EEG Signal Classification between Audio and Visual Stimulation and Multi-level Stress Detection

Submitted by

Trishita Ghosh Troyee
Student ID: 21MEE005F

A thesis submitted in partial fulfilment of the requirements for the degree of

MASTER of SCIENCE in Electrical and Electronic Engineering

Department of Electrical and Electronic Engineering

CHITTAGONG UNIVERSITY OF ENGINEERING AND TECHNOLOGY

MAY, 2025

Declaration

I hereby declare that the work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is cited.

Trishita Ghosh Troyee

Student ID: 21MEE005F

Department of Electrical and Electronic Engineering

Chittagong University of Engineering & Technology (CUET)

Dedication

To my husband, parents, and my family members for their continuous support.

List of Publications

Journal Article

- Publication 1: **Trishita Ghosh Troyee**, Mehdi Hasan Chowdhury, Md. Fazlul Karim Khondakar, Mahmudul Hasan, Md. Azad Hossain, M. Ali Akber Dewan and Quazi Delwar Hossain, “Stress Detection and Audio-Visual Stimuli Classification from Electroencephalogram”, IEEE Access, vol.12, no. September, pp.145417-145427, 2024, Doi: 10.1109/ACCESS.2024.3471590.

Conference

- Publication 2: **Trishita Ghosh Troyee**, Md.Fazlul Karim Khandakar, Mahmudul Hasan, Mehdi Hasan Chowdhury, “A Comparative Analysis of Different Preprocessing Pipelines for EEG-based Mental Stress Detection”, 6th International Conference on Electrical Engineering and Information & Communication Technology 2024, IEEE ICEEICT,2-4 May,2024, Doi: 10.1109/ICEEICT62016.2024.10534380.

Approval by the Supervisor

This is to certify that **Trishita Ghosh Troyee** has carried out this work under my supervision, and that she has fulfilled relevant Academic Ordinance of the Chittagong University of Engineering and Technology, so that she is qualified to submit the following thesis in application for the degree of MASTER of SCIENCE in Electrical and Electronic Engineering.

Dr. Mehdi Hasan Chowdhury

Professor

Department of Electrical and Electronic Engineering

Chittagong University of Engineering & Technology

Acknowledgment

I want to thank Dr. Quazi Delwar Hossain, Md. Fazlul Karim Khandakar, Mahmudul Hasan, Dr. Md. Azad Hossain and Dr. M. Ali Akber Dewan for their significant support and insights that helped me to complete the research work and write the thesis. My heartfelt gratitude goes to the examination committee members for their time and patience.

Also, I am grateful to my supervisor, Dr. Mehdi Hasan Chowdhury, for his continuous mentorship and endless support in every step of my thesis. His insights and knowledge, with a humble research approach, helped to complete the thesis.

I want to acknowledge Directory of Research and Extension (DRE), CUET for providing financial support for conducting the research.

I want to acknowledge the students of the Department of Biomedical Engineering, Chittagong University of Engineering & Technology, Bangladesh, for participating and helping me in the data collection of this study.

I am forever grateful to all the Electrical and Electronic Engineering and Department of Biomedical Engineering members for their continuous support.

Also, I would like to thank my parents, husband and daughter for their patience and support, encouragement, and patient.

.

ABSTRACT

Stress in the mind and body is a reaction to perceived difficulties or dangers. It can have significant impacts on mental and physical health, affecting cognitive abilities, emotional stability, and physical well-being. To control stress and avoid its long-term impacts, it is essential to comprehend these effects. Mental stress can be detected in many ways and Electroencephalogram (EEG) is one of them. EEG is the graphical representation of Brain's electrical activity. Regular mental stress gives rise to many mental disorders and it may cause various physiological and psychological diseases. As a result, early-stage detection of stress is very important. In this research, brain activity was recorded through EEG headset during inducing different levels of stress from audio-visual stimulus. To better evaluate visual and auditory stress, an automated system is designed to differentiate among various audio and visual evoked potentials. This may further help for designing different assistive devices for the people having visual and hearing disability. Again, many researchers worked on different level of stress detection, but four level stress detection is still unchecked. In this thesis, mental arithmetic tasks were used as both audio and visual stimuli. Here, a framework was proposed to classify different levels of stress in response to audio and visual stimuli and classification was done between these two stimuli by analyzing EEG signals. A proper pre-processing pipeline selection is essential to the effectiveness of EEG-based mental stress detection systems, as noisy EEG data are unlikely to produce improved findings. An ideal EEG pre-processing pipeline was suggested in this work and compared it to the conventional approach now in use. Using the two pre-processing pipelines, raw EEG data was pre-processed which was collected at lab environment. By extracting robust features from the denoised audio and visual data, binary and multi-level stress were classified. Four machine learning (ML) classification models were used for this purpose. On top of that, the audio and visual stimuli was classified with highest 98.37% accuracy using SVM. When the suggested pipeline for pre-processing EEG data was put into practice, a noticeable increase was found in classification accuracy over the traditional approach. With SVM, the best accuracy of 97.14%, 89.01%, 89.59% were achieved for two, three and four level stress detection using visual stimulation. By contrast, the conventional pipeline produced results of 85%, 77.67% and 66.6%. Again, for auditory stimulation, the highest accuracy of 94.51%, 87.7% and 82.63% was found for two, three and four level stress detection using SVM. On the other hand, the traditional pipeline produced results of 90%, 77.46% and 71.69% respectively.

সারাংশ

মানসিক ও শারীরিক চাপ হলো মস্তিষ্কের একটি স্বাভাবিক প্রতিক্রিয়া, যা বিভিন্ন সমস্যাকে বা বিপদকে অনুভব করার ফলে তৈরি হয়। দীর্ঘমেয়াদে এ ধরনের চাপ মানসিক ও শারীরিক স্বাস্থ্যের উপর গুরুতর প্রভাব ফেলতে পারে, যার ফলে মস্তিষ্কের কার্যক্ষমতা, আবেগের স্থিতিশীলতা এবং দেহের সামগ্রিক সুস্থতা ব্যাহত হয়। তাই, মানসিক চাপের প্রভাব বোঝা এবং তা নিয়ন্ত্রণ করা অত্যন্ত জরুরি। মানসিক চাপ শনাক্ত করার একটি কার্যকর মাধ্যম হলো ইলেকট্রোএনসেফালোগ্রাম (EEG), যা মস্তিষ্কের বৈদ্যুতিক কার্যকলাপের গ্রাফিকাল উপস্থাপনা। নিয়মিত মানসিক চাপ বিভিন্ন মানসিক ও শারীরিক রোগের জন্ম দিতে পারে। তাই প্রাথমিক পর্যায়ে চাপ শনাক্ত করা অত্যন্ত গুরুত্বপূর্ণ। এই গবেষণায়, অডিও-ভিজ্যুয়াল উদ্দীপনার মাধ্যমে ভিন্ন পর্যায়ের চাপ তৈরি করে EEG ডেটা সংগ্রহ করা হয়েছে। ভিজ্যুয়াল ও অডিটরি মানসিক চাপ বিশ্লেষণের জন্য একটি স্বয়ংক্রিয় ব্যবস্থা তৈরি করা হয়েছে, যা ভবিষ্যতে দৃষ্টিশক্তি ও শ্রবণক্ষমতার সমস্যায় আক্রান্ত ব্যক্তিদের জন্য সহায়ক ডিভাইস তৈরিতে সহায়তা করতে পারে। যদিও অনেক গবেষক বিভিন্ন স্তরের চাপ শনাক্ত করার কাজ করেছেন, চার পর্যায়ের চাপ শনাক্ত করার গবেষণা এখনো সীমিত। এ থিসিসে, আমি মানসিক গাণিতিক সমস্যাকে অডিও এবং ভিজ্যুয়াল স্টিমুলাস হিসেবে ব্যবহার করেছি এবং EEG সংকেত বিশ্লেষণের মাধ্যমে স্ট্রেসের বিভিন্ন স্তর এবং স্টিমুলাসের ধরন (অডিও বা ভিজ্যুয়াল) শ্রেণিবদ্ধ করেছি। নির্ভুল এবং কার্যকর ফলাফল পাওয়ার জন্য EEG ডেটার সঠিক প্রি-প্রসেসিং অত্যন্ত গুরুত্বপূর্ণ। তাই, আমি প্রচলিত পদ্ধতির সাথে তুলনা করে একটি উন্নত প্রি-প্রসেসিং পাইপলাইন প্রস্তাব করেছি। ল্যাবের পরিবেশে সংগৃহীত EEG ডেটা এই দুই পদ্ধতিতে প্রি-প্রসেস করা হয়েছে এবং তারপর শক্তিশালী ফিচার বের করে মানসিক চাপের দুই, তিন ও চার পর্যায় এবং অডিও-ভিজ্যুয়াল স্টিমুলাসের ক্লাসিফিকেশন করা হয়েছে। চারটি মেশিন লার্নিং মডেলের মাধ্যমে ক্লাসিফিকেশন করা হয়েছে। অডিও ও ভিজ্যুয়াল স্টিমুলাস শনাক্তে সর্বোচ্চ ৯৮.৩৭% নির্ভুলতা এসভিএম (SVM) মডেলের মাধ্যমে অর্জিত হয়েছে। প্রস্তাবিত প্রি-প্রসেসিং পদ্ধতি ব্যবহারে প্রচলিত পদ্ধতির তুলনায় ক্লাসিফিকেশনের নির্ভুলতা উল্লেখযোগ্যভাবে বেড়েছে। ভিজ্যুয়াল উদ্দীপনায় দুই, তিন ও চার পর্যায়ের স্ট্রেস শনাক্তে যথাক্রমে ৯৭.১৪%, ৮৯.০১% এবং ৮৯.৫৯% নির্ভুলতা পাওয়া গেছে, যেখানে প্রচলিত পদ্ধতিতে ফলাফল ছিল ৮৫%, ৭৭.৬৭% এবং ৬৬.৬%। একইভাবে, অডিটরি উদ্দীপনায় এসভিএম ব্যবহার করে যথাক্রমে ৯৪.৫১%, ৮৭.৭% এবং ৮২.৬৩% নির্ভুলতা অর্জিত হয়েছে, যেখানে প্রচলিত পদ্ধতির ফলাফল ছিল ৯০%, ৭৭.৪৬% এবং ৭১.৬৯%।

TABLE OF CONTENTS

Abstract.. vi
Table of Contents viii
List of Figures x
List of Tables xi
Nomenclature xii
1 Introduction..1
1.1 Background.. 1
1.2 Present State of the Problem.. 2
1.3 Specific Objectives 4
1.4 Significance of the Work 5
1.5 Thesis Outline.. 6
2 Background Study..7
2.1 EEG Signal and It's Different Bands 7
2.2 Various EEG Acquisition Methods 8
2.3 EEG Applications.. 10
2.4 Current Trends in Brain Computer Interfacing (BCI) Applications.................. 13
2.5 Mental Stress Detection.. 14
2.6 Available Public Datasets on Mental Stress 16
2.7 Different Stimuli Used for Mental Stress Induction 18
2.8 Mental Arithmetic Tasks for Stimulating Mental Stress 20
2.9 Active Brain Region for EEG Based Mental Stress Detection............................. 23
2.10 Audio Visual Stimuli Classification 26
2.11 Feature Extraction Techniques Used for Mental Stress Detection..................... 26
2.12 Summary and Implications 33
3 Literature Review 34
3.1 Stress Detection Using EEG.. 34
3.2 State-of-the-Art Works on Different Stimuli.. 35
3.3 Audio Visual Stimuli Classification 36
3.4 Pre-Processing Techniques.. 37
3.5 Feature Extraction Techniques.. 40

3.6 Machine Learning (ML) Models for EEG Classification 42

4 Data Collection 46

4.1 Dataset Description 46
4.1.1 Stimuli Design.. 46
4.1.2 Participants 48
4.1.3 EEG Channel Location Selection 48
4.1.4 EEG Data Collection... 48

5 Methodology 52

5.1 Framework.. 52

5.2 Pre-Processing 53
5.2.1 Raw EEG Data.. 53
5.2.2 Traditional Pre-Processing Pipeline... 54
5.2.3 Optimal Pre-Processing Pipeline.. 55

5.3 Feature Extraction.. 57

5.4 Classification and Detection... 62

6 Performance Evaluation..64

6.1 Results Using Traditional Pre-Processing Pipeline...................................... 64

6.2 Results Using Proposed Pre-Processing Pipeline... 69

6.3 Comparison between Traditional and Proposed Pre-Processing Pipeline....... 75

7 Conclusions 79

7.1 General summary 79

7.2 Key Findings.. 80

7.3 Significance of the work... 81

7.4 Recommendations for Further Study... 82

Bibliography 84

Appendices...102

Appendix A: Data Collection 102

Appendix B: Emotiv Epoc Flex 104

Appendix C: Turnitin Report 107

LIST OF FIGURES

Fig. 2.1. Emotiv epoch flex EEG acquisition headset 9
Fig. 2.2. R. Deshai et al. proposed experimental protocol for mental stress study ...22
Fig. 2.3. A. Sundaresan et al. proposed experimental design for mental stress study 22

Fig. 4.1. Experimental stages for single stimulus 47
Fig. 4.2. Real-time data collection scheme using 32-channel EEG 49
Fig. 4.3. Mathematical Word problem used as stimuli......................................50
Fig. 4.4. Raw EEG data from 16 channels before pre-processing......................51

Fig. 5.1. Framework of the proposed research work 52
Fig. 5.2. Raw EEG data of stressed state before pre-processing........................53
Fig. 5.3. Traditional pre-processing pipeline 54
Fig. 5.4. EEG data of stressed state after traditional pre-processing 54
Fig. 5.5. Optimal pre-processing pipeline 56
Fig. 5.6. EEG data of stressed state after proposed pre-processing 57
Fig. 5.7. Power spectral plot of alpha, beta, gamma, and theta after applying a bandpass filter for one epoch..58

Fig. 6.1. Confusion matrix for stress classification from visual stimuli 67
Fig. 6.2. Confusion matrix for stress classification from auditory stimuli.......68
Fig. 6.3. Confusion matrix for binary classification between visual and auditory stimuli 69
Fig. 6.4. Confusion matrix for stress classification from visual stimuli 73
Fig. 6.5. Confusion matrix for stress classification from auditory stimuli.......74
Fig. 6.6. Confusion matrix for binary classification between visual and auditory stimuli 75

LIST OF TABLES

Table 5.1. Mathematical formulation of time domain and frequency domain features used in this work 59

Table 6.1. Binary stress classification from visual stimuli....................................65

Table 6.2. Three level stress classification from visual stimuli...........................65

Table 6. 3. Four level stress classification from visual stimuli 65

Table 6.4. Binary stress classification from auditory stimuli..............................65

Table 6.5. Three level stress classification from auditory stimuli 66

Table 6.6. Four level stress classification from auditory stimuli........................66

Table 6.7. Binary classification between visual and auditory stimuli 66

Table 6.8. Binary stress classification from visual stimuli....................................70

Table 6.9. Three level stress classification from visual stimuli...........................70

Table 6.10. Four level stress classification from visual stimuli 70

Table 6.11. Binary stress classification from auditory stimuli............................71

Table 6.12. Three level stress classification from auditory stimuli 71

Table 6.13. Four level stress classification from auditory stimuli......................71

Table 6.14. Binary classification between visual and auditory stimuli 72

Table 6.15. Comparison summary between the two pre-processing pipelines for binary stress classification from visual stimuli 75

Table 6.16. Comparison summary between the two pre-processing pipelines for three level stress classification from visual stimuli 76

Table 6.17. Comparison summary between the two pre-processing pipelines for four level stress classification from visual stimuli.........76

Table 6.18. Comparison summary between the two pre-processing pipelines for binary stress classification from auditory stimuli 76

Table 6.19. Comparison summary between the two pre-processing pipelines for three level stress classification from auditory stimuli ..76

Table 6.20. Comparison summary between the two pre-processing pipelines for four level stress classification from auditory stimuli 77

Table 6.21. Comparison summary between the two pre-processing pipelines for audio visual stimuli binary classification 77

Table 6.22. Comparison study for two and three level stress classification 78

NOMENCLATURE

AI: Artificial intelligence;
ANN: Artificial Neural Network;
ASR: Artifact Subspace Reconstruction;
AW: Approach-Withdrawal;
BCI: Brain-computer interface;
BPF: Band Pass Filter;
DE: Differential Entropy;
DFT: Discrete Fourier Transform;
DWT: Discrete Wavelet Transform;
DT: Decision Tree
ECG: Electrocardiogram;
EEG: Electroencephalography;
EMG: Electromyogram;
EOG: Electrooculogram;
ERP: Event Related Potential;
FAA: Frontal Alpha Asymmetry;
FFT: Fast Fourier Transform;
FIR: Finite Impulse Response;
fMRI: Functional magnetic resonance imaging;
fNIRS: functional near-infrared spectroscopy;
HPF: High Pass Filter;
ICA: Independent Component Analysis;
k-NN: k-Nearest Neighbours;
LDA: Linear Discriminant Analysis;
LPF: Low Pass Filter;
MEG: Magnetoencephalography;
ML: Machine learning;
MLP: Multi-layer Perceptron;
PET: Positron emission tomography;
PSD: Power spectral density;
RF: Random Forest;
SD: Standard deviation;
S-Golay: Savitzky-Golay;
SVM: Support Vector Machine;

1 Introduction

Mental stress detection and audio-visual stimuli classification is an emerging brain-computer interface (BCI) research field that aims to detect early stage stress level induced during solving mathematical problems of different difficulty levels and classify between two kinds of stimuli. It provides valuable insights for the doctors, psychologists, and researchers in this field to get a clear idea regarding different stress level and design assistive device for the eyesight and hearing disability problem. However, the status of Electroencephalography (EEG)-based multi-level stress detection specially the four-level stress detection during mental arithmetic problem solving is not explored yet and its classification accuracy is still below optimal. This chapter gives a brief review of mental stress. Thereafter the techniques adopted for classifying stress levels are depicted. Also, the problem statement of this thesis is shared. This chapter outlines the background in Section 1.1, the present state of the problem in Section 1.2 and specific objectives in Section 1.3. describes the significance of this research. Finally, Section 1.4 includes an outline of the remaining chapters of the thesis.

1.1 BACKGROUND

Mental stress is an inevitable problem that has an impact on people all over the world. Numerous elements of everyday life, including job, habit, and restless times, can cause mental stress. Again, climate change, lacking of security in society, study pressure, different social and family issues induce stress severely [1]. It has an impact on both a country's economy and the efficiency of each person's daily tasks. Mental stress may deteriorate both mental and physical health. Excessive stress may weaken the immune system. It can also create sleep disorder named insomnia and indigestion problem [2]. Mental stress has a direct impact on operators' emotions, conduct, and performance; it can even result in operational mishaps. It may ultimately decrease the quality of life and concentration level also [3]. Sometimes deep depression and suicidal tendency may also be induced from stress if it cannot be handled in a proper way. As a result, early stage stress detection is very important. Mental stress can be detected in many ways and Electroencephalography (EEG) is one of them. EEG is a method of recording electrical activity along a person's scalp that allows us to measure mental activity related to many types of subjective abilities [4]. It may effectively depict the physiological and pathological conditions of humans. The brain network has drawn a lot of interest and made significant advancements in the study of brain mechanisms because of the intricate relationships that exist between various anatomical and functional brain areas [5]. Again, for better interaction between humans and machines, it is essential to analyze the power spectrum of the brain in response to different audio and visual stimulus. To better evaluate visual and auditory stimuli, an automated system is designed to differentiate among various audio and visual evoked potentials. This may further help for designing different assistive devices for the community having visual and hearing disability.

1.2 PRESENT STATE OF THE PROBLEM

Psychosocial stress has been linked to poor quality of life by impacting people’s emotional behavior, ability to function at work, and mental and physical health [6]. The sympathetic nervous system (SNS) and the hypothalamus-pituitary-adrenocortical (HPA) axis are both activated during stress [7]. The adrenal cortex releases glucocorticoids, or cortisol, in response to stimulation of the HPA axis. Cortisol is a key player in the control of several physiological processes, including blood pressure, glucose levels, and carbohydrate metabolism. Many physical, immunological, and psychological health issues, such as anxiety, sadness, and post-traumatic stress disorder (PTSD), heart attacks, strokes, and immunological illnesses, are brought on by chronic SNS dysfunction [7]. Stress also modifies the anatomy and physiology of the brain. Stress levels may be assessed in a variety of ways. The most often utilized technique for determining a person’s degree of mental stress is standard questionnaire-based self-reporting [1],[2],[7],[8]. Different facial units can also be used for stress detection purpose [9]. Since emotions and affective states are linked to facial expressions, researchers are always searching for accurate methods to interpret the presence or combination of these states on a human face. Furthermore, it is debatable whether or not facial action unit intensity may be approximated and how precisely and consistently they can be measured [9]. Additionally, physical, and physiological measurements have also been used as impartial techniques to evaluate stress. A few physiological characteristics that are responsive to stress include voice, eye focus, pupil dilation, blink rate, and facial emotions[7]. Face landmarks and images are also successfully used for stress detection purpose because facial landmarks make it easier to comprehend movements of the lips, eyes, and head, they are more effective at helping you perceive stress [10].

Some physiological biomarkers such as electroencephalography (EEG), electrocardiography (ECG), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), galvanic skin response (GSR), positron emission topography (PET), and cortisol are also can be used for stress level detection [1],[3],[6],[7]. Sometimes, combination of two physiological signals were used for stress detection. For instance, multi-level stress was detected from the combination of EMG and ECG features using machine learning models [11]. The combination of skin potential response, SPR signal and ECG signal was used to detect multi-level stress during driving a car [12]. Again, a wireless sensor system having two ECG channels and two electrodermal activity (EDA) channels was used for multi-level stress classification. Here, EDA data helps to remove the heart rate variability [13]. MEG signals are also used for detecting post-traumatic stress disorder [14]. Sometimes bioimages were also used for stress classification and fMRI image biomarkers are one of them [15],[16].

Out of all these methods, EEG is chosen due to its many benefits, including its excellent temporal precision at millisecond scale, ease of use, inexpensive setup costs, comfortable and non-invasive data gathering in both clinical and workplace environments. [7]. Due to wireless nature, EEG signal is fully compatible with the real-world set-up. As EEG measures the brain's electrical activity directly, the signal change for mental stress variability is extremely high. EEG has emerged as the most extensively utilized neurophysiological signal in this industry because of all these benefits. Furthermore, EEG signal alterations are a more accurate, objective indicator of emotions since they are not subject to conscious manipulation [17]. The EEG data from the pre-frontal channel locations are highly sensitive to stress classification. EEG offers comprehensive data on several frequency bands (alpha, beta, theta, and delta, for example) that may be examined to learn more about different facets of stress levels and brain function. The development of complex algorithms for stress detection is made possible by this wealth of data. As a result, EEG is better than any other methods for mental stress detection.

Now a days, brain computer interfacing (BCI) is very popular because it can create a direct interaction between human brain and any external output device. One of the most important fields of BCI is audio, visual stimuli classification. In this case, the system can identify whether the stimuli are visual or auditory accurately. This system may further help the community who have vision or hearing disability.

In this field of mental stress detection and audio-visual stimuli classification, different kinds of audio, visual stimuli were used, and mental arithmetic problems are one of them to induce stress. However, none of the previous works employed math problems as auditory stimuli before and using this stimuli, three level stress was classified successfully but four level stress classification is still unchecked.

1.3 SPECIFIC OBJECTIVES

This research work aims to address the above-mentioned issues by designing various combinations of audio-visual stimuli and collecting real-time data from normal hearing, and normally sighted subjects, making a private dataset, building an optimal EEG pre-processing pipeline and compare the output with the traditional one, developing a system that will utilize EEG data to detect multi-level stress using machine learning, extracting the features from EEG data and classifying the auditory, visual which can further help us to implement hearing aid or assistive device or detect any device. Therefore, the specific objectives of this research are stated below:

1) To design and implement a data collection scheme for collecting EEG data of different Audio and Visual Stimulation.
2) To investigate the effects of the pre-processing pipeline in detecting different level stress and audio-visual stimuli classification.
3) To differentiate audio-visual stimuli responses from EEG data
4) To classify binary and multi-level stress using different Machine Learning algorithms.

