont et al., 2020; Jiang et al., 2019; Katmah et al., 2021; Sadruddin et al., 2024). A machine learning model will then be developed and fine-tuned to classify mental stress levels with a focus on enhancing the model's accuracy and reliability. The flow of these methodological steps is illustrated in the following illustration, Figure 1.1. The process begins with Data Collection, where EEG signals were recorded under controlled stress conditions. This is followed by Data Preprocessing, where noise and artifacts were removed to ensure clean and reliable data. Next, in Feature Extraction, key neural patterns related to stress, such as energy and entropy, were identified. Model Development then involved using these features to build a 1D-CNN model for classifying stress levels. Finally, Model Optimization refined the model's parameters to improve classification accuracy, ensuring reliable performance.

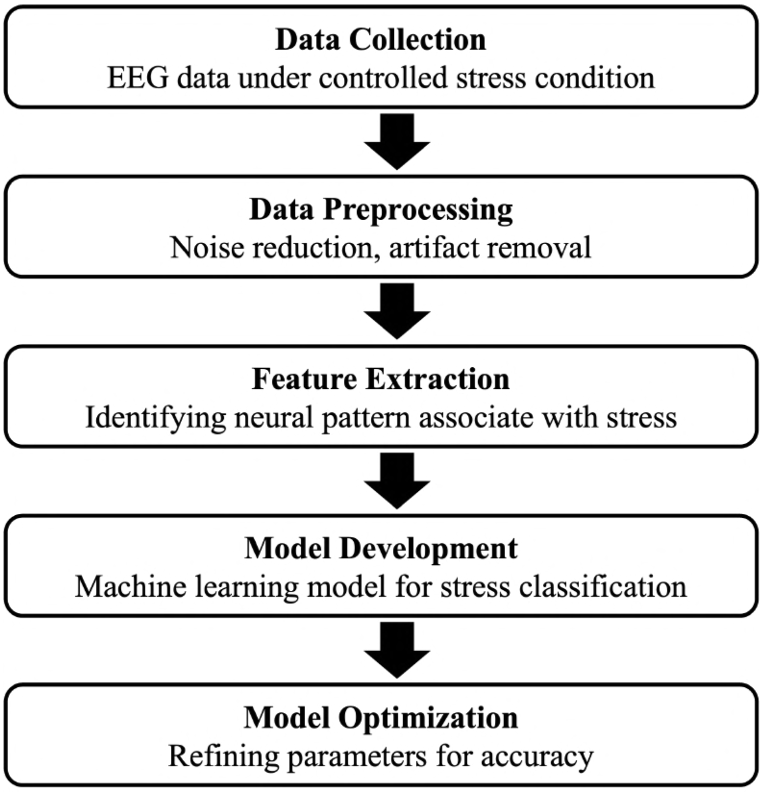

Figure 1.1: Methodology Overview

1.6 Contribution

In addressing the research questions posed, this study makes significant contributions to the following areas:

1. **Establishment of a Specialized EEG Dataset for Mental Stress Research:** A comprehensive EEG dataset was developed, specifically tailored to the study of mental stress among university students in Malaysia. This dataset, including multiple recordings from participants subjected to controlled, stress-inducing scenarios, fills a critical gap in the existing body of research. By providing an extensive and contextually relevant dataset, future studies are enabled to explore mental stress detection with greater accuracy and reliability.

2. **Advancement of EEG Data Preprocessing Techniques:** Recognizing the challenges inherent in analyzing EEG data, this research introduces an advanced preprocessing pipeline designed to enhance the quality of EEG signals for mental stress classification. By employing sophisticated noise reduction and artifact

removal methodologies, the pipeline significantly improves the integrity of the data, thereby laying a stronger foundation for the development of more effective mental health monitoring tools.

3. **Refinement of 1D-CNN Architecture for Stress Classification:** This study proposes an innovative Convolutional Neural Network (CNN) architecture, specifically optimized for the classification of mental stress using EEG data. The architecture incorporates a Modified Stochastic Gradient Descent (SGD) algorithm, uniquely adapted to the nuances of EEG signal processing. This contribution not only advances the technical understanding of EEG-based stress detection but also demonstrates superior classification accuracy compared to existing models.

1.7 Thesis Organization

The remainder of the thesis is organized as follows:

Chapter 2 introduces EEG technology as a tool for studying brain activity, highlighting its role in mental stress detection. It covers electrode placement, signal characteristics, and frequency bands, and reviews key literature on EEG-based stress detection, identifying gaps and challenges that this study addresses.

Chapter 3 outlines the research methodology, including participant selection, experimental design, and stress-inducing tasks. It details preprocessing steps like noise reduction and artifact removal and explains the feature extraction methods used for subsequent stress classification.

Chapter 4 provides a comprehensive overview of the data collection process, covering participant recruitment, ethical considerations, and the experimental setup. It also discusses the EEG equipment used and the stress-inducing tasks administered to participants.

Chapter 5 focuses on EEG data preprocessing and feature extraction. Techniques such as filtering and artifact removal are described, and their importance in extracting meaningful features (e.g., energy, entropy) for stress classification is discussed.

Chapter 6 details the development of a 1D-Convolutional Neural Network (1D-CNN) for mental stress classification, explaining the model architecture and the use of a Modified Stochastic Gradient Descent (SGD) algorithm. Model performance is evaluated and compared to other classification methods.

Chapter 7 revisits the study's objectives and summarizes its findings. It highlights the key contributions to EEG-based stress detection, such as the collection of a locally-relevant EEG dataset, the introduction of an advanced preprocessing pipeline, and the refinement of the 1D-CNN model. This chapter also discusses real-world applications of the model and acknowledges the study's limitations. Finally, it proposes directions for future research to further improve the model's accuracy and reliability in mental stress detection.

1.8 Chapter Summary

This chapter addresses the significant challenge of mental stress among Malaysian university students, underscored by various socio-economic, academic, and psychological pressures. The chapter discusses the inadequacy of current mental health monitoring approaches, which are predominantly reactive and reliant on subjective self-reporting, often missing early indicators of stress.

To address these limitations, this research focuses on developing a specialized EEG dataset tailored to the Malaysian university student demographic and creating a machine learning model optimized for precise stress detection. The chapter outlines the key research questions guiding the investigation, including the effective collection of EEG data, identification of suitable algorithms, and improvement of model performance. Additionally, it provides an overview of the research methodology, laying the foundation for the study's contributions. These contributions include advancements in EEG data processing techniques and the development of a novel 1D-CNN model for mental stress classification.

Table 1.2 presents a summary of the problem statement, objectives, research questions, and contributions of this study.

Table 1.2: Research Summary

Problem Statement	Research Question	Research Objective	Support Literature	Methodology	Contribution
Lack of Specific EEG Data: The scarcity of publicly accessible EEG datasets that accurately capture mental stress in Malaysian students poses a significant barrier to refining effective stress detection models. Existing datasets are either limited or focus on unrelated neurocognitive states, which impedes the creation of models tailored specifically for stress detection.	How can EEG data be effectively constructed and processed to reflect the stress levels of Malaysian university students?	To construct a robust EEG dataset from participants within Malaysia, ensuring the data reflects the unique environmental and demographic characteristics of the local population for stress detection research.	Badr et al., 2024; Katmah et al., 2021; Mueller et al., 2022	Cluster sampling and data collection	Create a dataset for future stress detection models
Challenges in Data Cleaning and the need for Accurate Feature Extraction: EEG signals are inherently noisy, and the presence of artefacts can distort the data, leading to inaccuracies in stress analysis. Effective noise reduction and artefact removal are crucial for ensuring the extracted features accurately reflect mental stress, providing a robust foundation for model development.	How do preprocessing and feature extraction techniques impact the accuracy of stress detection models using EEG data?	To enhance the dataset's suitability for stress classification by removing noise and artifacts, followed by extracting key time-domain and frequency-domain features.	Gauthier et al., 2022; Halim and Rehan, 2020; Haris et al., 2020; Tugnait, 2019	Performed using both automatic and manual feature extraction	Improved accuracy in stress detection using EEG by combining the automated and manual extracted feature

Problem Statement	Research Question	Research Objective	Support Literature	Methodology	Contribution
Limited optimization in existing stress detection models using EEG data, affecting classification performance	How can the proposed model be optimized to enhance its accuracy and reliability in classifying mental stress?	To refine and evaluate the 1D-CNN model with modified SGD to enhance stress classification performance	Badr et al., 2024 Jun and Smitha, 2016; Katmah et al., 2021 Jangde and Sisodia, 2023 Cao et al., 2023 Avola et al., 2024	refined 1D-CNN and modified SGD	A model that will contribute to future research and applications in stress detection, thereby advancing the field of mental health monitoring