1.4 SIGNIFICANCE OF THE WORK

Brain-Computer Interface (BCI) is an augmentative communication that permits a person to control an electronic device using brain waves. The results of this research specially the audio, visual stimuli classification is very significant for the BCI applications. As the whole system performed satisfactorily for the normal hearing and sighted people, this research's results can also be used for the blind and deaf people for classifying audio visual stimuli. Blind people can use this system for detecting visual stimuli and deaf people can be able to use this system for detecting audio stimuli. In traditional hearing and eyesight testing, the test decision is completely relied on subject's response and feedback how much they can hear or see any English alphabet. However, children and aged people sometimes give wrong feedback and as a result, the test result may also be wrong consequently. In this scenario, the audio visual stimuli classification system can be used for testing hearing and sighting condition for children and aged people and also the results can be compared with the traditional hearing and sight testing for better clarification of the test results.

Again, advanced pre-processing pipeline which proposed in this research, eliminates noise from the raw EEG data while preserving crucial information. Binary and multi-level stress including three and four level stress was classified successfully in this research which can help to diagnose the stress level at very early stage. Consequently, quality of life will be enhanced and mental health disorder like fatigue, irritability, and sleep disturbances will be reduced by taking proper steps.

1.5 THESIS OUTLINE

The thesis presents the EEG data collection process and design of a system which can detect both binary and multi-level stress. Another important part of this thesis is to classify audio visual stimuli.

The first chapter describes the background of mental stress detection and audio-visual stimuli classification. The present state of the problem, specific objectives, and the significance of the thesis outcomes are also discussed in this chapter. Chapter 2 shows a background study of the previous works in mental stress classification. The current research trend in this field including BCI application and EEG acquisition systems were explained. Additionally, particular emphasis has been paid to the active brain areas associated with both calm and stressed states. Different types of stress-inducing stimuli that other researchers have employed, and the pre-processing and analysis methods utilized for EEG-based mental stress detection were also elaborately discussed in this section. Chapter 3 illustrates literature review section where relevant articles were reviewed carefully and summary of the recent progress in the field of mental stress detection purpose was discussed. Also, previous studies were mentioned in this section. Chapter 4 exhibits the data collection scheme and discusses the data collection process of this work in detail. Chapter 5 displays the methodology section and discusses the whole procedure of doing this work elaborately. Chapter 6 highlights performance evaluation where all the results and findings are explained in detail. Chapter 7 draws the conclusions of the study, specifies the key findings and contributions of the works, and discusses the future possibilities in this field.

2 Background Study

This section will explore various EEG signal acquisition techniques, current mental stress research trends, types of stimuli should be used to elicit the different level of stress, available public datasets for mental stress detection, pre-processing techniques, features and machine learning techniques used for EEG-based mental stress detection and audio visual stimuli classification.

2.1 EEG SIGNAL AND IT'S DIFFERENT BANDS

Electroencephalogram (EEG) comprises up the time series data of evoked potentials originating from the brain's regular neuronal activity. Electrodes are applied to the scalp to capture human EEG data, which are then plotted as voltage magnitude against time. The amplitude of the EEG signal is correlated with its voltage. The scalp EEG's typical voltage range is 10–100 μV, with the range of 10–50 μV being more common in adults [18]. The frequency range can be broadly divided into many frequency components, such as alpha rhythm (8–13 Hz), beta rhythm (13–30 Hz), theta rhythm (4–8 Hz), and delta rhythm (0.5–4 Hz) [19].

Although the majority of EEG waves fall between 0.5 and 500 Hz, the following four frequency ranges are important for therapeutic purposes: Alpha, beta, theta, and delta.

Delta Waves: The frequency of delta waves is up to 3 Hz. With the biggest amplitude, it is the slowest wave. Adults in deep sleep and infants up to one year old are dominated by it [18].

Theta Waves: With a frequency range of 4 Hz to 7 Hz, it is a slow wave. When you relax and close your eyes, it comes out. Both adults and young children typically exhibit it [18].

Alpha waves: Alpha waves have frequencies between 7 and 12 Hz. There is rhythmic alpha activity on both sides of the head. When anybody close their eyes (in a relaxed condition), an alpha wave appears; when open them or experience stress, it goes away regularly. The waveform is regarded as normal [18], [19].

Beta waves: These waves have a tiny amplitude and are rapid. The range of its frequencies is 14 Hz to 30 Hz. It is more prevalent in individuals who are awake, nervous, or have their eyes open. Beta waves are most noticeable in the frontal direction and are often symmetrically distributed on both sides [18].

2.2 VARIOUS EEG ACQUISITION METHODS

Standardized electrodes positioned at the scalp are used to gather the brain's spiking activity for Electroencephalogram (EEG) information. These chaotic cumulative brain signals change according on the physical and/or mental activities that are being engaged in now [20].

Brain electrical activity is measured and recorded using EEG acquisition equipment, commonly referred to as EEG headsets or EEG caps. There are many kinds of EEG equipment available, from consumer-grade headsets to systems suitable for research. Several well-liked EEG acquisition tools consist of:

2.2.1. Research Grade EEG device:

Active Two by Biosemi:

EEG system with a high density and up to 256 channels. Active electrodes to record at low noise levels. It is extensively employed in clinical trials and research [21].

E-textile headband:

Brain Computer Interfacing (BCI) is now a days attracting many researchers where they need to acquire long term continuous EEG data. There are many kinds of EEG signal acquisition methods. Some researchers contributed for making the conventional EEG device more comfortable so that EEG signal can be acquired for long time data collection for various BCI application like wheelchairs, prosthetic implants, and home appliances. A wearable e- textile is such a device which integrates multiple flexible electrodes and other electrical connections. All the electrodes and interconnects are placed on the two opposite sides of the textile [22].

2.1.2. Consumer Grade EEG device:

Muse Headband:

Muse is an activity sensing headband that uses four electroencephalography (EEG) sensors to measure brain activity. An accompanying mobile app transforms the EEG signal into audio feedback, which is fed to the user through headphones [23]. It has been shown that Muse can be used for ERP research, with the benefit of being inexpensive and easy to set up. Specifically, it can quantify N200, P300, and reward positivity. In addition, it is widely used for a wide range of other applications, from health and wellbeing to scientific and medical research.

Emotiv epoch flex:

The data collected from the clinical amplifiers and the data obtained with this headset are of very different quality. The primary purpose of the tests was to examine how different sounds, or auditory stimuli, affected people's ability to focus when completing a variety of visually stimulating activities [24]. Since the Emotiv headsets often pre-process the recorded data, some information is removed from the collected signal, making the data used for this study unique. A data collection scheme using this device is shown in Fig. 2.1.

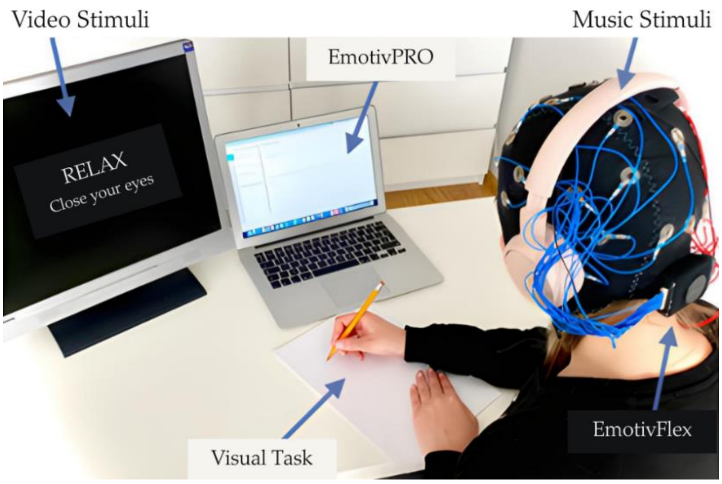


Fig. 2.1. Emotiv epoch flex EEG acquisition headset [24]

NeuroSky Mindwave:
Using cheap dry sensors, NeuroSky technology enables low-cost EEG-linked research and goods; previous EEGs need conductive gel applied between the sensors and the head. The systems additionally use embedded (chip level) solutions for signal processing and output, as well as hardware and software for electrical "noise" reduction.

OpenBCI:
For biosensing applications, OpenBCI is an incredibly versatile open-source hardware choice [25]. The board supports electrocardiography and electromyography (EMG), and it can process EEG data. The EEG channels have the option to be set up in bipolar or monopolar mode, and they can accept three analog and up to five external digital inputs. Through a Wi-Fi interface, data flow can also be accessed by the Transmission Control Protocol (TCP). There are two primary ways to connect to a computer using OpenBCI. By using a USB adapter that makes use of the exclusive RFDuino interface, the computer detects the board as a serial device in the default serial connection [26]. It contains a protocol adapted from Bluetooth with the goal of achieving fast data transmission rates.

2.3 EEG APPLICATIONS

Electroencephalogram is related to brain electrical activity of human brain in response to various daily activities and diseases. As, human brain is major organ of central nervous system, the recording of brain electrical activity will be changed/modified with any neural disorder and diseases. So, many diseases can be detected from EEG signal.

Many severe progressively worsening neurodegenerative and fatal illness of brain cells like Alzheimer’s Disease, Parkinson, epilepsy can be detected from EEG signal at very early stage from specifying different biomarkers [27]. Due to increasingly aging country populations, the number of persons with dementia globally is presently around 55 million, and by 2030, that number is expected to rise to 78 million. Alzheimer's disease (AD) is responsible for 60 to 70 percent of dementia cases, making dementia the sixth most common cause of death worldwide (WHO Accessed on 7 Feb 2022) [28]. Alzheimer's disease (AD) is a crippling neurological illness that results in cognitive decline and memory loss, personality changes because of brain cell death and atrophy [28]. Daily activity evaluation is used to identify AD. Rather than focusing just on localized brain involvement, the theory of AD as a disconnection syndrome postulates a functional or anatomical separation of broader brain regions [29]. There are four phases in the development of AD. "MCI," or mild cognitive impairment, is the term used to describe the initial stage. It typically causes some memory loss. Their skills in other cognitive domains and functional tasks are retained. Six to 25% of MCI patients go on to get AD [30], [31], [32]. The subsequent phase is distinguished by an increasing cognitive deficiency. The terms "mild AD" and "moderate AD" refer to the second and third stages, respectively, and "severe AD" to the last stage [30], [32]; Again, seizures of epilepsy, a chronic neurological condition, are characterized by abrupt, undesired disruptions and erratic patient behavior. Epilepsies are a spectrum of brain illnesses ranging from life-threatening to severely incapacitating [33] and EEG is a valuable tool for diagnosing epilepsy and detecting epileptic seizures because it provides vital physiological data that may be used to mimic the functioning of the human brain [34]. After Alzheimer's disease, Parkinson's disease (PD) is the second most prevalent neurological illness. Patients with Parkinson's disease (PD) who are deficient in the neurotransmitter dopamine are first treated with oral levodopa supplementation, which is a precursor to dopamine, to address motor symptoms such bradykinesia (slowness of movement), stiffness, or tremor [35], [36]. The dynamical characteristics were used to the analysis and categorization of EEG-based brain activity as EEG data contain chaotic features. In motor areas of the brain, the chaotic behavior is changed by PD-related β synchronization [20].

Various sleep stage can also be classified through EEG signal data. As a normal physiological habit, sleep is an essential component of human existence that affects not only physical and physiological recovery but also mental, emotional, and overall health. As a result, good sleep monitoring, which forms the basis for the diagnosis and treatment of sleep disorders, has drawn more and more attention [37]. The AASM sleep stage classification standard combines the deep sleep of S3 and S4 into SWS stage, while the R&K standards categorize the entire sleep process into six categories: Wake, S1, S2, S3, S4, and REM sleep phases [38]. Since manual sleep staging by qualified sleep specialists is laborious, subjective, and time-consuming, several automated techniques have been created for precise, effective, and objective sleep staging. Deep learning techniques have recently been effectively developed for EEG based sleep staging, showing encouraging outcomes [39]. Due to its simplicity of use, single-channel EEG has lately gained popularity for sleep monitoring [40]. Phase-locked value (PLV) was used to construct the functional connectivity network and analyze the brain interaction during sleep stages for different frequency bands in order to investigate the EEG based brain mechanisms of sleep stages through functional connectivity, particularly from different frequency bands [40]. When sleep quality is not good enough, it will hamper the daily activities and active working hours also reduced consequently. As a result, it will further produce different mental disorder like Major Depressive Disorder (MDD) and deep depression. Because they significantly affect people's social and economic well-being and are a major contribution to the global illness burden, mental diseases pose serious challenges to public health. According to World Health Organization predictions, mental illnesses will account for the majority of disabilities globally by 2020 [41]. When MDD strikes, it can have a significant impact on a patient's life. Anhedonia altered appetite and bodily changes, poor sleep quality, sluggish thinking, lack of willpower activity, easy exhaustion, excessive self-blame, and other symptoms are frequently experienced by patients with major depressive disorder (MDD). Professional depression rating instruments such as the 17-item Hamilton rating scale (HAMD17) are the mainstay of clinical practice when it comes to diagnosing major depressive disorder (MDD) [42]. Again, records show that the number of persons with depression has increased by 18% over the past ten years, with a much larger proportion of female patients than male patients [43]. It is an illness with mild, moderate, or severe symptoms. Individuals experiencing depression may feel guilty, have depressed moods, difficulty concentrating, lose interest in routine tasks, have low self-esteem, and even consider suicide [43].

2.4 CURRENT TRENDS IN BRAIN COMPUTER INTERFACING (BCI) APPLICATIONS

Typically, a BCI system records brain activity and converts it into commands or messages that an application can comprehend and use to carry out a certain job [44]. Industry 4.0 is a quickly developing field that uses digital tools and cyber-physical systems to reorganize conventional techniques. To boost industrial performance, BCI-based solutions are garnering increased attention in this industry. These solutions optimize industrial operators' cognitive load, facilitate human-robot interactions, and increase the security of operations under critical situations [45]. An application of the BCI system might be something like a system that allows the user to move a cube on a computer screen left or right just by visualizing the left- or right-hand movement. The field of brain-computer interface has come a long way in recent years, not only in helping people with disabilities, but also in developing new applications such as controlling home appliances with just your mind or playing video games without the need for physical controls [44], [46]. The benefits of this sector are also being utilized by several industries, including entertainment, automation, security, and education.
Medical application:
BCI allows us to monitor an individual's mental state as well as identify and even forecast health problems like tumors, sleep disorders, etc. People with disabilities can utilize prosthetic limbs with brain-computer interfaces (BCI) to partially restore their movement and do some household tasks [44], [47].

Home automation:

BCI is applicable to home automation. The signals produced by human brain may be used to operate a variety of gadgets in homes. This has a profound effect on how people interact with surroundings [44], [48].

Marketing, advertisement, and entertainment:

Using EEG, several studies have examined the degree of memory of various advertising, offering a means of assessing advertisements. There are many games that may be created that engage players' minds [44], [49].

Education:

Neurofeedback measures the degree of clarity of studied material by using electrical impulses from the brain. The feedback—which could be particular to a learner—is used to create individualized engagement [44], [50].

Security:

It is possible to create security systems that employ brain signals from the user for authentication, such as cognitive biometrics or electrophysiology, which are more secure than passwords, biometrics, or other techniques. Because cognitive biometrics and electrophysiology rely on brain impulses that are imperceptible to outside observers, they are considered more secure than other biometric techniques [44], [46].

2.5 MENTAL STRESS DETECTION

When a person feels that a situation is too difficult for them to handle, it causes physical and mental reactions and these reactions are called mental stress. Everybody experiences stress daily, to varied degrees. Stress is becoming more and more common in today's culture as a result of things like personal obligations, social pressures, financial worries, and work pressure. Individual coping strategies and resilience have an impact on how stress affects each person. While some people may have physical illnesses, weariness, or cognitive challenges, others may have emotional symptoms like anger and frustration. Numerous disorders, including depression, stroke, cardiovascular disease, cognitive decline, and speech impairments, have been linked to mental stress [51]. Stress is usually caused by an individual's emotional, mental, or physical resistance to novel challenges or stresses [52]. Individuals without a pre-existing mental illness can manage stress in a natural way, while those with autism or intellectual disabilities may find it more difficult to communicate sensitively and empathize with others. Meanwhile, the coronavirus (COVID-19) has changed society by forcing people to stay at home and negatively influencing their behavior. The nationwide lockdown, job loss, and overall misery all contribute to stress and mental instability [53]. Stress analysis based on brain signals may be a more effective way to help those who struggle with conventional communication abilities.

Traditional psychological tests of stress have given way to data-driven techniques that use physiological signals as a result of advances in artificial intelligence and machine learning. One physiological indicator that is often used to identify mental stress is heart rate variability, or HRV. The autonomic nervous system (ANS) regulates the fluctuation in the time intervals between successive heartbeats, which is known as HRV. Reduced HRV results from a shift in the balance between the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS) when a person is under stress [54]. But Because HRV is readily impacted by bodily movements, it can be challenging to differentiate between alterations brought on by exercise or posture adjustments and those resulting from stress. Though it is not exclusive to stress, HRV is a reflection of autonomic nervous system activity and is also impacted by emotions, weariness, and general health [55].

Another indicator is Galvanic Skin Response (GSR), also known as Electrodermal Activity (EDA). The autonomic nervous system (ANS) regulates sweat gland activity, which affects the electrical conductivity of the skin, which is measured by GSR [56]. The sympathetic nervous system is triggered when someone is under stress, which causes them to perspire more and, as a result, increase their skin conductivity. But sometimes GSR spikes can be caused by abrupt external stimuli (such as bright light or loud noise), which might result in erroneous stress readings. Again, GSR measurements rely on the location of the sensor (e.g., fingers, palms, wrists), shifting electrodes might produce contradictory findings [57].

Furthermore, behavioral markers like speech patterns, facial expressions, and typing habits, in addition to textual information from written correspondence and social media, offer important insights on an individual's stress levels.

Stress analysis using EEG data can have a significant influence on the field of Barin Computer Interfacing (BCI) research, as mental tension produces variance in EEG signals [58]. For mental stress classification, EEG signal data is recorded when stress is induced by showing or listening different visual or audio stimuli to the subjects. In order to determine stress levels based on cerebral activity, EEG analyzes brainwave patterns. With electrodes applied to the scalp, EEG records changes in frequency bands including alpha, beta, theta, and gamma to monitor electrical activity in the brain. Increased beta waves and reduced alpha waves are frequently linked to stress, suggesting a higher emotional and cognitive burden [59]. Using EEG data, machine learning and signal processing techniques are frequently used to categorize stress levels. This non-invasive method is useful for workplace stress management, mental health monitoring, and tailored treatments to enhance wellbeing.

2.6 AVAILABLE PUBLIC DATASETS ON MENTAL STRESS

There are few public datasets on mental stress. Some of the important datasets are discussed below:

2.6.1 DEAP dataset:

This mental stress categorization challenge uses EEG signals from the Emotion Analysis using Physiological Signals (DEAP) dataset [60],[61]. This dataset includes the feelings that music videos evoked. To create this dataset, 32 people in the 19–37 age range underwent testing. Every participant viewed forty videos of music. EEG data were obtained using the 10-to-20 electrode placement technique for one minute while the observer watched. A unique experiment ID is assigned to every music video. Signals from 40 distinct channels were captured for each experiment ID. Eight of these 40 channels are peripherals, while 32 are EEG channels. The particulars pertaining to these channel descriptions are thoroughly recorded in [61]. The primary goal of this research is to use EEG signal analysis to determine if a subject is in a relaxed or stressed condition. This dataset is used by many researchers for mental stress classification purpose [62], [63], [64], [65], [66], [67]. Hamatta et al.[63] used this public dataset for the purpose of detecting mental stress utilizing EEG, PPG, and GSR devices in order to gather the various sorts of physiological signals using these sensors.

Another available public dataset is used by A. Islam et al. [68]. The occipital O2 EEG data files used in this research are provided in physionet ATM's EDF (European Data Format) format, at the recommendation of two national institutions: NIBIB and NIGMS. These institutes are part of NIH award number 2R01GM104987-09 [69].

2.6.2 SEED dataset:

The SJTU Emotion EEG Dataset (SEED) [62], a publicly available emotion dataset, has 15 participants (seven males and eight females) with mean ± standard deviation of 23.27 ± 2.37 years who underwent an emotion-inducing experiment. Each participant had to watch 15 carefully chosen video clips, each lasting four minutes, that included positive, neutral, and negative stimuli to elicit the appropriate emotional state. There were three data collection sessions, with fifteen trials or movies in each session. Each participant's 62 EEG channels were sampled at a rate of 1000 to record the data. The worldwide 10–20 approach was used to select where to deploy the 62 EEG channels [62], [70].

2.6.3 EDPMSC Dataset:

The SJTU Emotion EEG Dataset (SEED) [71], a publicly available emotion dataset, has 15 participants (seven males and eight females) with mean ± standard deviation of 23.27 ± 2.37 years who underwent an emotion-inducing experiment.

Each participant had to watch 15 carefully chosen video clips, each lasting four minutes, that included positive, neutral, and negative stimuli to elicit the appropriate emotional state. There were three data collection sessions, with fifteen trials or movies in each session. Each participant's 62 EEG channels were sampled at a rate of 1000 to record the data. The worldwide 10–20 approach was used to select where to deploy the 62 EEG channels. After comparing the pre-active and post-active phases, the dataset's author concluded that the pre-active phase is better at recognizing stress. Therefore, in this work, they utilized the precative phase to create the suggested model [62], [71].

2.6.4 CLAS Dataset:

The CLAS dataset is a source of labelled physiological recordings that include synchronized ECG, PPG, and EDA signals that were taken while test participants were engaged in an interactive or perceptual activity that was specifically created for them [72]. The interactive activities are specifically intended to assess several components of the individual's cognitive ability, level of attention and focus, or brief cognitive load. The test taker is given a series of deliberately constructed logical and mathematical tasks with a fixed deadline for timely responses to acquire both a quantitative and qualitative assessment of these features. The test subjects are exposed to a sequence of carefully chosen stimuli intended to induce emotions in the perceptual tasks. The test takers in the perceptual tasks are usually instructed to only view the visuals or to follow the video clips. The CLAS dataset uses each person's unique physiological signal fluctuations to record the emotional states and mental states produced during the numerous interactive and perceptual activities. Both person-specific and person-independent modelling are possible according to the dataset's architecture.

2.7 DIFFERENT STIMULI USED FOR MENTAL STRESS INDUCTION

Different stimuli are used to create mental stress in clinical and research settings; each one focuses on a different facet of the human stress response. The cognitive, emotional, social, physiological, and environmental stressors are the major categories into which these stimuli may be divided. Which kinds of stressor should be selected depends on application, research objectives and goals.

2.7.1 Cognitive stressor:

Tasks that test a person's capacity for mental processing are known as cognitive stressors, and they frequently result in elevated stress and cognitive load. Typical instances consist of:

1. **Mental Arithmetic activities (MAT):** These activities, which include serial subtraction, demand participants to complete intricate arithmetic operations within time limits [59].
2. **Stroop Test:** In the Stroop Task, participants are given color words printed in incongruent ink colors (for example, "RED" printed in blue ink). They must identify the ink color while preventing their automatic reading of the word [73].

2.7.2 Emotional Stressor:

Affective cues are used by emotional stressors to trigger stress reactions. One example is Negative Pictures and videos.

Negative Pictures and Videos: A standardized collection of pictures provided by the International Affective Picture System (IAPS) has been utilized to elicit emotional reactions in participants.

2.7.3 Psychological Stressor:

These stressors include situations that create stress by means of psychological pressure or social assessment. One example is Trier Social Stress Test (TSST). The Trier Social Stress Test (TSST) creates a sense of social evaluative stress by having participants execute mental math and give an impromptu speech in front of an inattentive audience [74].

2.7.4 Physiological Stressors:

Direct physical difficulties that trigger the body's stress response systems are known as physiological stressors. One example is Cold Pressor Test.

Cold Pressor Test: To induce a physiological stress response, participants submerge their hand in ice-cold water for a predetermined amount of time [59].

2.7.5 Environmental Stressors:

Stress may be created by manipulating the environment. One example is Noise stressor.

Noise Stress: Being around loud or erratic noises might make you feel more stressed.

2.8 MENTAL ARITHMETIC TASKS FOR STIMULATING MENTAL STRESS

Mental arithmetic tasks (MAT) are very popular for inducing stress level and classify different level of stress. Many authors used MAT for inducing stress [6],[7],[75-79]. Saidatul et al. [80] employed MAT where the process starts with calm picture, moves through easy, moderate, and difficult stages, and concludes with calm image . A minute will pass between each step. There will be 12 questions in total for each level of the mental math assignment, with an average response time of 5 seconds. Three sets of mathematical operations are included at each step, such as four addition problems, four subtraction problems, and four multiplication problems.

Likun Xia et al. [81] used a paradigm based on MIST [78] which is a computer-based instrument that is frequently used to explicitly analyze reactions under stress and control settings. It causes modest psychological stress in terms of physiology and brain activity [82], [83]. The four consecutive blocks that made up each session were recuperation, mental math, rest, and habituation. The primary component of the trial design was the mental arithmetic task block. In distinct sessions, the work was carried out in a different way under both stress and control circumstances. The math exercises were same for both cases. In level 1, addition and subtraction were limited to two numbers; in level 2, addition and subtraction were limited to three numbers; in level 3, addition and subtraction were limited to four numbers; and in level 4, any four operations involving four numbers were included.

Omneya Attallah [64] employed MAT as a stressor where two conditions data were recorded. In the non-stressful condition, the tasks are counting; in the stressed state, they involve serial subtraction of two integers. The first step in each serial subtraction attempt is to vocally subtract four integers from two. Psychosocial stress is defined as serial subtraction for 15 minutes [84], and it was employed in [85]. Thus, the design of the data collecting process in [85] necessitated a high level of cognitive effort from the participants. When a person puts in more effort to complete activities, the emotional background changes because of this demanding mental load.

R. Deshai et al. [86] used MAT for inducing different levels of stress which is shown in Fig. 2.2. During data collection procedure, the participant is requested to remain quiet for two minutes in the first stage and his calm data is captured in this time interval. The topic is required to answer several arithmetic problems in the second phase. Based on the degree of difficulty, the questions are given to the subjects in three categories. The participant is instructed to provide accurate answers to all questions and refrain from speculating. To achieve a high-quality, noise-free signal, the participant is told to limit hand movements and do mental computations. Subjects are directed to respond to the questions as soon as they show up on the screen. The patient is answering the question while EEG data is being recorded in parallel.

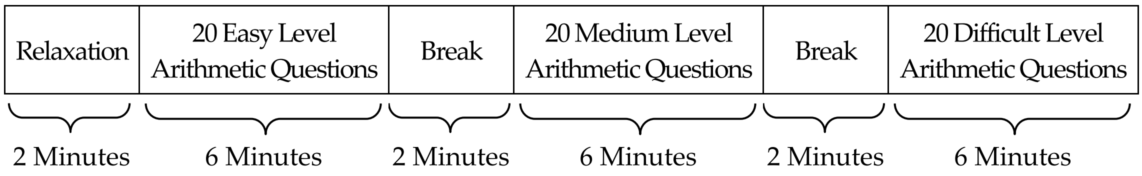


Fig. 2.2. R. Deshai et al. proposed experimental protocol for mental stress study [86]

Avirath Sundaresan et al. [87] also used MAT where a preliminary 120-second EEG baseline recording (referred to as "Baseline"), participants engaged in a 25-minute session that included four primary blocks of stress induction and breath modulation exercises. A stressor with an enhanced arithmetic number challenge was presented at the start of each block shown in Fig. 2.3. Timed mental arithmetic has been used extensively to produce stress [76], [77]. To reduce the risk of overstimulating participants with ASD, a commonly used mental arithmetic task was simplified for specific mental stress induction paradigm.

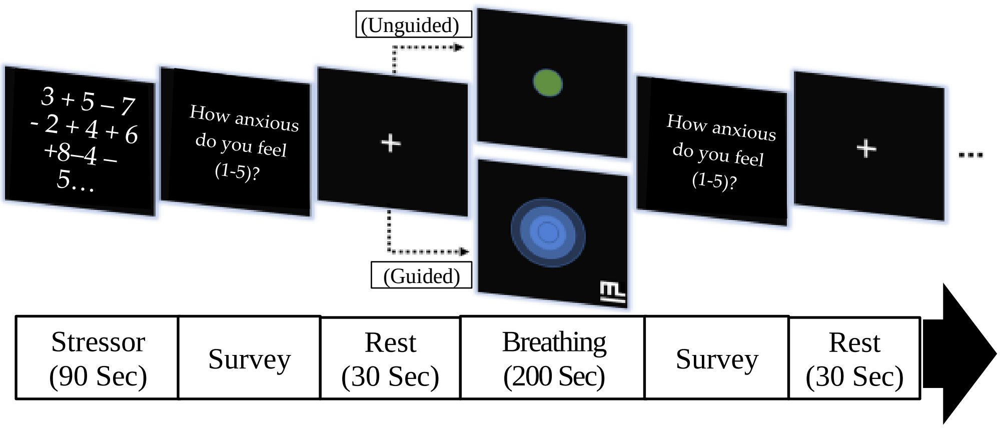


Fig. 2.3. A. Sundaresan et al. proposed experimental design for mental stress study [87]

After the mental stress induction, there was a 200-second breathing time. Participants were given the option to breathe at their own pace (unguided breathing) during the first and third breathing periods. However, during the second and fourth breathing periods, they were given access to a custom-generated breathing entrainment system that guided breath airflow in and out of the lungs at a relaxing pace of approximately 6 brpm [78], [79]. The system included both visual (a growing/shrinking circle that indicated the target respiration speed) and auditory (musical patterns that mimicked the sounds of inhalation and exhalation) guides.

Two tests were utilized by J. W. Ahn et al. [77] to induce stress: the Stroop color word test and a mental arithmetic test. A viable and dependable technique for producing medium levels of stress is the Stroop color word test [88], [89] The goal of this test is to have the subject select the colors in which the names of colors appear when they are displayed in a color other than the color that corresponds to their name. There were fifty-six test stimuli in all, and each one was shown for one second at random. The individuals were instructed to consider the appropriate color, and the response was shown on the screen at the conclusion of each stimulus, as speaking might impact the HRV. The participants view three- or four-digit numbers on a screen, and the digits are put together until the final number is one. Lastly, the subject inputs whether the outcome is an odd or even number using a keyboard. The screen indicates whether the subject's input was correct or incorrect for each stimulus, and 5 seconds were counted for each stimulus before going on to the next to increase the participants' level of stress [77].

2.9 ACTIVE BRAIN REGION FOR EEG BASED MENTAL STRESS DETECTION

Several brain areas are frequently the focus of EEG-based mental stress detection. The following are the main areas of interest:

1. Prefrontal Cortex (PFC): Plays a role in decision-making, personality expression, sophisticated cognitive behavior, and social behavior regulation. It is an important area for controlling emotions and managing stress.

2. The Anterior Cingulate Cortex (ACC) is involved in impulse control, decision-making, and emotion regulation. It is frequently linked to the psychological side of stress.

3. Parietal Lobes: Associated with direction in space and processing of sensory information. This area is important because stress can change how the senses are processed.

4. Temporal Lobes: Essential for storing memory and processing auditory information. Stress can affect how well your memory works.

5. Insular cortex, or the Insula, is a region of the brain that is involved in awareness and performs a variety of tasks that are typically related to emotion or homeostasis management.

6. The hippocampal area is important for memory and stress reaction, even though it cannot be tested directly with an EEG. It influences other regions that can.

Many researchers worked on the number of channels optimization for mental stress detection from EEG signal. Ala Hag et al. [62] successfully optimized the EEG channels number to eight and those channels locations are 'AF3', 'FC5', 'F8', 'Fp1', 'AF4', 'P7', 'Fp2', 'F7'. The activation function led to a significant reduction in the number of EEG channels. Specifically, the suggested CCHP chooses EEG channels for each subject that have a strong correlation with their mental state class and a less correlation with other channels in the same class. Accurate performance was improved by choosing pertinent channels that have a strong correlation with the class (stress/calm). In a similar vein, the low channel–channel-based correlation from the same class was used to eliminate the redundant channels. Each participant was therefore given access to many key channels that are most effective in differentiating mental stress activities. They rated the important channels according to the modal frequency of those channels, with the high occurrence channels being placed highest, and so on, to identify a common channel among all subjects. They evaluated several sets of ranking channels, 1, 5, 8, 9, 15, 19, and 32 EEG channels, to see which collection of channels delivers an acceptable accuracy [62]. They also discovered that just 8 EEG channels can substantially categorize the mental stress level without considerably impairing performance. Omneya Attallah [64] also tried to find out the most significant channels for stress detection from EEG signal. Their research work looks at the bare minimum of electrodes needed at the location, which has a bigger influence on stress assessment and detection. The findings are contrasted with other feature extraction techniques presented in the literature to evaluate the efficacy of the suggested approach. They are also contrasted with cutting-edge methods that have been documented for stress identification.

Ali et al. [90] tried to differentiate between two conditions- relaxed and focused by analyzing EEG signal. The focused sample was captured by the authors as the individual was working through an arithmetic test while keeping their eyes open. A signal cut of points between -120 and 120 uV was chosen [90].

The EEG signal captured at a calm condition in a quiet environment while the participant was listening to a slow music track without blinking or other artifacts. The voltage values of the signal depicted in the time domain range from -28 to 41 μV, with an average of 20.23 μV [90]. Both samples had different characteristics, such as the focused sample having a larger maximum amplitude than the relaxed sample and the focused sample having a higher spectrum power than the relaxed state sample.

Likun Xia et al. [81] tried to detect stress at very early stage and found nineteen channels- Fp1, Fp2, F3, F4, F7, F8, C3, C4, T3, T4, T5, T6, P3, P4, O1, O2, Fz, Cz, and Pz most significant for stress detection purpose. On the other hand, O. AlShorman et al. [58] found the frontal region more significant for mental stress detection after comparing with the other region of the brain during stress induction by putting the dominant hand under the ice water for 60 seconds.

2.10 AUDIO VISUAL STIMULI CLASSIFICATION

Many researchers worked on classification among different types of stimuli. However, these works are not focused on stress detection. G. S. Mouni et al. [91] classified among three types of stimuli named- audio, visual and cognitive stimuli. They found best accuracy for the visual stimuli. Audio, visual, and audio-visual stimuli multi class classification was done by Y. Dasdimir et al. [92]. But in this case, they found the best accuracy for the audio-visual stimuli. J. Leoni et al. [93] employed several types of stimuli but they found best accuracy for the picture and non-picture (audio-video) based stimuli. T. Agarwal et al. [94] employed LSTM method for classifying audio and visual stimuli. Dr. E. G. M. Kanaga et al. [95] did multi class classification among for auditory, somatosensory, and cognitive events and found the highest accuracy for somatosensory stimuli. These findings not only help neuroscientists identify ERPs more quickly and accurately, but they also open the door for BCIs to potentially offer users more features by utilizing the variety of stimuli that the system can identify. Since most BCI systems on the market today rely on visual cues or visual input, they might not be suitable for severely incapacitated patients who have lost their capacity to see or regulate their eye movements. D. Kim et al. [96] developed the first online ASSR-based BCI system, proving that a completely vision-free BCI system could be realized.

2.11 FEATURE EXTRACTION TECHNIQUES USED FOR MENTAL STRESS DETECTION

A crucial stage in the classification of EEG data is feature extraction, which has several benefits such as dimensionality reduction, noise reduction, better classification performance, improved interpretability, and real-time processing ease. Retaining just the most pertinent data for the classification job is the aim of feature extraction, which enhances computing efficiency and lowers the chance of overfitting.

Relative Gamma:

As part of the affective-state (Stressed vs. Relaxed) classification task, the following measures of relative gamma (RG) [97], [98] activity were calculated. For each of the four-second windows, the power spectral distribution was calculated using the z-transformed EEG. Averaging this distribution over all electrodes was done. The power ratio between the gamma and other rhythms (such as gamma/delta, gamma/theta, gamma/alpha1, gamma/alpha2, gamma/alpha3, and gamma/beta) was used to calculate the RG. It was also computed to get the inverse of each frequency band, which are 1/delta, 1/theta, 1/alpha1, 1/alpha2, 1/alpha3, 1/beta, and 1/gamma.

Power Spectra of EEG Sub-bands:

A signal's power in terms of frequency may be determined using its power spectrum [80], [98]. In research on neuromarketing, this attribute is most frequently utilized. The Discrete Fourier Transform (DFT) of the EEG signal sequence $x(n)$ is first calculated using the Fast Fourier Transform (FFT) method to get the power spectra of the EEG sub-bands, as indicated by Equation (1). A signal's original time domain can be converted to its frequency domain using this kind of Fourier analysis. The signal sequence $x(n)$ is broken down into its component frequencies using the DFT.

$$X_k = \sum_{n=0}^{N-1} x_n . e^{-\frac{i2\pi kn}{N}} \quad (1)$$

where N is the data size, bn is the input value at index n, and X_k denotes the frequency component at index k. The power spectral density (PSD) of various EEG sub-bands has then been calculated using various periodogram approaches, such as Welch's Periodogram [126], as indicated by Equation (2).

$$P_f = \frac{1}{N} \sum_{n=0}^{N-1} |x_n(k)|^2 \quad (2)$$

where, upon windowing, P_f displays the PSD of Xn (k) corresponding to the nth segment and the kth frequency point. This method is widely used to determine the relative strength of several EEG frequency bands, such as δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz), and γ (30 ~ Hz), which are then utilized as characteristics in neuromarketing applications. In some research, the spatiotemporal standard deviation of activity for every EEG time point was obtained using Global Field Power (GFP).

Power Spectral Density (PSD):

In signal processing, spectral analysis is often employed to track signals of interest, particularly for biomedical data [99], [100]. Power spectral density (PSD) is a characteristic that may be able to differentiate between the electrical activity of the brain under various psychological settings [101]. It may also be used to measure stress levels. PSD illustrates how the patients' varying stress levels affect the power of the beta, alpha, and theta frequency bands of the EEG. Numerous techniques, including the greatest entropy approach and the Fourier Transform method, can be used to determine PSD. Welch's power spectral density estimate [102], which is based on the Fourier Transform, was employed in this investigation.

PSD explains the signal's power distribution throughout a specific frequency. PSD was computed with a 50% overlap using the Welch technique [103]. The characteristics from this group were the mean and variance of the PSD for each band in each channel. This feature group yielded forty values in total from four channels and five bands, denoted as FG1 = [fδ(1,8) fθ (1,8) fα(1,8) fβ(1,8) fγ (1,8)] [67], [75], [80], [86], [98], [104].

Discrete Wavelet Transform (DWT):

Numerous research that employed the DWT approach to extract wavelet coefficients as EEG characteristics corresponding to various EEG frequency bands can be found in the literature [62], [68], [86]. DWT is applied in the biological signals time-frequency analysis. This DWT's non-stationary properties make it very helpful for analyzing EEG signals. By employing long time frames for low frequencies and short time frames for higher frequencies, this transform generates an accurate time-frequency assessment. Through repeated application of the low-pass and high-pass filters to the input signal, DWT circumvents the limitations of the Fast Fourier Transform (FFT). In each step, it divides the signal into detailed coefficients (high pass) and approximation coefficients (low pass). It only breaks down low-frequency components following a signal's initial degree of breakdown. At every stage of the signal's breakdown in the wavelet packet decomposition scenario, filtering operations are performed in both approximate and detailed coefficients [105].

Wavelet coefficients are produced by the DWT by the convolution operation, which is a two-function multiplication procedure. Every wavelet's inner product with the input signal yields a different coefficient. Equation 3 can be used to express the DWT numerically.

$$D(i,j) = \sum_{n=0}^{M-1} x(n).\varphi_{i,j}^{*}(n) \tag{3}$$

where $\varphi i,j*(n)$ is the scaling wavelet function and $x(n)$ is a signal of length n. A filter bank made up of several high- and low-pass filters is employed in DWT decomposition. Wavelet detail coefficients are produced by high-pass filters, whereas approximation coefficients are produced by low-pass filters. The number of wavelet decomposition levels and the choice of wavelet method determine the accuracy of the DWT analysis.

Katz Fractal Dimension:

A metric called Katz's Fractal Dimension (KFD) is used to express how complicated or rough a signal or form is. Because it preserves the nuances of the waveform, it is very helpful for studying time-series data, like EEG signals. KFD is one of numerous techniques used to determine the fractal dimension, which provides information about the data's non-linear characteristics [62], [106], [107]. KFD is computed with the following formula:

$$KFD = \frac{log_{10}(L)}{log_{10}(d) + log_{10}(a)} \quad (4)$$

Where:

The time series' overall length is denoted by L.

The Euclidean distance, or d, separates the time series' starting and ending points.

The average distance between consecutive locations is denoted by a.

Katz's Fractal Dimension is a useful tool for measuring signal complexity in the study of EEG and other time-series data. It is a helpful characteristic in many signal processing and machine learning applications because of its applicability in EEG data categorization, which may aid in comprehending and interpreting the underlying brain dynamics [59], [108].

Relative Power:

The power in a particular frequency band divided by the overall power is how the relative power is calculated from the absolute power of the frequency bands. One characteristic that is frequently employed in EEG-based stress detection is relative power. It offers information on how the power is distributed over the different frequency bands of the EEG signal, which can represent a range of mental conditions and cognitive functions, including stress.

The power in a particular frequency band divided by the total power across all frequency bands is known as relative power. By comparing the contributions of various frequency bands to the total EEG activity, this normalization facilitates comparison and offers a more insightful indicator of the signal's properties [62], [81], [106]. From a mathematical perspective, it is represented as Eq.

$$Relative\ Power = \frac{Power\ in\ Band}{Total\ Power} \times 100\% \quad (5)$$

Coherence:

For each of the four frequency bands, the coherence is calculated between 64 electrode pairs of homologous and intrahemispheric sites for each participant at each stage of the experiment. It is a metric for connectivity that characterizes the strength of the relationship between two brain regions. It can be defined as the product of the auto-spectra of two signals (|Hu||Hv|) and the ratio of cross-spectra (|Huv| 2). The Pearson correlation coefficient for the frequency domain variables is interpreted as follows [81]. From a mathematical perspective, it is represented as Eq. 6.

$$Coherence = \frac{|H_{uv}|^2}{|H_u||H_v|} \tag{6}$$

Phase Difference:

The phase angle difference between two EEG signals or components at a specific frequency is referred to as the phase difference in EEG signal processing. Understanding the synchronization and connection between distinct brain areas is crucial since it can shed light on a variety of neurological and cognitive processes. A brain connectivity metric called phase difference, or lag, quantifies the interval of time between two EEG signals that are occurring at separate places. It is calculated for every band at every level for 64 pairs of homologous and intrahemispheric sites [81].

Energy of Wavelet Decomposition Coefficients:

A metric used to characterize the distribution of signal power across various scales or frequency bands is the energy of wavelet decomposition coefficients. It can assist in determining which frequency bands are more active or contain more information in the context of EEG signal processing [76],[86].

The wavelet coefficients' energy sheds light on the activity in various frequency ranges. Higher energy in the beta band, on the other hand, may be linked to tension or active thought, whereas higher energy in the alpha band may imply relaxation. In machine learning models for EEG classification, energy levels are frequently included as features to aid in the differentiation of various mental states or situations [76], [86].

Higuchi Fractal Dimension (HFD):

A technique called Higuchi Fractal Dimension (HFD) may be used to estimate a time series' fractal dimension, which gives an indication of how complicated it is. It is very helpful for deciphering EEG signals as it can depict the complexity and irregularity of patterns of brain activity.

HFD analyzes a time series' structure at several scales to determine how complicated it is. Its foundation is the idea of fractal dimension, which explains how a pattern's level of detail varies depending on the size at which it is measured [67], [86]. A approach for quantifying signal complexity that may not be properly captured by linear methods is provided by HFD. HFD is more noise-resistant than other fractal dimension measures, which makes it appropriate for EEG data, which frequently include a variety of artifacts.

The Higuchi Fractal Dimension is a useful tool for deciphering the complicated dynamics of brain activity from the complexity of EEG data. Its versatility and efficacy in recording the subtleties of cerebral processes are highlighted by its application for mental stress detection.

Petrosian Fractal Dimension (PFD)

PFD is intended to offer a rapid and computationally efficient way to estimate the fractal dimension of a time series. The number of sign changes in a signal's derivative, or the number of times the signal's trajectory changes direction, is used to determine how complex a signal is. PFD measures the intricacy of EEG signals, allowing it to differentiate between various cognitive and affective states. PFD is one of the most significant features for mental stress detection [86]. The equation of PSD is given below:

$$PFD = \frac{log_{10}(L)}{log_{10}(L) + log_{10}\left(\frac{L}{L+0.4L_{\delta}}\right)} \tag{7}$$

Alpha and Beta Asymmetries:

A connection metric called asymmetry shows how differently stimulated two different parts of the brain are from one another. The difference in the amplitudes of the signals that are normalized to the sum of their amplitudes is used to calculate it.

The term "alpha and beta asymmetries" describes the variations in alpha and beta frequency band activity or power between the brain's left and right hemispheres.

The usual range of the alpha band is 8–13 Hz. It is most noticeable when the eyelids are closed and is linked to a calm wakeful state. The difference in alpha strength between the brain's left and right hemispheres is known as alpha asymmetry. Positive numbers imply a relative increase in left hemisphere activation as they show more alpha power in the right hemisphere than the left. Negative numbers indicate a proportional increase in right hemisphere activation and stronger alpha power in the left hemisphere [81], [98].
Usually, the beta band spans between 13 and 30 Hz. It is linked to mental states that are focused, attentive, and active. As with alpha asymmetry, the difference in beta power between the left and right hemispheres is used to compute beta asymmetry [81], [98].

2.12 SUMMARY AND IMPLICATIONS

In this research, EEG data was collected using both audio and visual stimuli. Mathematical word problems having three difficulty levels were shown before participants. Advanced pre-processing pipeline was used for removing noise from the raw EEG data. Binary and multi-level stress was detected from both audio and visual stimuli was done in this work. Moreover, binary classification was performed of EEG data for audio and visual stimuli having significant improvement of accuracy. In the next consequent sections, detailed methodology, results, and discussions and finally conclusion of the proposed work will be discussed.

3 Literature Review

This section will explore extensive literature review on current mental stress research trends, types of stimuli should be used to elicit the different level of stress, pre-processing techniques, features and machine learning techniques used for EEG-based mental stress detection and audio visual stimuli classification.

3.1 STRESS DETECTION USING EEG

Stress levels may be assessed in a variety of ways. The most often utilized technique for determining a person's degree of mental stress is standard questionnaire-based self-reporting [1],[2],[7],[17]. Additionally, physical, and physiological measurements have also been used as impartial techniques to evaluate stress. A few physiological characteristics that are responsive to stress include voice, eye focus, pupil dilation, blink rate, and facial emotions [17]. Some physiological biomarkers such as electroencephalography (EEG), electrocardiography (ECG), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), galvanic skin response (GSR), positron emission topography (PET), and cortisol are also can be used for stress level detection [1],[3],[6],[7],[109]. H. Costin et al. [54] classified two level stress from heart rate variability and morphological variability. They found morphologic variability more effective for mental stress detection [54]. Again, B. Sunarfri Hantono et al. [55] classified stress level from heart rate variability where they collected data using photoplethysmography (PPG). Out of all these methods, EEG is chosen due to its many benefits, including its excellent temporal precision at millisecond scale, ease of use, inexpensive setup costs, and non-invasive data gathering [7]. EEG has emerged as the most extensively utilized neurophysiological signal in this industry because of all these benefits.