CHAPTER 2

LITERATURE REVIEW

Chapter 2 presents the literature review on EEG-based mental stress detection. The chapter begins with an exploration of the existing data collection procedures, focusing on methodologies employed for acquiring EEG data in the context of mental stress studies, including controlled experiments. This is followed by an examination of various sampling methods and data cleansing techniques crucial for ensuring data integrity and reliability. The discussion then moves to feature extraction methodologies, emphasizing their role in improving the precision of stress classification. Additionally, the chapter reviews different model used in EEG-based research, with a particular emphasis on their effectiveness in mental stress detection. Finally, a comprehensive survey of the current state-of-the-art approaches is presented, concluding with a gap analysis that identifies opportunities for future research and enhancements, which will be summarized in the final section of the chapter.

2.1 Introduction

EEG-based mental stress detection is an emerging field that harnesses the non-invasive capabilities of EEG to evaluate psychological stress through the analysis of brain wave patterns. By examining frequency bands such as alpha, beta, theta, and gamma, EEG signals offer valuable insights into neural activity and mental states, making them a powerful tool for detecting stress. (Badr et al., 2024; Bakare et al., 2024). The importance of datasets in this field cannot be overstated, as they serve as the cornerstone for training and validating machine learning models designed to classify stress levels. EEG-based stress detection relies on a range of machine learning and deep learning techniques, making the quality and comprehensiveness of the datasets pivotal to the accuracy and reliability of the detection models.

For instance, models like k-Nearest Neighbors (k-NN) and Support Vector Machine (SVM) have been employed to classify stress levels, with k-NN showing superior performance in some studies (Bakare et al., 2024). Deep learning approaches, particularly Convolutional Neural Networks (CNNs) have also been explored, with CNNs being the most frequently used due to their ability to handle complex data representations (Badr et al., 2024). The choice of model and its architecture significantly impacts the classification accuracy, with some studies achieving up to 88% accuracy using spectral and topographical data representations (Badr et al., 2024).

Datasets play a pivotal role in the development and evaluation of these models. The size and quality of the dataset, as well as the representation of EEG data, are critical factors influencing model performance (Khan & Ahmad, 2024). The preprocessing of EEG data, including artifact removal and feature extraction, is essential for enhancing model accuracy. Techniques such as Independent Component Analysis (ICA) have been employed to improve data quality for both offline and online stress detection scenarios (Chang et al., 2024). The integration of EEG data with machine learning models has shown promising results in various studies. For instance, the use of wavelet-based feature extraction methods has been effective in classifying stress levels, achieving high accuracy with decision tree classifiers (Kit et al., 2023). Similarly, the application of SVM and other machine learning algorithms has demonstrated the potential for accurate stress detection, with some studies reporting classification accuracies as high as 96.85% after preprocessing (Troyee et al., 2024).

Despite these advancements, challenges remain, particularly regarding the generalizability of models across different subjects and conditions. Inter-subject variability and the need for robust models that can handle diverse EEG data representations are ongoing areas of research (Badr et al., 2024).

2.2 EEG: A Tool to Study Brain

In 1929, German psychiatrist Hans Berger made a significant discovery that introduced a new diagnostic tool for neurology and psychiatry: the electroencephalogram (EEG) (La Vaque, 1999). Since then, EEG has become one of the most important tools for studying brain functionality. Over time, numerous portable and powerful EEG recording devices have been developed (T. J. Sullivan et al., 2008).

EEG measures the electrical activity of the brain by detecting the voltage differences between pairs of electrodes placed on the scalp. This method allows for the analysis of brain activity as it responds to various natural and recurrent stimuli, which can provide insights into different brain states and human behaviors. Although EEG has relatively low spatial resolution, it compensates with its high temporal resolution, making it well-suited for detecting brain waves and induced electric potentials that occur at frequencies typically between 1 and 100 Hz (Nunez & Srinivasan, 2006; T. J. Sullivan et al., 2008).

EEG is a highly effective tool for examining a wide range of neuronal circuits within the human brain. By placing electrodes on the scalp, EEG captures the electrical activity generated by neural processes, ensuring a strong connection to record this activity accurately (Rana et al., 2017). Thanks to its high temporal resolution, EEG is particularly well-suited for observing the rapid changes in brain activity associated with different mental states. The amplitude and frequency of the EEG waveform provide valuable insights into an individual's level of consciousness.

The five fundamental brain waves—alpha, beta, theta, delta, and gamma—each have distinct characteristics, as shown in Table 2.1 and Figure 2.1. Recent research on mental stress has found that elevated frequencies of alpha and beta waves are often linked to increased stress and anxiety. EEG signals, captured and recorded through various methods such as scalp EEG, offer a detailed view of brain activity and its connection to mental states.

To capture these brain waves and study their relationship with mental states, EEG signals are recorded through various methods, including scalp EEG. Figure 2.2 illustrates a typical EEG recording setup, where a human wears a device that captures and records EEG signals. The brain, containing approximately 100 billion neurons, is a highly complex organ where each neuron is constantly transmitting and receiving signals via an intricate network of connections. All thoughts and actions are encoded in the brain's electrical signals, which can be measured and recorded. Although EEGs measure very low voltage potentials, they are sensitive enough to detect significant signals, such as those generated by blinking eyelids.

Table 2.1: The Five Fundamental Brain Waves and Their Characteristics (Abhang et al., 2016)

EEG Band	Frequency Range (Hz)	Brain States
Delta δ	1–4	Sleep
Theta θ	4–8	Mediation, Inward Focused
Alpha α	8–12	Very relaxed, passive attention
Beta β	13–25	Anxiety, active , external focused, relaxed
Gamma γ	≥ 25	Concentration

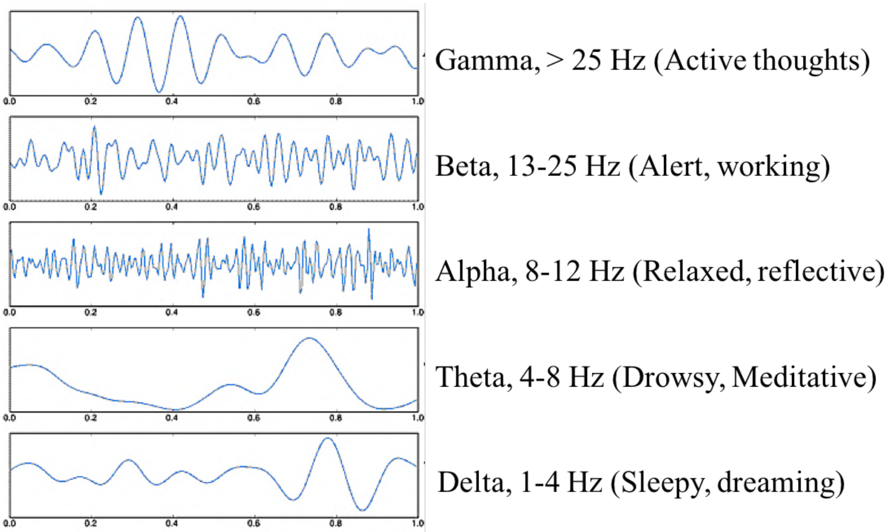

Figure 2.1: Brainwaves Frequencies (Abhang et al., 2016)

2.3 Overview of Existing Datasets in EEG-Based Stress Detection

The development and validation of EEG-based mental stress detection models rely heavily on the availability of high-quality datasets. Several prominent EEG datasets