Furthermore, EEG signal alterations are a more accurate, objective indicator of emotions since they are not subject to conscious manipulation [17].

The majority of investigations focused on classifying stress based on visual inputs. Several of them focused on multi-level stress detection or binary stress detection. A few of them dealt with multi-level and binary stress. When it came to binary stress categorization using visual stimuli, G. Jun [55] and H. Altaf [56] showed that 96% and 95% of the time, respectively, was the greatest accuracy. However, using solely visual stimuli, A. Akella [57], Q. Yao [3], and F. Al-shargie [7] were able to accurately classify multi-level stress with the maximum accuracy—91%, 89.88%, and 94.79%, respectively. Visual stimuli were used by E. Perez Valero [1] and A. R. Subhani [6] in their investigation, although both binary and multi-level stress were accurately identified. Auditory stimulation—the process by which people become emotionally invested in listening to different problems—is another significant stressor in daily life. One study examined the effects of different music tracks as auditory cues on binary and multiclass stress [58]. Nevertheless, no researcher classified mental stress using both aural and visual inputs.

3.2 STATE-OF-THE-ART WORKS ON DIFFERENT STIMULI

A challenging or stimulating stimulus that induces stress is called a stressor (sometimes called a stress factor). Different kinds of stimuli were used to evoke stress. Montreal imaging Stress task (MIST) was used by Eduardo et al. [1] which is one of the most validated stress inducers. A modified version of the Trier Social Stress Test (TSST) was used by A. Akella [69] and his fellow researchers to generate a controlled stress response. A construction workers' EEG data was collected while they worked in the real construction sites and occupational stress was classified by H. Jebilli et al. [70]. A simulated drone piloting training session was used to evoke stress by Qunli Yao et al. [3]. Different virtual reality environment based stroop test was also used to induce mental stress [71]. Instead of using only visual stimuli, some authors designed auditory stimuli such as music tracks to evoke stress [12], [72], [73]. Sometimes combination of both audio and visual stimuli such as movie clips were used to give rise to mental stress [74]. The PSS-10 questionnaire was used by S.M.U. Saeed et al. [75] where the questionnaire was given to the participants, and they then had an interview with the psychology specialist. The interview lasted 25 minutes on average. The psychology expert placed each participant in either the stress or the control group based on their PSS scores and interview results. N. Phutela et al. [74] used indian movie clips for inducing stressed and amusement like condition. Four movie snippets were screened to the participants. The suggested study draws inspiration for the use of stress elicitation material from the work of authors in, who evaluate stress during video watching using EEG, arousal, and valence dimensions. These authors have employed the circumplex model of affect, which links stress to high arousal and low valence. Stress raises arousal since it activates the mind, but it is an unpleasant activation, thus the valence is poor. Because the subjects could better relate to these movies, they were specially selected from Indian cinema snippets. To relieve the participant from the effects of the stressful and non-stressed movies, a 2-minute gap was included after each clip [74]. On the other hand, A. Arsalan et al. [67] collected EEG data for mental stress detection during the participants prepared for giving a talk upon an unknown topic. Following another period of relaxation, the participants were brought to a different room to make their presentation in front of an actual audience. There were perhaps fifteen to twenty-five persons in the audience, including staff and students. Although recorded during the presentation (activity phase), the EEG data were not used in this investigation. Following the talk, the participants were brought back to the recording room, where three minutes of post-activity EEG data were collected [67].

3.3 AUDIO VISUAL STIMULI CLASSIFICATION

Many researchers worked on classification among different types of stimuli. However, these works are not focused on stress detection. G. S. Mouni et al. [91]

classified among three types of stimuli named- audio, visual and cognitive stimuli. They found best accuracy for the visual stimuli. Audio, visual, and audio-visual stimuli multi class classification was done by Y. Dasdimir et al. [92]. But in this case, they found the best accuracy for the audio-visual stimuli. J. Leoni et al. [93] employed several types of stimuli but they found best accuracy for the picture and non-picture (audio-video) based stimuli. T. Agarwal et al. [94] employed LSTM method for classifying audio and visual stimuli. Dr. E. G. M. Kanaga et al. [95] did multi class classification among for auditory, somatosensory, and cognitive events and found the highest accuracy for somatosensory stimuli. These findings not only help neuroscientists identify ERPs more quickly and accurately, but they also open the door for BCIs to potentially offer users more features by utilizing the variety of stimuli that the system can identify. Since most BCI systems on the market today rely on visual cues or visual input, they might not be suitable for severely incapacitated patients who have lost their capacity to see or regulate their eye movements. D. Kim et al. [96] developed the first online ASSR-based BCI system, proving that a completely vision-free BCI system could be realized

3.4 PRE-PROCESSING TECHNIQUES

EEG signals are highly sensitive to noises such as power line interference (50/60 Hz) caused by power line frequency, movement artifacts generated by muscle contractions (Electromyogram, or EMG), visual signals produced by eye movements (Electrooculogram, or ECG), and cardiac signals (Electrocardiogram, or ECG). These sounds are eliminated during the pre-processing step, which also gets the signal ready for additional processing inside the targeted frequency range. It is essential to properly pre-process the raw EEG data since noisy EEG data will probably not produce improved findings. EEGLAB is very famous pre-processing tool used for noise removal by many authors [110]. Some authors also used other software like Neuroguide [111], NIC [112], Brain Vision analyzer [113] for data cleaning purpose.

EEG signal is affected by low-frequency disturbances from a variety of sources, including skin-electrode drift, head, facial muscle and body movements, electrode wires, deep and irregular breathing, perspiration on the scalp, temperature variation, baseline wander and eye movements, can interfere with EEG. The sluggish variations in the EEG signal over a few seconds are indicative of low-frequency noise. Conversely, eye blinks (EOG) and muscular contractions (EMG), in the ECG, power line interferences produce high-frequency noise. Elevated-frequency noise appears as abrupt up- and down-swings in the EEG output. Because the frequency spectrum of the EEG signal spans around 0.5 to 100 Hz, band pass filters (BPFs) are frequently used to exclude high- and low-frequency noise [67], [78], [87], [97], [106], [112], [113], [114]. The signal that falls between the two cutoff frequencies of the BPF- lower and higher- is permitted to go through the filter. The cutoff frequencies, such as 4-45 Hz, are modified to fall within the required EEG range. Saidatul et al.[115] introduced elliptic filter because this filter has a lower order than other FIR filters like Butterworth, it was employed. In this case, phase distortion was prevented by doing both forward and backward filtering. Savitzky-Golay (S-Golay) filter was used by some authors [116] because of its computational efficiency. The S-Golay filter can analyze large EEG datasets without causing unnecessary computing overhead, making it appropriate for real-time applications. It efficiently lowers high-frequency interference without compromising the integrity of the low-frequency components, which are frequently the major focus of EEG research. Moreover, this filter maintains the original shape and characteristics of the signal, such as peaks and troughs, in contrast to other smoothing filters that have the potential to alter the signal's shape [116].

Low Pass Filter (LPF) [62], [117]and High Pass Filter (HPF) [62], [79], [117]were also found to be used independently in certain investigations, with the HPF using just the higher cutoff frequency and the LPF using only the lower cutoff frequency. A notch filter, which responds entirely different from a BPF, is frequently used to get rid of power line interference (50/60 Hz) [62], [78], [79], [106], [118].

Re-referencing techniques used for EEG data pre-processing by some authors [78]when a new reference point or set of reference points is used to recalculate the recorded signals. By removing artifacts and noise from the EEG data, this procedure can greatly improve its quality. Fast Fourier Transform (FFT) is used by some authors [79].

One blind source separation method that is frequently utilized as a pre-processing tool for mental stress detection [62], [106], [117] is Independent Component Analysis (ICA). When analyzing EEG data, Independent Component Analysis (ICA) is a potent statistical method that divides a multivariate signal into additive, independent components. Rebuilding the cleaned EEG signal from the remaining components aids in the removal or correction of the discovered artifact components. From the EEG data, ICA can successfully extract a variety of artifacts, including eye blinks, muscular activity (EMG), and cardiac signals (ECG). ICA can separate the unique spatial and temporal patterns found in these artifacts. The EEG data's SNR is improved by ICA by separating and eliminating artifacts, which facilitates the detection and analysis of brain signals. In some research, Fast ICA [78] was used also which was created to carry out ICA more rapidly and effectively. Its foundation is a fixed-point iteration approach designed to optimize the statistical independence metric known as non-Gaussianity. Principle Component Analysis (PCA) is used by Qiang Wang et al. [67] for constructing feature space. By lowering dimensionality and noise, PCA helps to simplify the handling and visualization of data [67]. ICA, on the other hand, is very useful for cleaning EEG data and isolating brain activity from artifacts since it is necessary for separating mixed signals into separate sources. Depending on the objectives of the EEG analysis and the characteristics of the data, PCA or ICA should be used. As a pre-processing method, segmentation is also frequently used to split a signal into different epochs with the same statistical properties in terms of frequency and time [67], [97], [111], [116]. S.M.U. Saeed et al. [119] used welch periodogram for segmentation purpose by using a 128-sample window length with a 50% overlap.

The raw data for an EEG is captured from the subject's scalp surface using electric impulses. The gathered raw data for different kinds of stimuli classification purpose also includes noise from interference caused by the subject's eye or muscle movements, as well as underlying electrical impulses from the subject's brain. Band pass filter (BPF) following by notch filter is mostly used for removing unnecessary portion of data [92], [95]. ICA is used for ocular, muscular and motion artifact related noises by the most of the authors [91], [92]. In some cases, PCA is also used by few authors [95]. The multiple artifact rejection method (MARA), which is based on ICA, was used by Y. Dasdemir et al [92]. Only the occurrences reported with a 90% confidence level or higher were eliminated, or around one or two components for each participant in this research. Prior to averaging, computerized artifact rejection was carried out by J. Leoni et al [93]. An amplitude more than 50 μV from peak to peak was required for the rejection of artifacts. About 5% of cases were rejected because of this process. In stead of using any pre-processing techniques D. Kim et al. used Fast Fourier Transform (FFT) [96]. Using a sliding window that lasted one second and had a 50% overlap, this technique was used to calculate the frequency spectrums of each epoch. For every epoch, the estimated frequency spectrums were tallied and averaged across time. In some cases, for classifying between two unbalanced data creates biased results. Before processing the data further, this problem was resolved by randomly under sampling the majority labels by Marianna Kocturova et al. [120].

3.5 FEATURE EXTRACTION TECHNIQUES

From the previous works, it is known which features were used to detect stress. katz Fractal Dimension feature was used by R. Katmah et al. [59]. M. J. Hasan used 40 features including mean, kurtosis, and hjorth parameters [60]. D. Shon et al. used 10 features including hjorth parameters, mean, standard deviation, and frontal alpha asymmetry [110]. L.Shi used differential entropy and compared the performance with other features [121]. R.Zhang used spectral entropy for inter session performance prediction purpose [122]. Alpha and beta asymmetry was used by S. M. U. Saeed et al. [98] for mental stress detection purpose. DWT was used by several researchers [123] for determining the power spectra of EEG signal.

High-dimensional time-series data, which make up EEG data, might need a lot of processing power to handle. By reducing the dimensionality, feature extraction helps to organize the data. By separating pertinent brain signals from noise and artifacts, feature extraction can produce cleaner data that is more suited for categorization.

The features used for audio visual stimuli classification is almost similar to mental stress detection. Y. Dasdemir et al. [92] classified different affective states from audio visual stimuli. He used Hjorth parameters, mean, variance, standard deviation, and first/second differences as time domain features and did FFT and welch periodogram to find out the frequency domain features [92]. G Sri Mouni et al. [91] computed event-related potentials (ERPs), which are the brain's time-locked electrical reactions to a particular stimulus or event for classifying audio visual and cognitive stimuli. ERPs may be examined by comparing the waveforms between various experimental conditions or groups and averaging the EEG data across trials [91]. Besides of using some common features, M. Kocturova et al. [120] added some special features like spectral flux and shannon entropy to classify speech activity from EEG signal. Do-Won Kim et al. [96] used FFT to find out the frequency domain features to classify attention level to different auditory stimuli.

3.6 MACHINE LEARNING (ML) MODELS FOR EEG CLASSIFICATION

Both supervised and unsupervised machine learning techniques were used in the trials pertaining to mental stress. When using labeled data for supervised learning, distinct stress levels are determined by the type of stress inducer. All the EEG data are labeled since each stress level is quite distinct. These labels let the classifier identify signals of different stress levels in the training datasets. A label-free dataset is utilized to forecast the multi-level stress throughout the testing phase. Conversely, prior experience with stress level labeling is not required for unsupervised learning techniques. The most commonly employed unsupervised machine learning technique is k-Nearest Neighbors (k-NN), while the most often used supervised techniques are Support Vector Machine (SVM), Neural Network (NN), Logistic Regression (LR), Naïve Bais (NB), Random Forest (RF), Regression, and Linear Discriminant Analysis (LDA).

A strong machine learning method called Support Vector Machine (SVM) is frequently used to categorize EEG data, notably when detecting mental stress. Rich information regarding brain activity may be found in EEG data. SVMs can be very useful in differentiating between different mental states, such anxious vs calm, by identifying the best feature space border across classes. Using a hyperplane to divide several classes, SVM classifies data. New data is classified using the hyperplane, which is dependent on the training set. The SVM is a helpful technique for detecting mental stress because of its accuracy and ease of calculation. This model is used by many authors [62], [71], [98], [107], [124] for classifying various stress level. A. Hemakom et al. [124] combined ECG and EEG data and employed six machine learning models where SVM outperformed than the other models. For binary stress detection they found 79.81% accuracy for the female participants and 73.77% accuracy for the male participants [124].

Several studies employed LDA contrasting with SVM classifier [64], [76], [123]. The prominent statistical technique known as linear discriminant analysis (LDA) is used to identify mental stress in EEG data. When the objective is to identify a linear feature combination that optimally divides two or more classes, LDA is especially well-suited for such cases. The linear feature combination that optimizes the ratio of between-class variation to within-class variance is found using LDA. The discriminant function that best divides the classes is the outcome of this. It is primarily employed in dimensionality reduction methods to convert 2D planes into 1D planes. Next, it contains two criteria: minimizing variation inside the class and maximizing the distance between the means of two classes [76].

K-NN, an unsupervised learning model, may be used as a tool for classification and regression. The k-NN method predicts the test sample's category based on the K training samples that are its nearest neighbors. In contrast to the hyperplane of SVM, k-NN creates a decision boundary between many distinct classes [125]. After SVM, it is the most frequently used models for mental stress detection [62], [64], [98], [76], [87], [107]. Being a non-parametric technique, the k-NN algorithm does not make any explicit assumptions on the distribution of the underlying data. This makes it adaptable and simple to use for dividing EEG signals into distinct mental states [62].

When analyzing EEG data, Random Forest is a potent ensemble learning technique that works well for identifying mental stress. It works especially well with complicated datasets that include a lot of features, such those produced from EEG waves [124]. During training, Random Forest generates several decision trees, from which it extracts the mean prediction (for regression tasks) or the mode of the classes (for classification tasks) for each tree. Using subsets of the data and characteristics, it constructs many decision trees, and then aggregates the forecasts from each tree to arrive at the final prediction. Compared to individual decision trees, this method enhances generalization and decreases overfitting. Random Forest is applicable to jobs involving both regression and classification [64]. Due to its versatility, robustness and interpretability, this model is frequently used for mental stress detection purpose [62], [64], [124].

Although traditional machine learning models achieved very significant classification accuracy, neural network is also employed for mental stress detection purpose. Most widely used neural network techniques are Recurrent Neural Network (RNN) [87], Long Short-Term Memory Network (LSTM) [75], [87] Convolutional Neural Network (CNN) [75] and Multi-layer Perceptron (MLP) [71], [126]. They imitate the structure of the human brain by using neurons or dispersed nodes layered in a framework. They create non-linear boundaries to make judgments about large amounts of data. This adaptive strategy allows computers to grow by learning from their mistakes. They are getting more and more popular for interpreting data in mental stress detection, although they still need a lot of attributes and data samples [125]. M. A. Hafeez et al. classified three level stress using LSTM and CNN and found highest accuracy 70.67% and 90.46% respectively [75]. CNN provides better result as CNN's advantages is its ability to extract local features, or spatial insights from the data, which is useful for learning hierarchical relationships from the data's local neighbourhoods. With an overall accuracy of 93.27%, a multiclass two-layer LSTM RNN deep learning classifier was used to identify mental stress from continuous EEG by A. Sundaresan et al [87]. Their work offers promise for an EEG-based BCI for the real-time assessment and mitigation of mental stress through a closed-loop adaptation of respiration entrainment. They successfully apply an LSTM RNN classifier for the first time to identify stress states from EEG in both ASD and neurotypical adolescents [87].

The machine learning algorithm used for audio visual stimuli classification is almost similar to mental stress detection. In some case the authors introduced deep learning algorithm instead of traditional machine learning algorithm. Tejas Agarwal et al. [94] used LSTM for classifying EEG signal generated for audio visual stimuli. Boosted trees-based classification and Feed-forward neural networks-based classification methods were proposed by Jessica Leoni et al. [93]

for classifying different stimuli automatically from event related potential (ERP). Again, shallow Feed-Forward Artificial Neural Network having 100 hidden neurons was proposed by M. Kocturova et al.[120] On the other hand, some authors worked on traditional ML algorithm. For instance, E. G. M. Kanaga et al. [95] used KNN, RF and multi-layer perceptron (MLP) to classify auditory, somatosensory, and cognitive stimuli. G Sri Mouni et al. [91] also used KNN, SVM, LDA, LR, NB, RF and DT for classifying visual, audio and cognitive stimuli. Again, KNN and SVM used by Y. Dasdemir et al. [92] for classifying audio, video and audio-video stimuli.

4 Data Collection

The datasets utilized in this investigation are covered in this chapter. For this study, dataset was collected via experimentation which is covered in Section 3.1. In this section, the whole data collection procedure will be described in detail. This section includes three subsections having the dataset description, stimuli design and collection procedure.

4.1 DATASET DESCRIPTION

One dataset was used in this work. This dataset was made which includes EEG data collected by the authors at lab set-up following all the ethical requirements and data collection process was approved by the respective authority of Chittagong University of Engineering and Technology, Bangladesh. The whole data collection procedure followed the Helsinki protocol. To make this dataset, some steps were followed. First, to build a proper comprehension of the EEG signal for stress classification purpose, it was needed to design different audio and visual stimuli by using EMOTIV Builder before starting data collection process. Participants should fulfill all inclusion requirements, including not having any physical, mental, or head injuries and abstaining from drug or prescription use prior to the trial.

4.1.1 Stimuli Design

Obtaining EEG data while performing routine chores might provide a noisy signal. Conversely, if multiple stimuli are applied over an extended period, each stimulus may produce a strong peak, and the noise will be of average magnitude. The term "event related potential" (ERP) describes this behavior. For this reason, prior to collect data visual stimuli was designed where mathematical problems having three difficulty levels were given to evoke stress to subjects.

Different experimental stages of each stimulus were shown in Fig. 4.1. where the stimulus starts with the calibration phase. In calibration phase five seconds eyes close and five seconds eyes open data was collected followed by some general instruction phase. Then in the stimuli stage, audio or visual stimuli were heard or visualized by the subjects. Data was collected by using two kinds of stimuli-visual stimuli and audio stimuli.

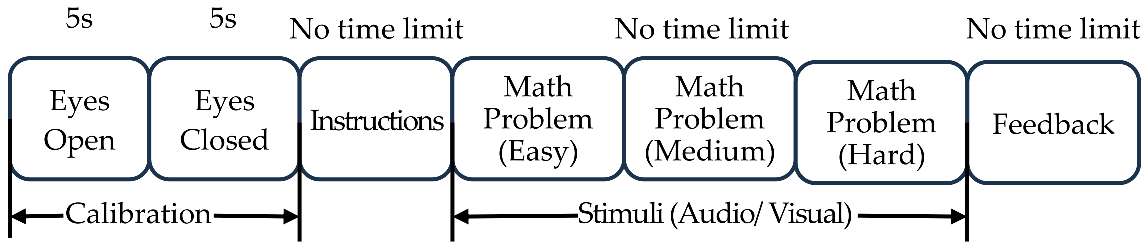


Fig. 4.1. Experimental stages for single stimulus

Three difficulty levels math problems were shown or heard separately following a random order after finishing each difficulty level math. In the visual stimuli, stress free data was taken where the subjects were remained relaxed with their eyes closed for five seconds. Then the problem was shown to the subjects where they could view the stimuli image as much time as they need to solve the math problem. During calculating the math problem, the brain signal was recorded which was labeled as stressed data. The duration of the visual stimuli was on average 150 seconds in the audio stimuli, the five seconds eye closed data was taken by following the same way as visual stimuli. But in this case, the mathematical problem was heard by the subjects using an earphone where the participants heard it only once and has no opportunity to repeat the audio. The duration of the audio stimuli was almost 35-45 seconds. During this time, the subjects need to listen the audio carefully and then solve the mathematical problem mentally without using any pen and paper. During calculating the math problem, the brain signal was recorded which was labeled as stressed data. Finally, the difficulty levels the subjects faced during solving the math problem was taken as feedback.

4.1.2 Participants

In this study, total participants were thirty. All of them were either undergraduate or graduate students. Among the participants, thirteen subjects were female, and eighteen subjects were male. With an average age of 22.5 years, the participants ranged in age from 19 to 25. None of them had any neurological or psychological conditions, and their vision was either normal or corrected to normal. All subjects gave written, informed permission before to the experiment and accepted a little payment for their efforts. Neither alcohol nor any other narcotic substance addiction affected any of the participants.

4.1.3 EEG Channel Location Selection

The Emotiv EPOC Flex headset (Emotiv Inc., San Francisco, California, U.S.A.) was utilized to record the EEG data. It features two reference electrodes, CMS and DRL, at the left and right mastoids, respectively, and 32 Ag-AgCl electrodes that are programmable in accordance with the worldwide 10/20 EEG standard. Total 30 subjects' data was collected in this dataset. The sampling frequency was 128 Hz and data were transmitted through Bluetooth communication. The number of channels were optimized, and data was collected from 16 channels named: Cz, Fz, Fp1, F7, F3, C3, P3, O1, Pz, Oz, O2, P4, C4, F4, F8 and Fp2. Because these channels are found very significant for mental stress classification in the previous literature [68], [127], [128].

4.1.4 EEG Channel Location Selection

Data has been collected from thirty participants, ages nineteen to twenty-five. Before providing any data, all participants were required to complete the authorization form. There was no history of brain disorders or visual issues among the patients. Alcohol or other narcotic substance addiction was absent in all the individuals. They were all paid a little fee and gave their voluntary participation. The institution's CHSR committee and the Directory of Research and Extension, DRE, gave their approval to this initiative. The subjects entered a noise-free room and all the subjects were given necessary instruction before collecting data. The lab set up was arranged for collecting EEG data. The room was organized with low lighting and electrical shielding, where participants were seated around 50 cm away from the computer display. A mouse and keyboard were provided to the participants so that the studies could continue. A mouse and keyboard were provided to the participants so that the studies could continue.