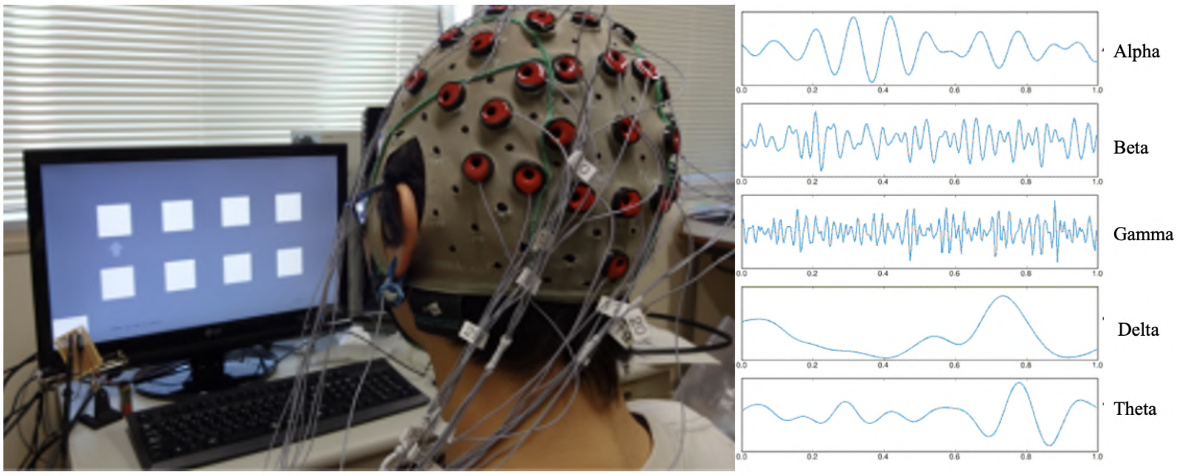

Figure 2.2: The electroencephalogram (EEG) of the human brain is recorded. The patient looks at a screen that displays stimuli that can activate the brain and generate an EEG signal. On the right, five distinct types of EEG signals are displayed.

have been widely used in emotion and stress-related studies, each contributing uniquely to the field. This section provides an overview of some of the most influential datasets, including DEAP, SEED, and other relevant datasets.

2.3.1 DEAP Dataset

The DEAP (Dataset for Emotion Analysis using Physiological Signals) dataset is one of the most extensively used datasets in the study of emotion recognition and stress detection. Created by S. Koelstra et al., 2011, DEAP contains EEG and peripheral physiological signals recorded from 32 participants as they watched 40 one-minute-long excerpts of music videos. The dataset is particularly valuable for its combination of multimodal data, which includes EEG signals, facial expressions, and peripheral physiological measures such as skin conductance and respiration (Gaddanakeri et al., 2024).

One of the strengths of the DEAP dataset is its large number of participants, which enhances the generalizability of the findings derived from it (Khateeb et al., 2021). The dataset also includes self-reported valence, arousal, and dominance ratings, allowing researchers to explore the relationship between physiological responses and subjective emotional experiences. The variety of stimuli used in DEAP, which are carefully selected to evoke a broad range of emotional responses, further increases the dataset's utility in studying complex emotional states and their neural correlates (Jha et al., 2024).

However, the DEAP dataset has certain limitations. While it provides a robust foundation for emotion-related studies, its direct applicability to stress detection is somewhat limited (Kulkarni & Patil, 2023). The controlled laboratory environment in which the data were collected may not fully capture the complexities of real-world stressors. Moreover, the short duration of the stimuli (only one minute per video) may not be sufficient to induce significant stress levels in participants, thus limiting the dataset's use in stress-specific research (R. A. L. Koelstra, 2012).

2.3.2 SEED Dataset

The SEED (SJTU Emotion EEG Dataset) is another highly regarded dataset in the field of EEG-based emotion and stress detection. Developed by Zheng and Lu, 2015, the SEED dataset consists of EEG recordings from 15 participants as they watched a series of film clips designed to elicit positive, neutral, and negative emotions. The dataset is collected using a 62-channel EEG system, providing high spatial resolution data that is particularly valuable for fine-grained analysis of brain activity associated with different emotional states.

The SEED dataset's strength lies in its focus on eliciting strong emotional responses, which makes it particularly relevant for stress detection studies (Saranya et al., 2023). The use of emotionally charged film clips as stimuli ensures that participants experience significant emotional fluctuations, which are crucial for studying the neural correlates of stress (Ma et al., 2022). Additionally, the dataset includes recordings from multiple sessions over different days, allowing researchers to investigate the stability and variability of emotional responses over time (Zheng & Lu, 2015).

Despite its strengths, the SEED dataset has certain limitations. The relatively small number of participants (15) may limit the generalizability of findings, particularly in studies aiming to develop models that can be applied across diverse populations (W.

Chan et al., 2023). Furthermore, while the dataset is effective for studying emotion-related EEG patterns, its focus on a limited set of emotions (positive, neutral, and negative) may not fully encompass the broader spectrum of stress-related neural activity (Zheng & Lu, 2015).

2.3.3 Other Similar EEG Dataset

In addition to DEAP and SEED, several other datasets have made significant contributions to the field of EEG-based detection. The AMIGOS dataset, for example, includes EEG, ECG, and GSR recordings from 40 participants as they watched videos designed to induce different levels of emotional arousal and valence. The AMIGOS dataset is particularly useful for its inclusion of both individual and group settings, providing insights into the social context of emotional and stress responses (Miranda-Correa et al., 2018).