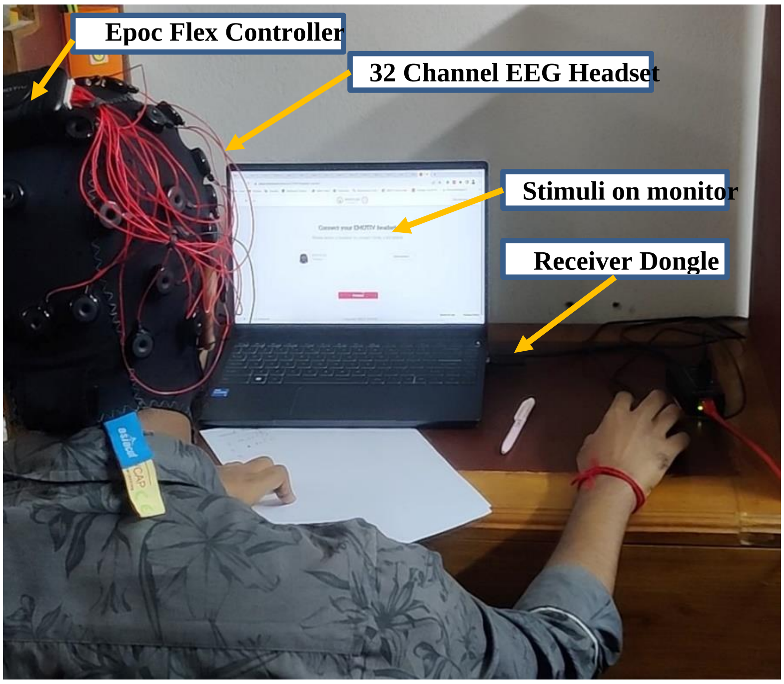


Fig. 4.2. Real-time data collection scheme using 32-channel EEG

Visual and audio stimuli was used to collect data. There was almost three weeks gap between audio and visual data collection. Three kinds of mathematical word problems having three difficulty levels- easy, medium, and hard were used to design the stimuli. In both the case of visual and audio stimuli, two phase data were collected- 5 seconds control data and stress induced data. After completing the whole experiment, the participants were given their feedback regarding how much difficulties they felt during solve the problem on scale 1 to 5 (very easy to very hard). Each subject need to solve total six problems (three problems as visual stimuli and three problems as audio stimuli) and relaxed data was also separated from the raw data. As a result, there are total 12 files for each participant in the dataset. Finally, there are total 360 (30*12) recording files in the dataset. In Fig. 4.2, real time EEG acquisition was shown in the lab setup. Sample of mathematical problem was shown in Fig. 4.3.

Do the math and write down the answer on paper

Siyan is 8 years older than Rifat. In four years Siyan will be twice as old as Rifat. How old is Siyan now?

Fig. 4.3. Mathematical Word problem used as stimuli

Raw EEG signal collected from 16 channels was shown in Fig. 4.4. In this Fig. 4.4, X axis scale was 20 milliseconds and Y axis scale was 300 microvolts. Out of all these 16 channels, F3, F4, F7, F8, FP1, FP2 were very significant for multi-level stress detection and audio-visual stimuli classification.

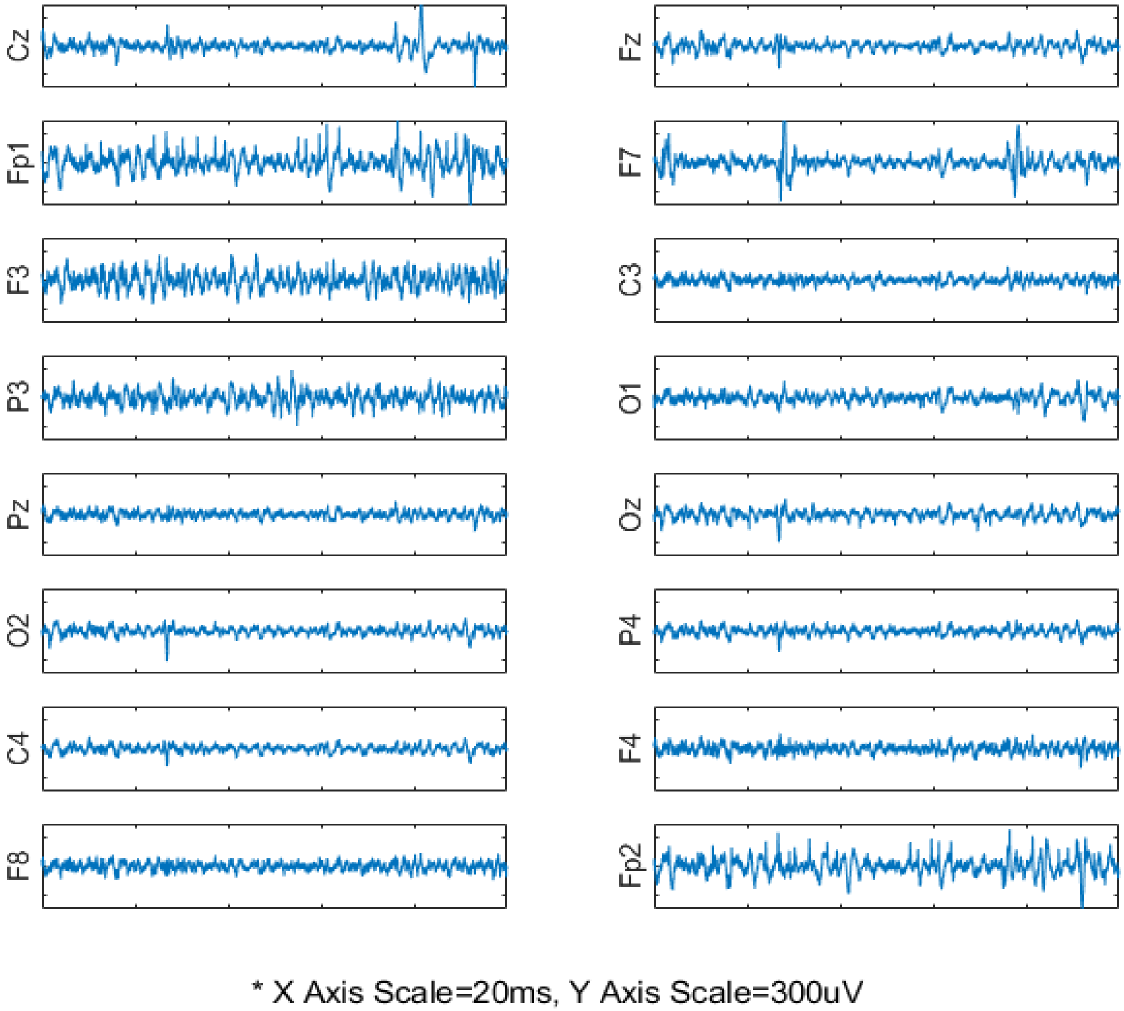


Fig. 4.4. Raw EEG data from 16 channels before pre-processing

5 Methodology

Research methodology used in this thesis are discussed in this section. Framework of the proposed research work was discussed in subsection 5.1. Two types of pre-processing pipeline and their effects were shown in subsection 5.2. EEG feature extraction and machine learning model deployment process for both mental stress detection and audio-visual stimuli classification were shown in subsection 5.3 and 5.4 respectively.

5.1 FRAMEWORK

EEG data was collected from 30 subjects in two different session for audio and visual stress inducing stimulation. An optimal pre-processing pipeline was used in this work for removing noise from the raw EEG data. After noise removal, necessary time domain and frequency domain features were extracted from the data. Finally, in this research work, binary and multi-level stress were classified from both audio and visual data with necessary analysis. Again, binary classification between audio and visual stimuli was also done in this research work. The framework of the proposed research work is shown in Fig. 5.1.

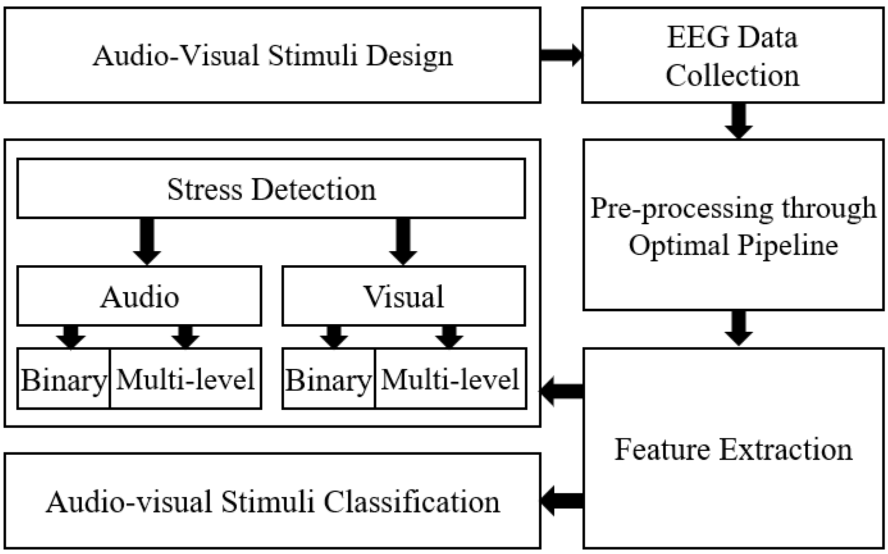


Fig. 5.1. Framework of the proposed research work

5.2 PRE-PROCESSING

EEG signals are highly sensitive to external noise and some physical noise like electromyogram (EMG) signals caused by muscle contractions, electrocardiogram (ECG) signals from the heart, and power line interference (50/60 Hz) signals resulting from power line frequency. To eliminate any undesirable signals included with the biosignals, pre-processing is required. In this experiment, two distinct pre-processing pipelines were used: the suggested pre-processing pipeline and the traditional pre-processing pipeline.

5.2.1 Raw EEG data

The two pre-processing methods were compared using the EEG dataset that was gathered, which was covered in the previous chapter. To compare the two pre-processing pipelines, only the EEG data was used that was both relaxed and extremely stressed. Advantage of the information gathered from aural and visual inputs was taken. As a result, the final dataset had 360 (30*12) recordings total—that is, twelve recordings for per individual. For better visibility, raw EEG data from two channels of a specific individual is shown in Fig. 5.2.

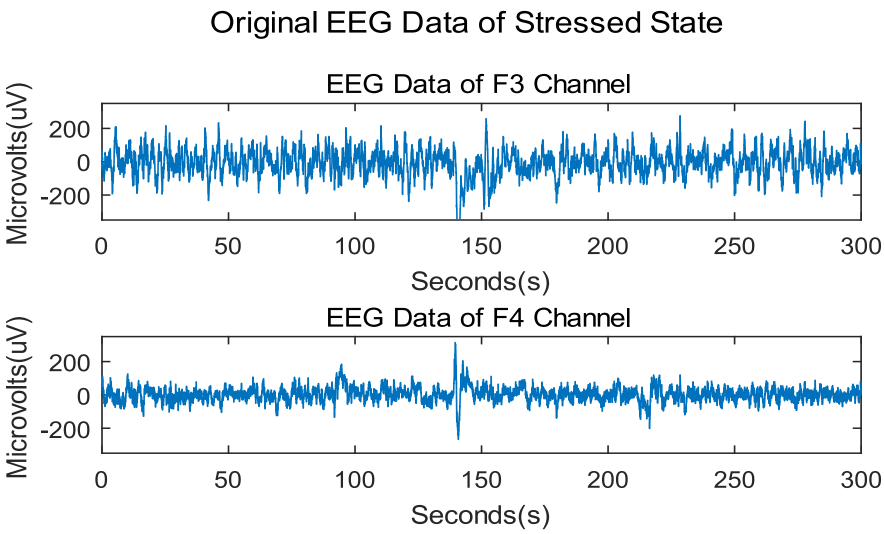


Fig. 5.2. Raw EEG data of stressed state before pre-processing

5.2.2 Traditional Pre-processing pipeline

This pipeline was one of the widely used techniques for de-noising EEG data [68], [128]. Here, power line interference was eliminated by utilizing a notch filter after the raw data had been filtered using a band pass filter (BPF) inside the EEG range. Then came Independent Component Analysis (ICA), and lastly the export of the pre-processed data. The traditional pre-processing pipeline was displayed in Fig. 5.3.

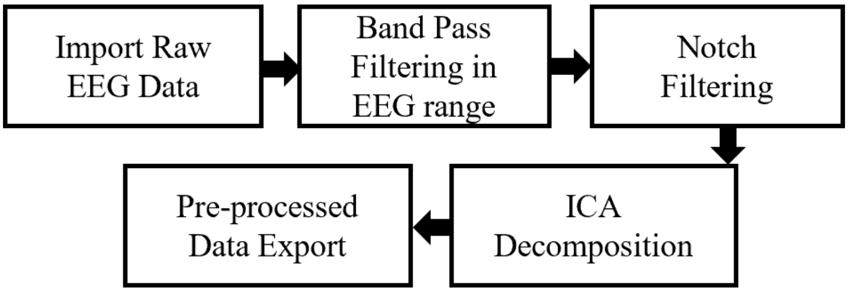


Fig. 5.3. Traditional pre-processing pipeline

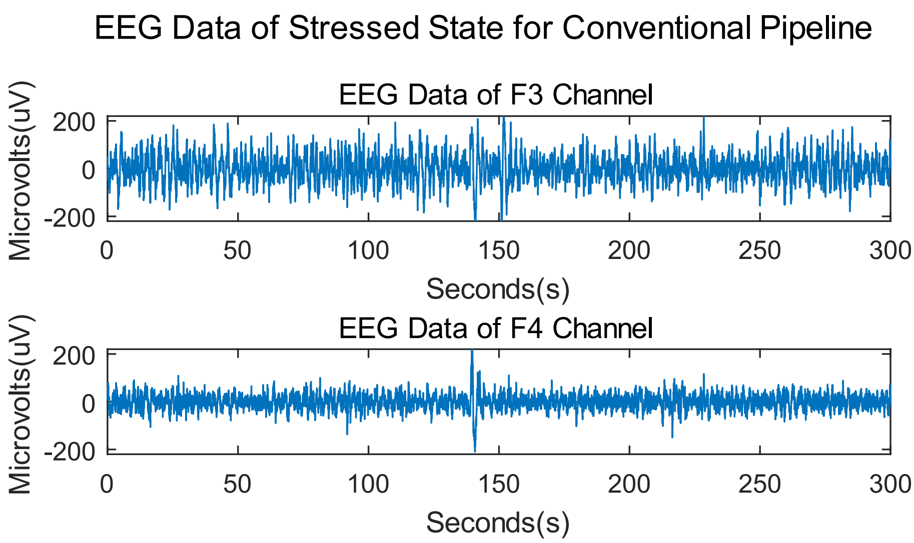


Fig. 5.4. EEG data of stressed state after traditional pre-processing

The raw EEG data was displayed in Fig. 5.2. prior to pre-processing. For enhanced visualization, two data channels (F3, F4) were shown. ICA was done following the completion of many stages in the conventional pre-processing pipeline. Infomax ICA was ran, and 16 components were discovered. By choosing a threshold value (0.9) for the eye and muscle data, it was possible to identify any component that had eye blink or muscle data more than 90%. Following ICA, motion artifacts were eliminated from the eye blink and muscle data, and clean data was retained. The clean data after traditional pre-processing was shown in Fig.5.4. This is seen in Fig. 5.3. for the conventional pre-processing pathway. The conventional approach can only filter out single data points that include excessive noise; it cannot function on a channel. It cannot concentrate on a particular section of the channel because it operates over the whole thing.

A novel pre-processing pipeline was suggested in 2023, per [129] and [130]. Since the prior approach was unable to eliminate noise completely from EEG data, this one was employed. With this innovative technique, they eliminated channel correlation and cleaned the raw data using Artifact Subspace Reconstruction (ASR) rejection before using ICA to break down the components. Lastly, before exporting the clean data, any eliminated channels were interpolated. But in this way, the original channel information was lost. For this reason, in this work, a unique pre-processing pipeline is proposed that will guarantee an improvement in data quality without sacrificing any meaningful channel information.

5.2.3 Optimal Pre-processing pipeline

In this research work, a new pre-processing pipeline was used which was proposed in two of the previous works [8], [131] to ensure the improvement in data quality without losing any significant channel information and compared the results with the traditional one. As automated pre-processing pipeline loss a significant amount of information although the process is bit quicker. For this reason, manual method instead of the automated one was used. The proposed pre-processing pipeline is shown in Fig. 5.5.

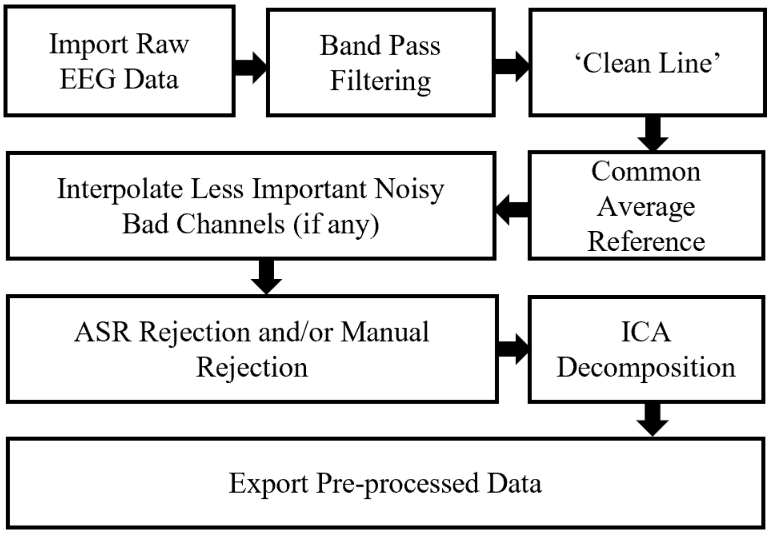


Fig. 5.5. Optimal pre-processing pipeline

According to the proposed method, notch filtering using clean line function was used after band pass filtering the raw data with 0.5 to 45 Hz cut off frequency. The EEG data may contain some sinusoidal power line interference after bandpass filtering. It is a must to make sure that the power line interference is eliminated as band pass filtering is not precise. Clean line function from EEGLAB 2022 in (MATLAB 2023a) adaptively assesses and removes sinusoidal noise (e.g., power line interference) from the ICA components or scalp channels using multi-tapering and a Thompson F-statistic [132]. Following that, a common average reference to re-reference the data was used. In addition, any noisy bad channels were identified and interpolated that were not essential to the application of interest. For EEG-based stress detection, any noisy poor channel—aside from the frontal ones—can be interpolated. Then, by examining the data, Artifact Subspace Reconstruction (ASR) rejection and/or manual rejection was done. ASR is a component-based method that requires little computation and may be used automatically [133]. Using the remaining components, the signal is rebuilt in this manner, eliminating the components with high variances. Using a reference data set devoid of artifacts, the ASR approach establishes criteria for choosing which components to reject. When the ASR rejection identified a sizable portion of the data that needed to be removed, manual rejection was done by simply removing the considerably noisy component of the data. Following that, I muscular and ocular artifacts were eliminated using ICA. Then, the whole data was divided into 4-second epochs with 10% overlapping. Total 2180 epochs were achieved for visual stimuli and 1985 epochs for auditory stimuli. Clean data produced by the recommended pre-processing pipeline was displayed in Fig. 5.6.

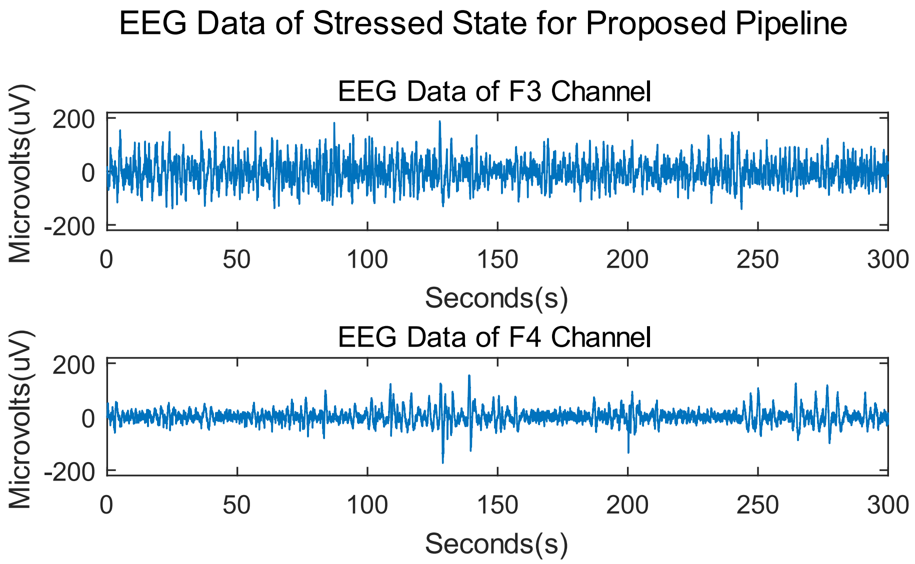


Fig. 5.6. EEG data of stressed state after proposed pre-processing

It was evident from a comparison of these two figures, Fig. 5.4, and Fig. 5.6, that the data obtained from the suggested pre-processing pipeline were more noise-free and clean than those obtained from the conventional pre-processing pipeline.

5.3 FEATURE EXTRACTION

Finding important and relevant information from EEG signals is the aim of feature extraction, which aims to provide insightful information for additional study. The previously processed EEG data was segmented into 10% overlapping 4-second epochs. From each channel of the data, four EEG frequency bands for each epoch were isolated: theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (above 30 Hz), as seen in Fig. 5.7.

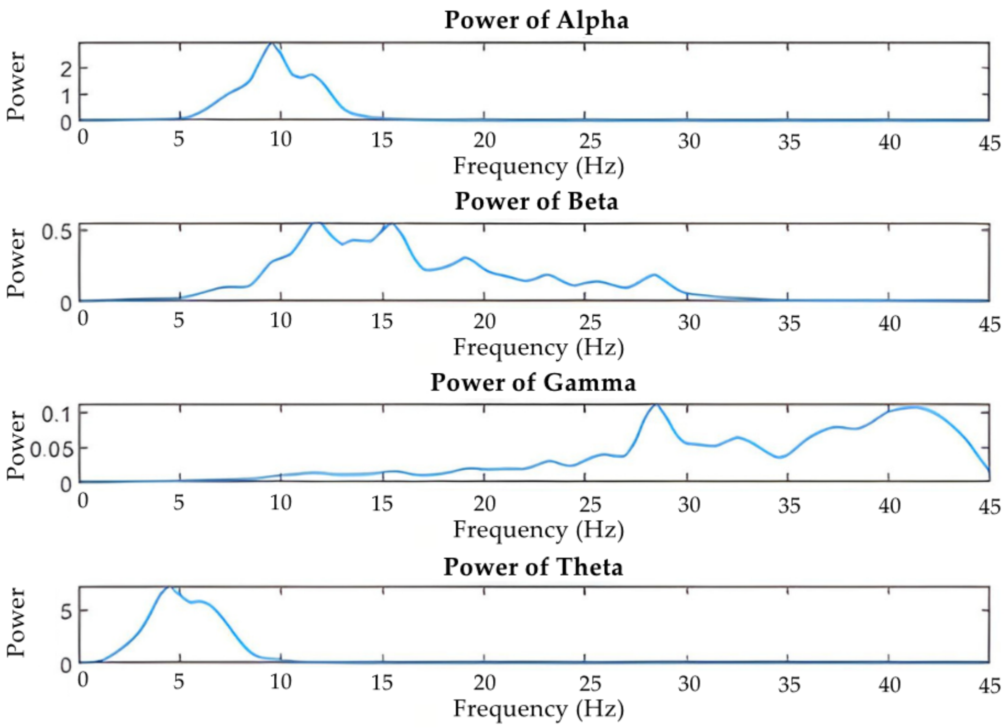


Fig. 5.7. Power spectral plot of alpha, beta, gamma, and theta after applying a bandpass filter for one epoch

Several important EEG features are identified in previous literatures. For example, ten characteristics were employed by D. Shon et al. [132] including frontal alpha asymmetry, mean, standard deviation, and hjorth parameters for mental stress detection. 40 characteristics, such as mean, kurtosis, and hjorth parameters, were employed by M. J. Hasan [60] for various mental stress state detection. In the research, it was taken into account every attribute from each band and retrieved 11 statistical features [60], [121], [122], [131] because these features are very significant for mental stress detection. Again, as traditional machine learning models were employed here, easily understandable features were selected by using trial and error method. The equations of all the features used in this research work is represented in Table 5.1.