Another notable dataset is the DREAMER dataset, which contains EEG and ECG recordings from 23 participants as they watched film clips selected to evoke specific emotional states (Garg et al., 2022). The dataset includes self-reported valence, arousal, and dominance ratings, making it a valuable resource for studies exploring the relationship between physiological signals and subjective emotional experiences. However, like DEAP and SEED, the DREAMER dataset's applicability to stress detection is somewhat limited by the nature of its stimuli, which are primarily designed to elicit emotions rather than stress (Katsigiannis & Ramzan, 2017).

These datasets collectively provide a rich resource for researchers studying EEG-based emotion and stress detection. However, each has its own set of limitations, particularly in terms of applicability to stress detection. The controlled environments and specific emotional stimuli used in these datasets may not fully capture the complexity of real-world stressors, underscoring the need for the development of new datasets that better reflect the diverse and dynamic nature of stress.

2.4 Comparison of Dataset Characteristics

In EEG-based research, particularly in the context of mental stress detection, the characteristics of datasets are critical in determining the validity, reliability, and generalizability of research findings. This section provides a comparative analysis of key characteristics across major EEG datasets, focusing on demographics and sample size, stress induction protocols, and data quality and preprocessing methods.

2.4.1 Stress Induction Protocols

The methods used to induce stress in participants are pivotal in EEG-based stress detection research, as they directly impact the quality and relevance of the data collected. Different stress induction protocols can result in varying levels of stress, which in turn affects the EEG signals recorded.

In the DEAP dataset, stress induction is indirect; participants are exposed to music videos designed to evoke a wide range of emotional responses, including stress. However, these stimuli primarily focus on general emotional arousal rather than targeted stress induction. Consequently, while the dataset is valuable for studying emotional responses, its direct applicability to stress-specific research is somewhat limited (R. A. L. Koelstra, 2012).

The SEED dataset employs emotionally charged film clips as stimuli, specifically selected to induce positive, neutral, and negative emotions. Although the negative clips are effective in inducing stress, the protocol is more emotion-focused rather than exclusively designed for stress induction. This approach, while useful for studying the neural correlates of emotion, may not fully capture the nuances of stress-specific EEG patterns (Zheng & Lu, 2015).

The AMIGOS dataset utilizes a combination of video clips and a controlled group environment to induce varying levels of emotional arousal, including stress. The inclusion of both individual and group settings allows for the study of social stressors, which are prevalent in real-world scenarios. This dual approach enhances the dataset's value for stress research, as it more accurately mimics the complex and varied nature of real-world stressors (Miranda-Correa et al., 2018).

Similarly, the DREAMER dataset uses film clips as stimuli to evoke specific emotional states. However, like the SEED dataset, the focus is primarily on emotion rather than stress specifically, which may limit its utility in studies aimed at exploring the neural mechanisms of stress. The stress induction in DREAMER is incidental, resulting from the emotional arousal induced by the stimuli rather than being a primary focus of the experiment (Katsigiannis & Ramzan, 2017).

The stress induction protocols utilized in these datasets significantly influence the results and their applicability to stress detection. Datasets such as AMIGOS, which use more realistic and varied stress induction methods, are better suited for developing models applicable to real-world stress detection. In contrast, datasets that rely on emotion-focused stimuli, like DEAP and SEED, may be more limited in their ability to capture stress-specific EEG patterns.

2.4.2 Data Quality and Preprocessing

Data quality and the preprocessing steps applied to EEG data are crucial factors that determine the reliability and usability of the dataset. Effective preprocessing can enhance the signal-to-noise ratio and remove artifacts, thereby improving the accuracy of subsequent analyses.

The DEAP dataset includes comprehensive preprocessing steps, such as the application of a 4-45 Hz bandpass filter to remove low-frequency drifts and high-frequency noise. Additionally, Independent Component Analysis (ICA) is employed to identify and remove artifacts such as eye blinks and muscle movements (Uddin, 2023). These preprocessing steps significantly enhance the quality of the EEG data, making it more suitable for emotional stress detection (R. A. L. Koelstra, 2012).

The SEED dataset undergoes similar preprocessing, including bandpass filtering and artifact removal using ICA. However, the dataset is distinguished by its high spatial resolution, as it utilizes a 62 channel EEG system. This higher resolution allows for more detailed analysis of brain activity but also necessitates more sophisticated preprocessing techniques to manage the increased data complexity (Zheng & Lu, 2015).