Table 5.1. Mathematical formulation of time domain and frequency domain features used in this work

Feature	**Equation**
F1(mean)	$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i$
F2(standard deviation)	$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \mu)^2}{N}}$
F3(varience)	σ^2
F4(skewness)	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i-\mu}{\sigma}\right)^3$
F5(kurtosis)	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i-\mu}{\sigma}\right)^4$
F6(activity)	$var(X)$
F7(mobility)	$\sqrt{\frac{var(X')}{var(X)}}$
F8(complexity)	$\frac{Mobility(X')}{Mobility(X)}$
F9(spectral entropy)	$\hat{p}(f) = \frac{P(f)}{\sum_{f=0.5}^{45} \mathrm{P(f)}}$
	$SH = -\sum_{f=0.5}^{45} \hat{p}(f)\log(\hat{p}(f))$
F10 (differential entropy)	$h_i(X) = \frac{1}{2}\log(2\pi e \sigma^2{}_i)$
F11(sample entropy)	$SampEn\ (m, r) = -ln\frac{B^{m+1}(r)}{B^m(r)}$
F12(frontal alpha asymmetry)	$\frac{\alpha(F4) - \alpha(F3)}{\alpha(F4) + \alpha(F3)}$
F13(Valence)	$\frac{\beta(F3)}{\alpha(F3)} - \frac{\beta(F4)}{\alpha(F4)}$
F14(average power)	$P_f = \frac{1}{N}\sum_{n=1}^{N}\lvert X_n(k)\rvert^2$

In Table 5.1, X is the EEG signal, N is total number of samples, $P(f)$ and $\hat{p}(f)$ are the power spectral density (PSD) and normalized power spectral density of EEG signal using Welch's method, $\alpha(F3)$, $\alpha(F4), \beta(F3)\ and\ \beta(F4)$ are average powers of Alpha and Beta bands of F3 and F4 channels respectively and $B^m(r)$ is calculated from the time series of EEG signal.

Some explanation regarding these features are given below:

Standard Deviation: The standard deviation measures how widely distributed the data are in relation to the mean. When it comes to standard deviation, data with little or low standard deviations are centred around the mean, whereas high or great standard deviations are widely distributed.

Variance: It means the statistical measurement of spreading of data with respect to the average value in a specific dataset.

Kurtosis: This statistical feature is used to measure how tailed a distribution is. The frequency of outliers is known as tailness. Excess kurtosis is the tailiness of the distribution relative to a normal distribution.

Skewness: The skewness of a distribution indicates how asymmetrical it is. A distribution is considered asymmetric when its left and right sides are not mirror reflections

One method for expressing a signal's statistical properties in the time domain is the Hjorth parameter, which contains three different types of parameters- Activity, Mobility, and Complexity. They provide details on the signal's amplitude variability, temporal dynamics variability, and spectral bandwidth variability [134].

Activity: The variance of the time function, or the activity parameter, may be used to determine the frequency domain power spectrum surface. In other words, if there are many or few high frequency components in the signal, the value of activity yields a big or small number [62], [134], [135].

Complexity: The complexity parameter shows how a signal's form resembles that of a pure sine wave [62], [134]. As the signal's structure becomes closer to that of a pure sine wave, the complexity value converges to 1. These three factors aid in time domain signal analysis in addition to providing information about a signal's frequency spectrum. Additionally, by using them, a lower computational complexity can be attained [134], [135].

Mobility: The square root of the ratio between the signal's first derivative's variance and its own is the mobility parameter. This parameter has a power spectrum standard deviation percentage [62], [134].

Sample Entropy: Sample entropy is the idea that a value from a series in an ordered system would be a suitable way to define it. It may be thought of as a measure of degree of randomness or regularity [136]. If there are more complex or non-ordered sequences in a series, the entropy will be higher, and vice versa. It lessened the bias brought on by self-matching [136].

Spectral Entropy: The spectrum complexity of a time series is measured by spectral entropy, which is derived from Shannon entropy. based on the inconsistent data buried in the EEG spectrum in the resting state [122].

Differential Entropy: Differential entropy, which is the entropy of a continuous random variable, is used to quantify the complexity of a continuous random variable. Minimum description length is also connected to differential entropy [121].

To determine each band's frequency domain component, a Welch periodogram was used. Three characteristics were retrieved from the frequency domain: average power, frontal alpha asymmetry, and valence [137].

Valence: Asymmetrical frontal hemisphere activity was linked to mental stress as valence [137]. Positive and negative valence levels are associated with activation of the left and right prefrontal areas, respectively. The idea that frontal EEG asymmetry might serve as an index of valence is supported by a substantial body of research [137].

Frontal Alpha Asymmetry: The frontal lobes of the right hemisphere in the cerebral hemisphere are asymmetrical in the left hemisphere as opposed to the right. In EEG electrodes, Fp1 and Fp2 are utilized to detect frontal lobe differences. The pre-frontal cortex of the brain is referred to as Fp [132], [137]. Each electrode yields the alpha wave band's power, which is then taken and subtracted from the absolute value and the log.

Average Power: The average band power, which is calculated as a single value that represents the frequency band's contribution to the signal's total power [138].

5.4 CLASSIFICATION AND DETECTION

Here, deep learning models are not employed as dataset was small and if deep learning was used, those models might be overfitted. After extracted all the features, several machine learning models are employed for mental stress detection and audio-visual stimuli classification. Out of all the models, four models performed better than the others. Those four models were- Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Decision Tree (DT) and Linear Discriminant. A short description of these four models and their effectiveness for mental stress detection and audio-visual stimuli classification are given below:

SVM: This model performed better for mental stress detection and audio-visual stimuli classification because of the high dimensional data available in EEG data, having the capability of handling non-linearity, high noise tolerance and well performance for small datasets. A regularization parameter (C) in SVM regulates the trade-off between minimizing classification errors and maximizing margin. This lessens the likelihood of overfitting, which is crucial for classifying mental stress and audio-visual stimuli because the data may be noisy and have a small sample size. By converting the input space into a higher-dimensional feature space using kernel functions, SVMs can handle non-linear data with efficiency [64].

KNN: One well-known and straightforward classifier that researchers frequently employ is the KNN classifier. It is an effective method for classifying patterns in nonparametric analysis. The training data (baseline data) and testing data have been compared in this classifier. The data will be assigned depending on which data appears about k more frequently after this classifier determines the value of k in the training data's neighbourhood. It performed better for classifying mental stress and audio-visual stimuli classification because of its sensitivity to subtle changes in the data, flexibility to various feature spaces, efficacy in low noise, and capacity to spontaneously adjust to the properties of the data without the need for intricate modelling [80].

Decision Tree: A supervised learning method that works well for regression and classification applications is the decision tree. It is a classifier with a tree-structure made up of internal, leaf, branch, and root nodes. Based on the characteristics of the provided dataset, the choice or test is carried out. The primary benefit is straightforward and helpful in resolving issues with decisions. Because of its intrinsic feature selection process, versatility with various data kinds and interactions, and capacity to handle non-linear correlations, decision trees perform well for classifying mental stress and audio-visual stimuli classification from EEG data. They are a sensible option for evaluating complicated EEG data linked to mental stress and audio-visual stimuli classification because of their interpretability, scalability, and resilience to noise and missing data [76].

Linear Discriminant Analysis: It is primarily employed in dimensionality reduction methods to convert 2D planes into 1D planes. Next, it contains two criteria: minimizing variation inside the class and maximizing the distance between the means of two classes. When classes have an equal number of samples, LDA performs effectively. LDA can efficiently identify between these groups in EEG-based mental stress classification and audio-visual stimuli classification. Because LDA can handle Gaussian-like distributions, minimize class separability, reduce dimensionality, and prevent overfitting, it works well for classifying mental stress from EEG data and audio-visual stimuli classification. It is a good option for categorizing mental stress based on EEG variables because of its interpretability, computational efficiency, and efficacy with both small and big datasets, especially when the data is consistent with the underlying assumptions of LDA [76] .

6 Performance Evaluation

The overall results of this research were discussed in this section. Results using the traditional pre-processing pipeline were discussed in subsection 6.1. Results using the proposed pre-processing pipeline were shown in subsection 6.2. Comparative study between these two pipelines were depicted in subsection 6.3.

6.1 RESULTS USING TRADITIONAL PRE-PROCESSING PIPELINE

In this subsection, results were shown for the traditional pre-processing pipelines. Binary and multi-level (three and four level) stress were classified successfully using traditional pre-processing pipeline following the similar way like proposed pre-processing pipeline. In this study, binary stress classification was performed on EEG data recorded during a relaxed state and on EEG data collected while hard math problems were solved. Three levels of stress were classified based on EEG data during the solving of math problems categorized as easy, medium, and hard. Additionally, four stress levels were identified, which included the relaxed state and the stress levels associated with solving easy, medium, and hard math problems. Finally, binary classification between audio and visual data using traditional pre-processing was also done.

The accuracy, precision, recall, and F1 scores for each machine learning model were shown for binary stress classification in Tables 6.1. and 6.4. In Tables 6.2. Table 6.3. Table 6.5 and Table 6.6, accuracy, macro F1 scores and weighted F1 scores for multi-level including both three level and four level stress classification for visual and auditory stimuli were shown.

In Table 6.7, results were shown in a tabular format for audio and visual EEG data binary classification. The study found that the best classification accuracy for visual stimuli was

85.26% for binary stress classification, 76.77% accuracy for three level stress classification and 67.46% accuracy for four level stress classification, while the best accuracy for auditory stimuli was 85.26% accuracy for binary stress classification, 77.46% accuracy for three level stress classification and 66.61% accuracy for four level stress classification.

Table 6.1. Binary stress classification from visual stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	84	61	69	65
Linear Discriminant	75	59	59	51
KNN	83	57	89	69
SVM	85	72	63	60

Table 6.2. Three level stress classification from visual stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	73.01	69	74
Linear Discriminant	71.26	68	72
KNN	75.53	73	76
SVM	77.67	73	79

Table 6.3. Four level stress classification from visual stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	50.17	46.45	53.03
Linear Discriminant	58.64	50.23	60.28
KNN	67.46	59.83	69.92
SVM	66.61	56.72	67.81

Table 6.4. Binary stress classification from auditory stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	85	81	79	80
Linear Discriminant	78	34	50	41
KNN	90	59	68	63
SVM	90	67	50	57

Table 6.5. Three level stress classification from auditory stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	57.31	57.12	57.31
Linear Discriminant	68.59	67.98	68.68
KNN	69.78	69.41	69.91
SVM	77.46	76.91	77.48

Table 6.6. Four level stress classification from auditory stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	55.51	57.62	56.20
Linear Discriminant	61.35	58.51	61.46
KNN	67.19	63.35	67.31
SVM	71.69	66.55	71.64

Table 6.7. Binary classification between visual and auditory stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	90.88	97	92	94
Linear Discriminant	93.67	95	93	94
KNN	95.71	98	94	96
SVM	97.21	98	97	97

By analysing all the results in tabular format, it is known that out of four machine learning models, SVM performed better in all cases of machine learning classification. As the dataset was linear in nature that is why SVM worked better.

In Fig. 6.1 (a), the best result found for binary stress classification was shown where the best accuracy was found 85.26% for SVM. Three level stress classification result was shown in Fig. 6.1. (b) where three different level stress was classified. Best accuracy 77.67% was found for SVM classifier. Again, for four level stress detection from visual stimuli, the best accuracy was found for SVM and that was 66.61% which is shown in Fig. 6.1. (c).

In the second steps of the work, binary and multi-level stress was classified from auditory stimuli. Here, mathematical word problem was heard by the participants instead of viewing the problem in image format. The audio was played for only once and then they need to solve that maths mentally which induces stress. In Fig. 6.2. (a), the best result found for binary stress classification was shown where the best accuracy was found 94.84% for SVM. Three level stress classification result was shown in Fig. 6.2. (b) where three different level stress was classified. The best accuracy found was 77.46% for SVM classifier. Finally, for four level stress detection from auditory stimuli, the best accuracy was found for SVM and that was 71.69% which is shown in Fig. 6.2. (c).

True Class \ Predicted Class	Relaxed	Stressed
Relaxed	11.27%	10.40%
Stressed	4.34%	73.99%

(a)

True Class \ Predicted Class	Low	Medium	High
Low	9.9%	2.33%	4.46%
Medium	3.49%	21.94%	5.05%
High	4.07%	2.91%	45.83%

(b)

True Class \ Predicted Class	Relaxed	Low	Medium	High
Relaxed	4.23%	6.44%	1.19%	0.85%
Low	6.78%	5.93%	1.19%	0.85%
Medium	1.69%	1.19%	19.66%	4.07%
High	3.39%	2.71%	3.05%	36.78%

(c)

Fig. 6.1. Confusion matrix for stress classification from visual stimuli
(a) binary (b) three level (c) four level

True Class	Relaxed	Stressed
Relaxed	8.45%	4.22%
Stressed	0.94%	86.38%

Predicted Class

(a)

True Class	Low	Medium	High
Low	17.03%	1.19%	4.79%
Medium	2.39%	26.14%	4.08%
High	4.31%	5.76%	34.29%

Predicted Class

(b)

True Class	Relaxed	Low	Medium	High
Relaxed	2.92%	0.90%	0.67%	1.57%
Low	0.45%	13.93%	4.04%	3.15%
Medium	0.67%	1.57%	24.72%	3.59%
High	1.35%	6.29%	4.04%	30.11%

Predicted Class

(c)

Fig. 6.2. Confusion matrix for stress classification from auditory stimuli
(a) binary (b) three level (c) four level

In the last stage of the research work, binary classification of EEG data between audio and visual stimuli was done. In Fig. 6.3, Confusion matrix for binary classification between visual and auditory stimuli was shown where best accuracy was found 97.21% for SVM.

True Class \ Predicted Class	Visual	Auditory
Visual	53.54%	1.72%
Auditory	1.07%	43.67%

Fig. 6.3. Confusion matrix for binary classification between visual and auditory stimuli

6.2 RESULTS USING PROPOSED PRE-PROCESSING PIPELINE

Insightful findings and all the results are described in this section. Total seven datasets were made by combining all the features extracted from the data. In first dataset only relaxed and stressed data features were combined for visual stimuli. In second dataset, three level stressed data features were combined for the visual stimuli. In third dataset, eye closed relaxed data and three level stressed data features were assembled for four class stress classification for visual stimuli. On the other hand, eye-closed and stressed data features for auditory stimuli were combined in the fourth dataset and three level stressed data features for auditory stimuli were combined in the fifth dataset. Again, eye closed relaxed data and three level stressed data features were assembled for four class stress classification for auditory stimuli in sixth dataset. Last but not the least, the seventh dataset was based on both the combination of audio and visual stimuli data features. Similarly, seven more datasets were made for the traditional pre-processing pipelines following the same way. In each case, 80% data was taken for training and 20% data was taken for testing purpose. Several machine learning models were employed, and four models outperformed out of all the models. Those four models were- Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Decision Tree (DT) and Linear Discriminant. The dataset was imbalanced initially as eye closed relaxed data was taken for five seconds whereas hard math problem solving involved higher time duration. Again, in multi-level stress detection dataset, three difficulty level math need different time duration for solving. The time limit for math solving was not fixed because othe target was to classify different levels of stress. If time limit was set for each level math solving, it will create e mental pressure for each case. In that scenario, different difficulties problems may exert same amount of stress. But the target was to classify multi-level stress. Along with that, all the datasets balanced before training ML models. SMOTE was used in this purpose to balance the dataset.

Table 6.8. Binary stress classification from visual stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	91.43	66	66	66
Linear Discriminant	93.93	73	83	77
KNN	97.12	94	83	88
SVM	**97.14**	**94**	**86**	**90**

Table 6.9. Three level stress classification from visual stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	74.00	70	74
Linear Discriminant	73.15	71	74
KNN	84.35	83	85
SVM	**89.01**	**87**	**89**

Table 6.10. Four level stress classification from visual stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	74.46	71.11	74.46
Linear Discriminant	73.48	73.10	73.48
KNN	85.27	85.14	85.27
SVM	**89.59**	**88.52**	**89.59**

Table 6.11. Binary stress classification from auditory stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	90.11	57	57	57
Linear Discriminant	80.77	49	52	49
KNN	93.96	73	67	74
SVM	**94.51**	**82**	**76**	**79**

Table 6.12. Three level stress classification from auditory stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	68.00	66.00	68.00
Linear Discriminant	73.00	72.00	73.00
KNN	86.00	86.00	86.00
SVM	**88.00**	**87.00**	**88.00**

Table 6.13. Four level stress classification from auditory stimuli

Model Name	Accuracy (%)	Macro F1 Score (%)	Weighted F1 Score (%)
Decision Tree	63.68	61.94	63.68
Linear Discriminant	69.74	64.43	69.74
KNN	79.47	73.90	79.28
SVM	**82.63**	**78.64**	**82.44**

The accuracy, precision, recall, and F1 scores for each machine learning model were shown for binary stress classification in Tables 6.8. and 6.11. In Tables 6.9. Table 6.10. Table 6.12. and Table 6.13, accuracy, macro F1 scores and weighted F1 scores for multi-level including both three level and four level stress classification were shown.

In Table 6.14, results were shown in a tabular format for audio and visual EEG data binary classification. The study found that the best classification accuracy for visual stimuli was 97.14% for binary stress classification, 89.01% accuracy for three level stress classification and 89.59% accuracy for four level stress classification, while the best accuracy for auditory stimuli was 94.51% accuracy for binary stress classification, 87.7% accuracy for three level stress classification and 82.63% accuracy for four level stress classification. This indicates that compared to auditory and visual evoked potentials, visual evoked potentials were more accurate for both binary and multi-level stress classification.

Table 6.14. Binary classification between visual and auditory stimuli

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	95.43	66	66	66
Linear Discriminant	93.93	73	83	77
KNN	97.12	94	83	88
SVM	**97.14**	**94**	**86**	**90**

By analysing all the results in tabular format, it is known that out of four machine learning models, SVM performed better in all cases of machine learning classification. As the dataset was linear in nature that is why SVM worked better. In Fig. 6.4 (a), the best result found for binary stress classification was shown where the best accuracy was found 97.14% for SVM. Three level stress classification result was shown in Fig. 6.4. (b) where three different level stress was classified. The best accuracy was found 89.01% for SVM classifier. Again, for four level stress detection from visual stimuli, the best accuracy was found for SVM and that was 89.59% which is shown in Fig. 6.4. (c).

In the second steps of the work, binary and multi-level stress was classified from auditory stimuli. Here, mathematical word problem was heard by the participants instead of viewing the problem in image format. The audio was played for only once and then they need to solve that maths mentally which induces stress. In Fig. 6.5. (a), the best result found for binary stress classification was shown where the best accuracy was found 94.51% for SVM. Three level stress classification result was shown in Fig. 6.5. (b) where three different level stress was classified. The best accuracy was found 87.70% for SVM classifier. Finally, for four level stress detection from auditory stimuli, the best accuracy was found for SVM and that was 82.63% which is shown in Fig. 6.5. (c).

True Class \ Predicted Class	Relaxed	Stressed
Relaxed	10.35%	2.14%
Stressed	0.714%	86.78%

(a)

True Class \ Predicted Class	Low	Medium	High
Low	16.89%	2.14%	8.85%
Medium	1.34%	34.05%	4.02%
High	1.34%	2.68%	35.12%

(b)

True Class \ Predicted Class	Relaxed	Low	Medium	High
Relaxed	6.09%	0.19%	0%	0.78%
Low	0%	12.18%	0.98%	2.55%
Medium	0%	1.375%	24.56%	2.75%
High	0%	0.98%	0.78%	46.76%

(c)

Fig. 6.4. Confusion matrix for stress classification from visual stimuli
(a) binary (b) three level (c) four level

True Class \ Predicted Class	Relaxed	Stressed
Relaxed	7.69%	3.85%
Stressed	1.65%	86.81%

(a)

True Class \ Predicted Class	Low	Medium	High
Low	17.88%	1.68%	2.79%
Medium	1.68%	27.93%	2.79%
High	1.40%	1.96%	41.90%

(b)

True Class \ Predicted Class	Relaxed	Low	Medium	High
Relaxed	2.89%	0.52%	1.31%	0.79%
Low	0%	17.63%	1.57%	2.1%
Medium	0.26%	0.79%	25.26%	4.21%
High	0.26%	1.84%	3.68%	36.84%

(c)

Fig. 6.5. Confusion matrix for stress classification from auditory stimuli
(a) binary (b) three level (c) four level

In Fig. 6.4. (a), (b) and 6.5. (b), (c), it is noticed that higher false values in multi-level stress classification comparing with the binary stress classification results because in binary classification, the highest stressed data and relaxed data was classified where the boundary line was more clear. On the other hand, in case of multi-level stress classification, three difficulty level math- easy, medium and hard problems were given to the participants where in few cases, some participants found the medium problem as hard and some hard problem seems medium level difficulty to them. As, difficulty level varies from participants to participants in very few cases, that is why some false values was received during multi-level stress classification.

In the last stage of the research work, binary classification of EEG data between audio and visual stimuli was done. In Fig. 6.6, Confusion matrix for binary classification between visual and auditory stimuli was shown where best accuracy was found 98.32% for SVM.

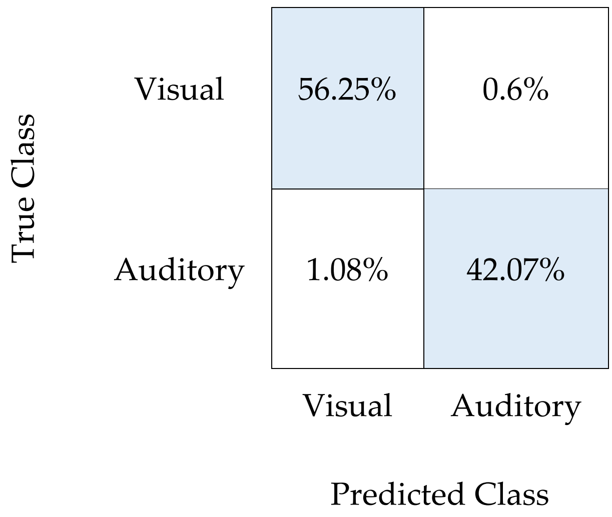


Fig. 6.6. Confusion matrix for binary classification between visual and auditory stimuli

6.3 COMPARISON BETWEEN TRADITIONAL AND PROPOSED PRE-PROCESSING PIPELINE

In this subsection, a comparison was shown between the two pre-processing pipelines. From the Table 6.15. 6.16. 6.17. 6.18. 6.19. 6.20. and 6.21, it can be said that the proposed pre-processing pipeline performed well than the traditional method. The proposed method cleaned data more efficiently and retained more information simultaneously.

Table 6.15. Comparison summary between the two pre-processing pipelines for binary stress classification from visual stimuli

Model Name	Traditional Pipeline	Proposed Pipeline
Decision Tree	83.82	91.43
Linear Discriminant	75.43	93.93
KNN	82.95	97.12
SVM	85.26	97.14

Table 6.16. Comparison summary between the two pre-processing pipelines for three level stress classification from visual stimuli

Model Name	Traditional Pipeline	Proposed Pipeline
Decision Tree	73.01	74.00
Linear Discriminant	71.26	73.15
KNN	75.53	84.35
SVM	77.67	89.01

Table 6.17. Comparison summary between the two pre-processing pipelines for four level stress classification from visual stimuli

Model Name	Traditional Pipeline	Proposed Pipeline
Decision Tree	50.17	74.46
Linear Discriminant	58.64	73.48
KNN	67.46	85.27
SVM	66.61	89.59

Table 6.18. Comparison summary between the two pre-processing pipelines for binary stress classification from auditory stimuli

Model Name	Traditional Pipeline	Proposed Pipeline
Decision Tree	85.00	90.11
Linear Discriminant	78.00	80.77
KNN	90.00	93.96
SVM	90.00	94.51

Table 6.19. Comparison summary between the two pre-processing pipelines for three level stress classification from auditory stimuli

Model Name	Traditional Pipeline	Proposed Pipeline
Decision Tree	57.31	68.00
Linear Discriminant	68.59	73.00
KNN	69.78	86.00
SVM	77.46	88.00

Table 6.20. Comparison summary between the two pre-processing pipelines for four level stress classification from auditory stimuli

Model Name	Traditional Pipeline	Proposed Pipeline
Decision Tree	55.51	63.68
Linear Discriminant	61.35	69.74
KNN	67.19	79.47
SVM	71.69	82.63

Table 6.21. Comparison summary between the two pre-processing pipelines for audio visual stimuli binary classification

Model Name	Traditional Pipeline	Proposed Pipeline
Decision Tree	93.88	95.71
Linear Discriminant	93.67	95.07
KNN	95.71	97.48
SVM	97.21	98.32

In addition to cleaning the data more effectively, the pipeline kept the relevant information in the data. As a result, it is advised for future studies to thoroughly review and pre-process the EEG data. Despite the potential time commitment, this method is worthwhile.