The AMIGOS dataset employs a combination of preprocessing techniques, including notch filtering to remove power line noise and bandpass filtering to isolate the relevant EEG frequency bands. Artifact removal is performed using both automatic and manual methods, ensuring that the final dataset is of high quality. The inclusion of both individual and group data in AMIGOS also necessitates careful preprocessing to account for potential interferences in group settings (Miranda-Correa et al., 2018).

The DREAMER dataset applies standard preprocessing steps, including bandpass filtering and artifact removal. However, the use of off-the-shelf, wireless EEG devices in this dataset presents unique challenges, as these devices are more susceptible to noise and signal degradation. Consequently, extensive preprocessing is required to ensure the data is of sufficient quality for analysis (Katsigiannis & Ramzan, 2017).

The preprocessing methods used in these datasets are critical in determining the final data quality. Datasets like DEAP and SEED, which employ advanced preprocessing techniques such as ICA, provide high-quality data that is more reliable for stress detection. In contrast, datasets like DREAMER, which use less sophisticated EEG equipment, may require more extensive preprocessing to achieve comparable data quality. The choice of preprocessing methods directly impacts the usability of the dataset in developing accurate and reliable stress detection models.

2.5 Limitations of Existing Datasets

While existing EEG datasets have significantly contributed to the development of emotional stress detection models, they also present certain limitations that impact their utility, generalizability, and broader applicability in research. This section addresses key limitations related to access and availability, specificity to mental stress (Uddin, 2023).

2.5.1 Access and Availability

The accessibility of EEG datasets is a critical factor that influences the extent to which researchers can utilize these resources to advance the field. Many EEG datasets, while publicly available, come with restrictions that limit their broader use. For instance, datasets such as DEAP and SEED, though widely used, require researchers to formally request access, often needing to agree to specific terms and conditions that govern the use of the data (R. A. L. Koelstra, 2012; Zheng & Lu, 2015). These restrictions, although necessary for protecting participant confidentiality and ensuring ethical use, can pose challenges for broader research and collaboration, particularly for researchers with limited resources or those working in institutions without robust support systems for data access.

Additionally, some datasets may not be freely available to the public and require a subscription or purchase, further limiting their accessibility. For example, certain proprietary datasets developed for commercial purposes are only accessible through paid licenses, which can restrict the ability of academic researchers to engage with and build upon these data resources.

The limited availability of diverse and large-scale datasets also hampers the ability to generalize findings across different populations and settings. Datasets such as AMIGOS and DREAMER are valuable resources but may not be as easily accessible as more widely distributed datasets, thereby limiting the potential for widespread validation of research findings (Katsigiannis & Ramzan, 2017; Miranda-Correa et al., 2018).

2.5.2 Specificity to Stress

A significant limitation of many existing EEG datasets is their focus on related but not entirely relevant mental states, such as general emotional arousal or cognitive fatigue, rather than specifically on stress. For instance, the DEAP and SEED datasets, while invaluable for studying emotional responses, primarily capture data related to emotional arousal rather than targeted stress induction (R. A. L. Koelstra, 2012; Zheng & Lu, 2015). This focus on broader emotional states can lead to the collection of EEG data that may not fully capture the neural signatures of stress, thereby limiting the applicability of these datasets in stress-specific research.

Moreover, datasets like DREAMER, which aim to induce specific emotional states using film clips, do not directly address the nuances of stress-related brain activity (Katsigiannis & Ramzan, 2017). The stress responses elicited in these experiments are often incidental and may not reflect the complexities of stress as experienced in real-world situations (Katsigiannis & Ramzan, 2017). This limitation is particularly critical for developing models that accurately detect and predict stress, as the neural mechanisms underlying stress are distinct from those associated with other emotional or cognitive states.

To advance the field of EEG-based stress detection, there is a clear need for datasets that specifically target stress induction, employing stimuli and experimental designs that are tailored to eliciting stress in a controlled yet ecologically valid manner. This would help in generating more accurate and reliable models that can be applied to real-world scenarios.

2.6 Data Collection Methodologies for EEG

The methodologies employed in collecting EEG data are critical in ensuring the reliability, validity, and reproducibility of research findings in EEG-based mental stress detection (Dong et al., 2024). This section delves into the various challenges associated with EEG data collection, focusing on technical difficulties, ethical and privacy issues, and the standardization and variability of stress-inducing protocols.