Table 6.22 summarizes different types of stimuli used in previous works. Most of the authors used mental arithmetic task as visual stimuli but none of them used mental arithmetic task as auditory stimuli for inducing stress. Besides that, none of the works classified four level stress and it is still unchecked. In all the works, the researchers employed traditional machine learning models and found satisfactory results. For visual stimuli, the highest accuracy for binary stress detection was 96% whereas in the research work 97.14% accuracy was found. Again, for three level stress detection, greatest accuracy was found 94.79% for visual stimuli whereas highest 89.01% accuracy was achieved. From audio stimuli, 87.7% highest accuracy was got for three level stress classification. Four level stress was also classified successfully and found highest accuracy 89.56% for visual stimuli and 82.63% for auditory stimuli.

Table 6.22. Comparison study for two and three level stress classification

Reference	Stimuli/Stressor Used	No. of Channels	No. of Subjects	No. of Features	Classification Type	Method	Accuracy
Altaf et al. [15]	Mental arithmetic exercises	1	30	12	Two-level stress	Naive Bayes	95%
Perez-Valero et al. [1]	Mental arithmetic task	8	20	2	Three level stress	SVM with smooth filter	81%
					Two-level stress	Multi-layer protection without filter	94%
Islam et al. [24]	Mental arithmetic task	21	11	4	Two-level stress	Ensemble Subspace KNN	77.3%
Akella et al. [8]	Mental arithmetic task	32	80	3	Three level stress	SVM	91%
Jun et al. [14]	Mental arithmetic task	14	10	-	Three level stress	SVM	75%
					Two-level stress		96%
Shargie et al. [5]	Mental arithmetic task	7	18	18	Three level stress	SVM with ECOC	94.79%
Hafeez et al. [39]	Montreal Imaging Stress Task-based mental arithmetic task	8	14	1	Three level stress	LSTM	70.67%
Chowdhury et al. [40]	Mental arithmetic task	1	5	1	Two-level stress	Random Forest	86.9%
Ahn et al. [41]	Mental arithmetic task	2	14	4	Two-level stress	SVM	77.9%
Rajendran et al. [42]	Mental arithmetic task	8	25	12	Two-level stress	SVM	95.83%
Saidatul et al. [43]	Mental arithmetic task	19	30	2	Three level stress	KNN	84%
Proposed Work	**Mathematical Word Problem as visual stimuli**	**16**	**30**	**14**	**Two level stress**	**SVM**	**97.14%**
					Three level stress		**89.01%**
					Four level stress		**89.59%**
	Mathematical Word Problem as audio stimuli				**Two level stress**		**95.51%**
					Three level stress		**87.17%**
					Four level stress		**82.63%**

7 Conclusions

This chapter presents the general methods and results of the investigation. It provides an overview of the approach and outcomes section discussion. This chapter also includes the study's relevance, important findings, and limitations. Researchers that are interested in this subject will find some ideas to work with under the paragraph on future research.

7.1 GENERAL SUMMARY

The goal of the developing field of brain-computer interface research on human mental stress detection is to identify stress levels early on since they can lead to more serious physical and psychological disorders. It offers psychologists and doctors insightful information that they may use to alter the way they advise and treat patients. Still, there is a lot to learn about the current state of EEG-based mental stress detection and its classification accuracy.

Since noisy EEG data is unlikely to produce improved findings, the effectiveness of an EEG-based preference prediction system mostly rests on the appropriate selection of an appropriate EEG pre-processing pipeline. Most of the research used a conventional EEG pre-processing pipeline, however more recently, the literature has introduced an advanced automated EEG pre-processing pipeline. A new EEG pre-processing pipeline was suggested in this study and have contrasted it with the traditional approach. Using the two pre-processing pipelines, the raw EEG data was pre-processed. After that, several machine-learning classification models were used and retrieved several statistical and frequency domain variables. The suggested pipeline for pre-processing EEG data was put into practice, and a noticeable increase in classification accuracy was observed.

By examining EEG data, earlier research has employed several machine learning models to forecast various stress levels. The majority of the works focused on classifying stress into two and three levels. There are not many studies that concentrate on the four-level stress categorization, and the accuracy was not good either. Once more, the majority of literary works categorized stress levels based on visual inputs. Only a small number of researchers employed auditory stimuli, and none of them used mathematical arithmetic problems as auditory stimuli. In this research, two, three and four levels of stress were classified from both visual and auditory stimuli. Again, a pre-processing pipeline was proposed for noise removal purpose and a significant improvement in accuracy was found comparing with the traditional way of pre-processing.

Finally, the binary classification of audio and visual stimuli was done with good accuracy. In conventional eye and hearing tests, the subject's respond to and input regarding how much they can see or hear any English alphabet is what determines the outcome of the test. But occasionally, elderly, and young people provide inaccurate input, which can lead to incorrect test results as well. So, in this study, audio and visual stimuli was classified successfully with higher accuracy and children and older adults' hearing and sighting conditions can be tested using this audio-visual stimulus categorization system. The test results can also be compared to those of standard hearing and sight testing to provide a clearer understanding of the findings.

7.2 KEY FINDINGS

The following summarizes the study's main conclusions:

- Auditory and visual stimuli was designed successfully. Real time EEG data was collected from the subjects and created a private dataset. An important finding of this research was that the medial-frontal brain region is particularly relevant to mental stress classification.

- An optimal EEG pre-processing pipeline was presented and compared it with the conventional techniques. For each classifier, the suggested pre-processing pipeline outperformed the traditional approach. With SVM, the best accuracy was achieved. The highest accuracy was 97.14%, 89.01%, 89.59% for two, three and four level stress detection using visual stimulation. By contrast, the conventional pipeline produced results of 85%, 77.67% and 66.6%.
- In this research, two, three and four level stress were classified from both visual and auditory stimuli. The highest accuracy for two, three and four level stress classification were 97.14%, 89.01% and 89.59% respectively from visual stimuli. On the other hand, 95.51%, 87.17%, 82.63% accuracy was found for two, three and four level stress classification from auditory stimuli.
- The audio and visual stimuli was successfully classified with 98.32% accuracy using the proposed pre-processing pipeline and 97.21% accuracy using the traditional pre-processing pipeline. These findings can create a great impact for eyesight and hearing test for children and aged people.

7.3 SIGNIFICANCE OF THE WORK

Traditional methods often classify stress as either "present" or "absent," or into only two levels (low/high). A four-level classification (e.g., no stress, mild stress, moderate stress, and high stress) offers a more nuanced view of a person's mental state. This enables early intervention, especially before stress becomes severe. Mental stress is a precursor to anxiety, burnout, and depression. Continuous monitoring using EEG with fine stress levels allows better tracking of changes in emotional and cognitive health. Especially valuable in high-risk environments for example: healthcare, military, aviation etc. Multi-class classification (four levels) improves the richness of training data, allowing more robust and accurate

AI models. Offers realistic feedback for biofeedback systems or adaptive environments (like adjusting workload or lighting based on stress levels). Personalized stress management systems (apps, wearables) can respond more precisely to the user's current stress level. Supports tailored therapies, such as cognitive behavioral therapy (CBT) or mindfulness programs, based on stress level detected.

Researchers studying brain activity and human behavior can correlate specific brainwave patterns with different stress intensities. Helps in understanding how stress affects memory, focus, and decision-making under various conditions.

In workplaces and schools, detecting and responding to moderate vs. high stress can help reduce errors and improve performance. Can be integrated into training simulations or learning platforms to optimize timing and difficulty based on user stress.

7.4 RECOMMENDATIONS FOR FURTHER STUDY

The categorization of mental stress based on electroencephalogram (EEG) is a fast-developing topic with great potential for theoretical and practical developments. One may help create stress detection systems that are more precise, dependable, and easy to use. These systems may have a significant impact on people's mental health and general well-being.

For automated feature extraction and categorization, one can investigate the use of deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs). Again, more advanced time-frequency analysis methods, including empirical mode decomposition (EMD) and wavelet transform, might be investigated to identify transitory and non-stationary stress-related characteristics in EEG data.

The robustness and accuracy of stress classification can be increased by combining EEG data with additional physiological markers, such as pupil dilation, galvanic skin response (GSR), and heart rate variability (HRV). For ongoing mental stress monitoring, real-time EEG processing and classification systems can be investigated. These systems might be used during crucial activities or in high-stress situations like the workplace.

There is a great opportunity to include cooperation with neuroscientists, psychologists, and physicians in order to get a deeper comprehension of the neurological foundations of stress and to validate the EEG characteristics and models utilized for stress categorization. There is a chance to investigate the integration of EEG-based stress detection into therapeutic treatments targeted at stress reduction in collaboration with neurofeedback specialists.

Bibliography

[1] E. Perez-Valero, M. A. Lopez-Gordo, and M. A. Vaquero-Blasco, "EEG-based multi-level stress classification with and without smoothing filter," *Biomed. Signal Process. Control*, vol. 69, p. 102881, 2021, doi: 10.1016/j.bspc.2021.102881.

[2] R. Gupta, M. A. Alam, and P. Agarwal, "Modified Support Vector Machine for Detecting Stress Level Using EEG Signals," *Comput. Intell. Neurosci.*, vol. 2020, 2020, doi: 10.1155/2020/8860841.

[3] Q. Yao, H. Gu, S. Wang, G. Liang, X. Zhao, and X. Li, "Exploring EEG characteristics of multi-level mental stress based on human-machine system," *J. Neural Eng.*, vol. 20, no. 5, 2023, doi: 10.1088/1741-2552/acfbba.

[4] R. Kishore Kanna and R. Vasuki, "Advanced study of ICA in EEG and signal acquisition using MyDAQ and lab view application," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 7, pp. 2799–2806, 2019.

[5] Z. Gao *et al.*, "Complex networks and deep learning for EEG signal analysis," *Cogn. Neurodyn.*, vol. 15, no. 3, pp. 369–388, 2021, doi: 10.1007/s11571-020-09626-1.

[6] A. R. Subhani, W. Mumtaz, M. N. B. M. Saad, N. Kamel, and A. S. Malik, "Machine learning framework for the detection of mental stress at multiple levels," *IEEE Access*, vol. 5, pp. 13545–13556, 2017, doi: 10.1109/ACCESS.2017.2723622.

[7] F. Al-shargie, T. B. Tang, N. Badruddin, and M. Kiguchi, "Towards multilevel mental stress assessment using SVM with ECOC: an EEG approach," *Med. Biol. Eng. Comput.*, vol. 56, no. 1, pp. 125–136, 2018, doi: 10.1007/s11517-017-1733-8.

[8] M. F. K. Khondakar, T. G. Trovee, M. Hasan, M. H. Sarowar, M. H.

Chowdhury, and Q. D. Hossain, "A Comparative Analysis of Different Pre-Processing Pipelines for EEG-Based Preference Prediction in Neuromarketing," *2023 IEEE Pune Sect. Int. Conf. PuneCon 2023*, 2023, doi: 10.1109/PuneCon58714.2023.10450086.

[9] G. Giannakakis, M. R. Koujan, A. Roussos, and K. Marias, "Automatic stress detection evaluating models of facial action units," *Proc. - 2020 15th IEEE Int. Conf. Autom. Face Gesture Recognition, FG 2020*, no. Fg, pp. 728–733, 2020, doi: 10.1109/FG47880.2020.00129.

[10] T. Jeon, H. Bae, Y. Lee, S. Jang, and S. Lee, "Stress recognition using face images and facial landmarks," *2020 Int. Conf. Electron. Information, Commun. ICEIC 2020*, vol. 00562, pp. 14–16, 2020, doi: 10.1109/ICEIC49074.2020.9051145.

[11] S. Pourmohammadi and A. Maleki, "Stress detection using ECG and EMG signals: A comprehensive study," *Comput. Methods Programs Biomed.*, vol. 193, 2020, doi: 10.1016/j.cmpb.2020.105482.

[12] P. Zontone, A. Affanni, R. Bernardini, A. Piras, and R. Rinaldo, "Stress detection through Electrodermal Activity (EDA) and Electrocardiogram (ECG) analysis in car drivers," *Eur. Signal Process. Conf.*, vol. 2019-Septe, pp. 1–5, 2019, doi: 10.23919/EUSIPCO.2019.8902631.

[13] A. Affanni, "Wireless sensors system for stress detection by means of ECG and EDA acquisition," *Sensors (Switzerland)*, vol. 20, no. 7, pp. 15–22, 2020, doi: 10.3390/s20072026.

[14] M. Huang, M. Risling, and D. G. Baker, "The role of biomarkers and MEG-based imaging markers in the diagnosis of post-traumatic stress disorder and blast-induced mild traumatic brain injury," *Psychoneuroendocrinology*, vol. 63, pp. 398–409, 2016, doi: 10.1016/j.psyneuen.2015.02.008.

[15] J. B. Allendorfer *et al.*, "FMRI response to acute psychological stress differentiates patients with psychogenic non-epileptic seizures from healthy controls – A biochemical and neuroimaging biomarker study,"

NeuroImage Clin., vol. 24, no. August, p. 101967, 2019, doi: 10.1016/j.nicl.2019.101967.

[16] X. Zhong *et al.*, “Childhood Maltreatment Experience Influences Neural Response to Psychosocial Stress in Adults: An fMRI Study,” *Front. Psychol.*, vol. 10, no. January, pp. 1–9, 2020, doi: 10.3389/fpsyg.2019.02961.

[17] M. F. K. Khondakar *et al.*, “A systematic review on EEG-based neuromarketing: recent trends and analyzing techniques,” *Brain Informatics*, vol. 11, no. 1, 2024, doi: 10.1186/s40708-024-00229-8.

[18] S. Khalighi *et al.*, “Classification of electroencephalogram (eeg) signal based on fourier transform and neural network,”ethesis.nitrkl, vol. 86, no. 1, pp. 1–2, 2015.

[19] J. J. Newson and T. C. Thiagarajan, “EEG Frequency Bands in Psychiatric Disorders: A Review of Resting State Studies,” *Front. Hum. Neurosci.*, vol. 12, no. January, pp. 1–24, 2019, doi: 10.3389/fnhum.2018.00521.

[20] S. A. A. Shah, L. Zhang, and A. Bais, “Dynamical system based compact deep hybrid network for classification of Parkinson disease related EEG signals,” *Neural Networks*, vol. 130, pp. 75–84, 2020, doi: 10.1016/j.neunet.2020.06.018.

[21] A. J. Ries, J. Touryan, J. Vettel, K. Mcdowell, and W. D. Hairston, “A comparison of electroencephalography signal acquired from Conventional and Mobile Systems,” Journal of Neuroscience and neuroengineering, pp. 10–20, 2014, doi: 10.1166/jnsne.2014.1092.

[22] M. R. Carneiro, A. T. De Almeida, and M. Tavakoli, “Wearable and Comfortable e-Textile Headband for Long-Term Acquisition of Forehead EEG Signals,” *IEEE Sens. J.*, vol. 20, no. 24, pp. 15107–15116, 2020, doi: 10.1109/JSEN.2020.3009629.

[23] S. Park and C. Han, “Design of Wearable EEG Devices Specialized for Passive Brain – Computer Interface Applications,” Sensors, mdpi ,2020, doi: 10.3390/s20164572.

[24] N. Browarska, A. Kawala-sterniuk, J. Zygarlicki, and M. Podpora, "brain sciences Comparison of Smoothing Filters ' Influence on Quality of Data Recorded with the Emotiv EPOC Flex Brain – Computer Interface Headset during Audio Stimulation,"brain sciences,mdpi, 2021.

[25] F. Laport, F. J. Vazquez-araujo, D. Iglesia, and P. M. Castro, "A Comparative Study of Low Cost Open Source," 2nd XoveTIC conference, pp. 20–22, September, 2019, doi: 10.3390/proceedings2019021040.

[26] Y. N. Cardona-álvarez, A. M. Álvarez-meza, D. A. Cárdenas-peña, G. A. Castaño-duque, and G. Castellanos-dominguez, "A Novel OpenBCI Framework for EEG-Based Neurophysiological Experiments,"sensors, mdpi, pp. 1–24, 2023.

[27] A. H. Al-Nuaimi *et al.*, "Robust EEG-based biomarkers to detect alzheimer's disease," *Brain Sci.*, vol. 11, no. 8, pp. 1–31, 2021, doi: 10.3390/brainsci11081026.

[28] S. Dogan *et al.*, "Primate brain pattern-based automated Alzheimer's disease detection model using EEG signals," *Cogn. Neurodyn.*, vol. 17, no. 3, pp. 647–659, 2023, doi: 10.1007/s11571-022-09859-2.

[29] M. Cejnek, O. Vysata, M. Valis, and I. Bukovsky, "Novelty detection-based approach for Alzheimer's disease and mild cognitive impairment diagnosis from EEG," *Med. Biol. Eng. Comput.*, vol. 59, no. 11–12, pp. 2287–2296, 2021, doi: 10.1007/s11517-021-02427-6.

[30] V. Bairagi, "EEG signal analysis for early diagnosis of Alzheimer disease using spectral and wavelet based features," *Int. J. Inf. Technol.*, vol. 10, no. 3, pp. 403–412, 2018, doi: 10.1007/s41870-018-0165-5.

[31] J. Seo, T. H. Laine, G. Oh, and K. A. Sohn, "EEG-based emotion classification for Alzheimer's disease patients using conventional machine learning and recurrent neural network models," *Sensors (Switzerland)*, vol. 20, no. 24, pp. 1–27, 2020, doi: 10.3390/s20247212.

[32] N. N. Kulkarni and V. K. Bairagi, "Extracting Salient Features for EEG-

based Diagnosis of Alzheimer's Disease Using Support Vector Machine Classifier," *IETE J. Res.*, vol. 63, no. 1, pp. 11–22, 2017, doi: 10.1080/03772063.2016.1241164.

[33] J. Saini and M. Dutta, "An extensive review on development of EEG-based computer-aided diagnosis systems for epilepsy detection," *Netw. Comput. Neural Syst.*, vol. 28, no. 1, pp. 1–27, 2017, doi: 10.1080/0954898X.2017.1325527.

[34] Z. Chen, G. Lu, Z. Xie, and W. Shang, "A unified framework and method for EEG-Based early epileptic seizure detection and epilepsy diagnosis," *IEEE Access*, vol. 8, pp. 20080–20092, 2020, doi: 10.1109/ACCESS.2020.2969055.

[35] N. Betrouni *et al.*, "Electroencephalography-based machine learning for cognitive profiling in Parkinson's disease: Preliminary results," *Mov. Disord.*, vol. 34, no. 2, pp. 210–217, 2019, doi: 10.1002/mds.27528.

[36] M. Koch, V. Geraedts, H. Wang, M. Tannemaat, and T. Back, "Automated Machine Learning for EEG-Based Classification of Parkinson's Disease Patients," *Proc. - 2019 IEEE Int. Conf. Big Data, Big Data 2019*, pp. 4845–4852, 2019, doi: 10.1109/BigData47090.2019.9006599.

[37] P. An, Z. Yuan, J. Zhao, X. Jiang, and B. Du, "An effective multi-model fusion method for EEG-based sleep stage classification," *Knowledge-Based Syst.*, vol. 219, 2021, doi: 10.1016/j.knosys.2021.106890.

[38] E. Eldele *et al.*, "An Attention-Based Deep Learning Approach for Sleep Stage Classification with Single-Channel EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 809–818, 2021, doi: 10.1109/TNSRE.2021.3076234.

[39] W. Qu *et al.*, "A Residual Based Attention Model for EEG Based Sleep Staging," *IEEE J. Biomed. Heal. Informatics*, vol. 24, no. 10, pp. 2833–2843, 2020, doi: 10.1109/JBHI.2020.2978004.

[40] H. Huang *et al.*, "Eeg-based sleep staging analysis with functional connectivity," *Sensors*, vol. 21, no. 6, pp. 1–15, 2021, doi: 10.3390/s21061988.

[41] S. Yasin, S. A. Hussain, S. Aslan, I. Raza, M. Muzammel, and A. Othmani, "EEG based Major Depressive disorder and Bipolar disorder detection using Neural Networks:A review," *Comput. Methods Programs Biomed.*, vol. 202, 2021, doi: 10.1016/j.cmpb.2021.106007.

[42] Y. Li *et al.*, "A novel EEG-based major depressive disorder detection framework with two-stage feature selection," *BMC Med. Inform. Decis. Mak.*, vol. 22, no. 1, pp. 1–13, 2022, doi: 10.1186/s12911-022-01956-w.

[43] G. Sharma, A. Parashar, and A. M. Joshi, "DepHNN: A novel hybrid neural network for electroencephalogram (EEG)-based screening of depression," *Biomed. Signal Process. Control*, vol. 66, no. December 2020, p. 102393, 2021, doi: 10.1016/j.bspc.2020.102393.

[44] P. Lahane, J. Jagtap, A. Inamdar, N. Karne, and R. Dev, "A review of recent trends in EEG based Brain-Computer Interface," *ICCIDS 2019 - 2nd Int. Conf. Comput. Intell. Data Sci. Proc.*, pp. 1–6, 2019, doi: 10.1109/ICCIDS.2019.8862054.

[45] K. Douibi, S. Le Bars, A. Lemontey, L. Nag, R. Balp, and G. Breda, "Toward EEG-Based BCI Applications for Industry 4.0: Challenges and Possible Applications," *Front. Hum. Neurosci.*, vol. 15, no. August, pp. 1–8, 2021, doi: 10.3389/fnhum.2021.705064.

[46] K. Värbu, N. Muhammad, and Y. Muhammad, "Past, Present, and Future of EEG-Based BCI Applications," *Sensors*, vol. 22, no. 9, 2022, doi: 10.3390/s22093331.

[47] M. Rashid *et al.*, "Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review," *Front. Neurorobot.*, vol. 14, no. June, pp. 1–35, 2020, doi: 10.3389/fnbot.2020.00025.

[48] K. M. Hossain, M. A. Islam, S. Hossain, A. Nijholt, and M. A. R. Ahad, "Status of deep learning for EEG-based brain–computer interface applications," *Front. Comput. Neurosci.*, vol. 16, no. i, 2023, doi: 10.3389/fncom.2022.1006763.

[49] G. Vecchiato *et al.*, “Enhance of theta EEG spectral activity related to the memorization of commercial advertisings in Chinese and Italian subjects,” *Proc. - 2011 4th Int. Conf. Biomed. Eng. Informatics, BMEI 2011*, vol. 3, no. October, pp. 1491–1494, 2011, doi: 10.1109/BMEI.2011.6098615.

[50] K. A. Sorudeykin, “An Educative Brain-Computer Interface,” IEEE East-West Design & Test International Symposium, Moscow, September 2009, link: http://arxiv.org/abs/1003.2660

[51] A. A. Rahman *et al.*, “Detection of Mental State from EEG Signal Data: An Investigation with Machine Learning Classifiers,” *KST 2022 - 2022 14th Int. Conf. Knowl. Smart Technol.*, pp. 152–166, 2022, doi: 10.1109/KST53302.2022.9729084.

[52] L. Malviya and S. Mal, “CIS feature selection based dynamic ensemble selection model for human stress detection from EEG signals,” *Cluster Comput.*, vol. 26, no. 4, pp. 2367–2381, 2023, doi: 10.1007/s10586-023-04008-8.

[53] R. Lakhan, A. Agrawal, and M. Sharma, “Prevalence of Depression, Anxiety, and Stress during COVID-19 Pandemic,” *J. Neurosci. Rural Pract.*, vol. 11, no. 4, pp. 519–525, Oct. 2020, doi: 10.1055/s-0040-1716442.

[54] R. Costin, C. Rotariu, and A. Pasarica, “Mental stress detection using heart rate variability and morphologic variability of EeG signals,” *EPE 2012 - Proc. 2012 Int. Conf. Expo. Electr. Power Eng.*, no. Epe, pp. 591–596, 2012, doi: 10.1109/ICEPE.2012.6463870.

[55] B. S. Hantono, L. E. Nugroho, and P. I. Santosa, “Mental stress detection via heart rate variability using machine learning,” *Int. J. Electr. Eng. Informatics*, vol. 12, no. 3, pp. 431–444, 2020, doi: 10.15676/ijeei.2020.12.3.3.

[56] R. F. Navea, P. J. Buenvenida, and C. D. Cruz, “Stress Detection using Galvanic Skin Response: An Android Application,” *J. Phys. Conf. Ser.*, vol. 1372, no. 1, pp. 0–6, 2019, doi: 10.1088/1742-6596/1372/1/012001.

[57] S. Sriramprakash, V. D. Prasanna, and O. V. R. Murthy, “Stress Detection

in Working People," *Procedia Comput. Sci.*, vol. 115, pp. 359–366, 2017, doi: 10.1016/j.procs.2017.09.090.

[58] O. AlShorman *et al.*, "Frontal lobe real-time EEG analysis using machine learning techniques for mental stress detection," *J. Integr. Neurosci.*, vol. 21, no. 1, pp. 1–11, 2022, doi: 10.31083/j.jin2101020.

[59] R. Katmah, F. Al-Shargie, U. Tariq, F. Babiloni, F. Al-Mughairbi, and H. Al-Nashash, "A review on mental stress assessment methods using eeg signals," *Sensors*, vol. 21, no. 15, 2021, doi: 10.3390/s21155043.

[60] M. J. Hasan and J. M. Kim, "A hybrid feature pool-based emotional stress state detection algorithm using EEG signals," *Brain Sci.*, vol. 9, no. 12, 2019, doi: 10.3390/brainsci9120376.

[61] S. Koelstra *et al.*, "DEAP: A database for emotion analysis; Using physiological signals," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 18–31, 2012, doi: 10.1109/T-AFFC.2011.15.

[62] A. Hag, F. Al-Shargie, D. Handayani, and H. Asadi, "Mental Stress Classification Based on Selected Electroencephalography Channels Using Correlation Coefficient of Hjorth Parameters," *Brain Sci.*, vol. 13, no. 9, 2023, doi: 10.3390/brainsci13091340.

[63] H. S. A. Hamatta *et al.*, "Genetic Algorithm-Based Human Mental Stress Detection and Alerting in Internet of Things," *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/4086213.

[64] O. Attallah, "An effective mental stress state detection and evaluation system using minimum number of frontal brain electrodes," *Diagnostics*, vol. 10, no. 5, 2020, doi: 10.3390/diagnostics10050292.

[65] R. Sali, H. Roohafza, M. Sadeghi, E. Andalib, H. Shavandi, and N. Sarrafzadegan, "Validation of the revised stressful life event questionnaire using a hybrid model of genetic algorithm and artificial neural networks," *Comput. Math. Methods Med.*, vol. 2013, 2013, doi: 10.1155/2013/601640.

[66] M. Kang, S. Shin, J. Jung, and Y. T. Kim, "Classification of Mental Stress

Using CNN-LSTM Algorithms with Electrocardiogram Signals," *J. Healthc. Eng.*, vol. 2021, 2021, doi: 10.1155/2021/9951905.

[67] Q. Wang and O. Sourina, "Real-time mental arithmetic task recognition from EEG signals," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 2, pp. 225–232, 2013, doi: 10.1109/TNSRE.2012.2236576.

[68] A. Islam, A. K. Sarkar, and T. Ghosh, "EEG signal classification for mental stress during arithmetic task using wavelet transformation and statistical features," *2021 Int. Conf. Autom. Control Mechatronics Ind. 4.0, ACMI 2021*, vol. 0, no. July, pp. 8–9, 2021, doi: 10.1109/ACMI53878.2021.9528230.

[69] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals.," *Circulation*, vol. 101, no. 23, 2000, doi: 10.1161/01.cir.101.23.e215.

[70] W. L. Zheng, J. Y. Zhu, and B. L. Lu, "Identifying stable patterns over time for emotion recognition from eeg," *IEEE Trans. Affect. Comput.*, vol. 10, no. 3, pp. 417–429, 2019, doi: 10.1109/TAFFC.2017.2712143.

[71] A. Arsalan, M. Majid, A. R. Butt, and S. M. Anwar, "Classification of Perceived Mental Stress Using A Commercially Available EEG Headband," *IEEE J. Biomed. Heal. Informatics*, vol. 23, no. 6, pp. 2257–2264, 2019, doi: 10.1109/JBHI.2019.2926407.

[72] V. Markova, T. Ganchev, and K. Kalinkov, "CLAS: A Database for Cognitive Load, Affect and Stress Recognition," *Proc. Int. Conf. Biomed. Innov. Appl. BIA 2019*, 2019, doi: 10.1109/BIA48344.2019.8967457.

[73] B. Yan et al. , "EEG Evidence of Acute Stress Enhancing Inhibition Control by Increasing Attention," brain sciences ,2024,doi:10.3390/brain sci14101013.

[74] G. Vanhollebeke, M. Kappen, R. De Raedt, C. Baeken, P. van Mierlo, and M. A. Vanderhasselt, "Effects of acute psychosocial stress on source level EEG power and functional connectivity measures," *Sci. Rep.*, vol. 13, no. 1, pp. 1–13, 2023, doi: 10.1038/s41598-023-35808-y.

[75] M. A. Hafeez and S. Shakil, “EEG-based stress identification and classification using deep learning,” *Multimed. Tools Appl.*, vol. 83, no. 14, pp. 42703–42719, 2024, doi: 10.1007/s11042-023-17111-0.

[76] V. G. Rajendran, S. Jayalalitha, K. Adalarasu, and R. Mathi, “Machine learning based human mental state classification using wavelet packet decomposition-an EEG study,” *Multimed. Tools Appl.*, no. 0123456789, 2024, doi: 10.1007/s11042-024-18725-8.

[77] J. W. Ahn, Y. Ku, and H. C. Kim, “A novel wearable EEG and ECG recording system for stress assessment,” *Sensors (Switzerland)*, vol. 19, no. 9, 2019, doi: 10.3390/s19091991.

[78] A. Hag et al., “EEG Mental Stress Assessment Using Hybrid Multi-Domain Feature sets of Functional Connectivity Network and Time Frequency Features,” Sesnsors, 2021, doi: 10.3390/s21186300.

[79] A. H. Id, D. Atiwiwat, and P. Israsena, “ECG and EEG based detection and multilevel classification of stress using machine learning for specified genders : A preliminary study,” plos one, pp. 1–24, 2023, doi: 10.1371/journal.pone.0291070.

[80] S. A., P. Murugesa Pandiyan, and S. Yaacob, “The Assessment of Developed Mental Stress Elicitation Protocol Based on Heart Rate and EEG Signals,” *Int. J. Comput. Theory Eng.*, vol. 7, no. 3, pp. 207–213, 2015, doi: 10.7763/ijcte.2015.v7.958.

[81] L. Xia, A. Saeed, and A. Rauf, “Biomedical Signal Processing and Control A physiological signal-based method for early mental-stress detection,” *Biomed. Signal Process. Control*, vol. 46, pp. 18–32, 2018, [Online]. Available: https://doi.org/10.1016/j.bspc.2018.06.004

[82] K. Dedovic, A. Duchesne, J. Andrews, V. Engert, and J. C. Pruessner, “The brain and the stress axis: The neural correlates of cortisol regulation in response to stress,” *Neuroimage*, vol. 47, no. 3, pp. 864–871, 2009, doi: 10.1016/j.neuroimage.2009.05.074.

[83] J. C. Pruessner *et al.*, “Stress regulation in the central nervous system: evidence from structural and functional neuroimaging studies in human populations - 2008 Curt Richter Award Winner,” *Psychoneuroendocrinology*, vol. 35, no. 1, pp. 179–191, 2010, doi: 10.1016/j.psyneuen.2009.02.016.

[84] Y. Noto, T. Sato, M. Kudo, K. Kurata, and K. Hirota, “The relationship between salivary biomarkers and state-trait anxiety inventory score under mental arithmetic stress: A pilot study,” *Anesth. Analg.*, vol. 101, no. 6, pp. 1873–1876, 2005, doi: 10.1213/01.ANE.0000184196.60838.8D.

[85] I. Zyma *et al.*, “Electroencephalograms during mental arithmetic task performance,” *Data*, vol. 4, no. 1, pp. 2–7, 2019, doi: 10.3390/data4010014.

[86] R. Desai, P. Porob, P. Rebelo, D. R. Edla, and A. Bablani, “EEG Data Classification for Mental State Analysis Using Wavelet Packet Transform and Gaussian Process Classifier,” *Wirel. Pers. Commun.*, vol. 115, no. 3, pp. 2149–2169, 2020, doi: 10.1007/s11277-020-07675-7.

[87] A. Sundaresan, B. Penchina, S. Cheong, V. Grace, A. Valero-Cabré, and A. Martel, “Evaluating deep learning EEG-based mental stress classification in adolescents with autism for breathing entrainment BCI,” *Brain Informatics*, vol. 8, no. 1, 2021, doi: 10.1186/s40708-021-00133-5.

[88] M. Willmann, C. Langlet, J. P. Hainaut, and B. Bolmont, “The time course of autonomic parameters and muscle tension during recovery following a moderate cognitive stressor: Dependency on trait anxiety level,” *Int. J. Psychophysiol.*, vol. 84, no. 1, pp. 51–58, 2012, doi: 10.1016/j.ijpsycho.2012.01.009.

[89] F. Teixeira-Silva, G. B. Prado, L. C. G. Ribeiro, and J. R. Leite, “The anxiogenic video-recorded Stroop Color-Word Test: Psychological and physiological alterations and effects of diazepam,” *Physiol. Behav.*, vol. 82, no. 2–3, pp. 215–230, 2004, doi: 10.1016/j.physbeh.2004.03.031.

[90] A. Ali, R. Afridi, T. A. Soomro, S. A. Khan, M. Y. A. Khan, and B. S. Chowdhry, “A Single-Channel Wireless EEG Headset Enabled Neural

Activities Analysis for Mental Healthcare Applications," *Wirel. Pers. Commun.*, vol. 125, no. 4, pp. 3699–3713, 2022, doi: 10.1007/s11277-022-09731-w.

[91] G. Sri Mouni, E. Grace Mary Kanaga, M. Bhuvaneswari, and S. P. Gandu, "An Experimental Investigation on the Classification Accuracy of Visual, Audio and Cognitive Stimuli-based EEG Signals for BCI Application," *6th Int. Conf. Inven. Comput. Technol. ICICT 2023 - Proc.*, no. Icict, pp. 982–987, 2023, doi: 10.1109/ICICT57646.2023.10134045.

[92] Y. Daşdemır and R. Özakar, "Affective states classification performance of audio-visual stimuli from EEG signals with multiple-instance learning," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 30, no. 7, pp. 2707–2724, 2022, doi: 10.55730/1300-0632.3964.

[93] J. Leoni, S. C. Strada, M. Tanelli, K. Jiang, A. Brusa, and A. M. Proverbio, "Automatic stimuli classification from ERP data for augmented communication via Brain–Computer Interfaces," *Expert Syst. Appl.*, vol. 184, no. January, p. 115572, 2021, doi: 10.1016/j.eswa.2021.115572.

[94] T. Agarwal, S. Raturi, T. K. Vybhav, and M. Singh, "Classification of EEG signal using LSTMs under Audiovisual Stimuli," *Proc. 2020 IEEE Int. Conf. Commun. Signal Process. ICCSP 2020*, pp. 1229–1232, 2020, doi: 10.1109/ICCSP48568.2020.9182092.

[95] E. G. M. Kanaga, J. Sthuti, C. B. Sharon, and J. K. Reethu, "A comparitive analysis of classification algorithms on different stimuli for EEG based BCI applications," *Proc. Int. Conf. Trends Electron. Informatics, ICOEI 2019*, no. Icoei, pp. 1424–1428, 2019, doi: 10.1109/ICOEI.2019.8862678.

[96] D. W. Kim, H. J. Hwang, J. H. Lim, Y. H. Lee, K. Y. Jung, and C. H. Im, "Classification of selective attention to auditory stimuli: Toward vision-free brain-computer interfacing," *J. Neurosci. Methods*, vol. 197, no. 1, pp. 180–185, 2011, doi: 10.1016/j.jneumeth.2011.02.007.

[97] M. Bagheri and S. D. Power, "Investigating hierarchical and ensemble

classification approaches to mitigate the negative effect of varying stress state on EEG-based detection of mental workload level - and vice versa," *Brain-Computer Interfaces*, vol. 00, no. 00, pp. 1–12, 2021, doi: 10.1080/2326263X.2021.1948756.

[98] S. M. U. Saeed, S. M. Anwar, H. Khalid, M. Majid, and U. Bagci, "EEG based classification of long-term stress using psychological labeling," *Sensors (Switzerland)*, vol. 20, no. 7, pp. 1–15, 2020, doi: 10.3390/s20071886.

[99] F. M. Al-Shargie, T. B. Tang, N. Badruddin, and M. Kiguchi, "Mental stress quantification using EEG signals," *IFMBE Proc.*, vol. 56, no. October 2017, pp. 15–19, 2016, doi: 10.1007/978-981-10-0266-3_4.

[100] V. Vanitha and P. Krishnan, "Real time stress detection system based on EEG signals," *Biomed. Res.*, vol. 2016, no. Special Issue 2, pp. S271–S275, 2016.

[101] N. Hayatee, A. Hamid, N. Sulaiman, S. Armiza, M. Aris, and Z. H. Murat, "Evaluation of Human Stress Using EEG Power Spectrum," International Colloquium on Signal Processing & Its Applications, CSPA, May 2016, doi: 10.1109/CSPA.2010.5545282.

[102] B. C. Love, "Comparing supervised and unsupervised category learning," psychonomic bulletin & review, vol. 9, no. 4, pp. 829–835, 2002.

[103] P. D. Welch, "The Use of Fast Fourier Transform for the Estimation of Power Spectra," *IEEE Trans. audio Electroacoust.*, vol. AU-15, no. 2, pp. 70–73, 1967, Link: https://ieeexplore.ieee.org/document/1161901

[104] A. Arsalan, M. Majid, A. R. Butt, and S. M. Anwar, "Classification of Perceived Mental Stress Using A Commercially Available EEG Headband," *IEEE J. Biomed. Heal. Informatics*, vol. PP, no. c, p. 1, 2019, doi: 10.1109/JBHI.2019.2926407.

[105] V. G. Rajendran, S. Jayalalitha, and K. Adalarasu, "EEG Based Evaluation of Examination Stress and Test Anxiety Among College Students," *Irbm*, vol. 43, no. 5, pp. 349–361, 2022, doi: 10.1016/j.irbm.2021.06.011.

[106] A. Hag, D. Handayani, M. Altalhi, T. Pillai, T. Mantoro, and M. H. Kit, “A wearable single EEG channel analysis for mental stress state detection,” *Sensors*, vol. 21, pp. 1–20, 2021, doi: 10.3390/s21248370.

[107] A. Hag *et al.*, “Enhancing EEG-based mental stress state recognition using an improved hybrid feature selection algorithm,” *Sensors*, vol. 21, pp. 1–20, 2021, doi: 10.3390/s21248370.

[108] B. A. Garro, R. Salazar-Varas, and R. A. Vazquez, “EEG Channel Selection using Fractal Dimension and Artificial Bee Colony Algorithm,” *Proc. 2018 IEEE Symp. Ser. Comput. Intell. SSCI 2018*, pp. 499–504, 2018, doi: 10.1109/SSCI.2018.8628837.

[109] A. Asif, M. Majid, and S. M. Anwar, “Human stress classification using EEG signals in response to music tracks,” *Comput. Biol. Med.*, vol. 107, no. August 2018, pp. 182–196, 2019, doi: 10.1016/j.compbiomed.2019.02.015.

[110] M. Bagheri and S. D. Power, “Investigating hierarchical and ensemble classification approaches to mitigate the negative effect of varying stress state on EEG-based detection of mental workload level - and vice versa,” *Brain-Computer Interfaces*, vol. 8, no. 1–2, pp. 26–37, 2021, doi: 10.1080/2326263X.2021.1948756.

[111] L. Xia, A. Saeed, and A. Rauf, “Biomedical Signal Processing and Control A physiological signal-based method for early mental-stress detection,” cyber enabled intelligence, vol. 46, pp. 18–32, 2018.

[112] V. G. R. S. Jayalalitha and K. A. R. Mathi, “Machine learning based human mental state classification using wavelet packet decomposition-an EEG study,” *Multimed. Tools Appl.*, no. 0123456789, 2024, doi: 10.1007/s11042-024-18725-8.

[113] R. Desai, P. Porob, P. Rebelo, and D. Reddy, “EEG Data Classification for Mental State Analysis Using Wavelet Packet Transform and Gaussian Process Classifier,” *Wirel. Pers. Commun.*, vol. 115, no. 3, pp. 2149–2169, 2020, doi: 10.1007/s11277-020-07675-7.

[114] H. Jebelli, M. Habibnezhad, M. M. Khalili, M. S. Fardhosseini, and S. Lee, "Multi-level assessment of occupational stress in the field using a wearable EEG headset," *Constr. Res. Congr. 2020 Safety, Work. Educ. - Sel. Pap. from Constr. Res. Congr. 2020*, no. March, pp. 140–148, 2020, doi: 10.1061/9780784482872.016.

[115] A. Saidatul, P. M. Pandiyan, and S. Yaacob, "The Assessment of Developed Mental Stress Elicitation Protocol Based on Heart Rate and EEG Signals," International Journal of Computer Theory and Engineering, Vol. 7, No. 3, June 2015, doi: 10.7763/IJCTE.2015.V7.958.

[116] O. Attallah, "diagnostics An E ff ective Mental Stress State Detection and Evaluation System Using Minimum Number of Frontal Brain Electrodes,"diagnostics, mdpi, vol. 10, issue 5, 2020, doi: 10.3390/diagnostics/10050292.

[117] A. Sundaresan, B. Penchina, S. Cheong, V. Grace, A. V. Cabré, and A. Martel, "Evaluating deep learning EEG - based mental stress classification in adolescents with autism for breathing entrainment BCI," *Brain Informatics*, 2021, doi: 10.1186/s40708-021-00133-5.

[118] M. A. Hafeez and S. Shakil, "EEG - based stress identification and classification using deep learning," *Multimed. Tools Appl.*, vol. 83, no. 14, pp. 42703–42719, 2024, doi: 10.1007/s11042-023-17111-0.

[119] S. Muhammad, U. Saeed, S. M. Anwar, H. Khalid, M. Majid, and U. Bagci, "EEG Based Classification of Long-Term Stress Using Psychological Labeling,"sensors, mdpi, vol.10, issue.7 pp. 1–15, 2020, doi: 10.3390/s20071886.

[120] M. Koctúrová and J. Juhár, "A novel approach to EEG speech activity detection with visual stimuli and mobile BCI," *Appl. Sci.*, vol. 11, no. 2, pp. 1–12, 2021, doi: 10.3390/app11020674.

[121] R. N. Duan, J. Y. Zhu, and B. L. Lu, "Differential entropy feature for EEG-based emotion classification," *Int. IEEE/EMBS Conf. Neural Eng. NER*, pp.

81–84, 2013, doi: 10.1109/NER.2013.6695876.

[122] R. Zhang *et al.*, “Predicting Inter-session Performance of SMR-Based Brain–Computer Interface Using the Spectral Entropy of Resting-State EEG,” *Brain Topogr.*, vol. 28, no. 5, pp. 680–690, 2015, doi: 10.1007/s10548-015-0429-3.

[123] M. Bagheri and S. D. Power, “Simultaneous Classification of Both Mental Workload and Stress Level Suitable for an Online Passive Brain–Computer Interface,” *Sensors*, vol. 22, no. 2, 2022, doi: 10.3390/s22020535.

[124] A. Hemakom, D. Atiwiwat, and P. Israsena, “ECG and EEG based detection and multilevel classification of stress using machine learning for specified genders: A preliminary study,” *PLoS One*, vol. 18, no. 9 September, pp. 1–24, 2023, doi: 10.1371/journal.pone.0291070.

[125] F. S. Rawnaque *et al.*, “Technological advancements and opportunities in Neuromarketing: a systematic review,” *Brain Informatics*, vol. 7, no. 1, 2020, doi: 10.1186/s40708-020-00109-x.

[126] N. Phutela, D. Relan, G. Gabrani, P. Kumaraguru, and M. Samuel, “Stress Classification Using Brain Signals Based on LSTM Network,” *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/7607592.

[127] T. Y. Wen and S. A. Mohd Aris, “Hybrid Approach of EEG Stress Level Classification Using K-Means Clustering and Support Vector Machine,” *IEEE Access*, vol. 10, pp. 18370–18379, 2022, doi: 10.1109/ACCESS.2022.3148380.

[128] R. A. Movahed, G. P. Jahromi, S. Shahyad, and G. H. Meftahi, “A major depressive disorder classification framework based on EEG signals using statistical, spectral, wavelet, functional connectivity, and nonlinear analysis,” *J. Neurosci. Methods*, vol. 358, no. November 2020, 2021, doi: 10.1016/j.jneumeth.2021.109209.

[129] A. Delorme, “EEG is better left alone,” *Sci. Rep.*, vol. 13, no. 1, pp. 1–12, 2023, doi: 10.1038/s41598-023-27528-0.

[130] H. Kim, J. Luo, S. Chu, C. Cannard, S. Hoffmann, and M. Miyakoshi, "ICA's bug: How ghost ICs emerge from effective rank deficiency caused by EEG electrode interpolation and incorrect re-referencing," *Front. Signal Process.*, vol. 3, no. April, pp. 1–9, 2023, doi: 10.3389/frsip.2023.1064138.

[131] T. G. Troyee, F. K. Khandakar, M. Hasan, and M. H. Chowdhury, "A Comparative Analysis of Different Preprocessing Pipelines for EEG-based Mental Stress Detection," 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), May, 2024.

[132] D. Shon, K. Im, J. H. Park, D. S. Lim, B. Jang, and J. M. Kim, "Emotional stress state detection using genetic algorithm-based feature selection on EEG signals," *Int. J. Environ. Res. Public Health*, vol. 15, no. 11, 2018, doi: 10.3390/ijerph15112461.

[133] M. Plechawska-Wójcik, P. Augustynowicz, M. Kaczorowska, E. Zabielska-Mendyk, and D. Zapała, "The Influence Assessment of Artifact Subspace Reconstruction on the EEG Signal Characteristics," *Appl. Sci.*, vol. 13, no. 3, 2023, doi: 10.3390/app13031605.

[134] S.-H. Oh, Y.-R. Lee, and H.-N. Kim, "A Novel EEG Feature Extraction Method Using Hjorth Parameter," *Int. J. Electron. Electr. Eng.*, vol. 2, no. 2, pp. 106–110, 2014, doi: 10.12720/ijeee.2.2.106-110.

[135] F. Feradov, T. Ganchev, and V. Markova, "Automated Detection of Cognitive Load from Peripheral Physiological Signals based on Hjorth's Parameters," *Proc. Int. Conf. Biomed. Innov. Appl. BIA 2020*, pp. 85–88, 2020, doi: 10.1109/BIA50171.2020.9244287.

[136] G. J. A. Jiang *et al.*, "Sample entropy analysis of EEG signals via artificial neural networks to model patients' consciousness level based on anesthesiologists experience," *Biomed Res. Int.*, vol. 2015, 2015, doi: 10.1155/2015/343478.

[137] M. Aldayel, M. Ykhlef, and A. Al-Nafjan, "Recognition of Consumer

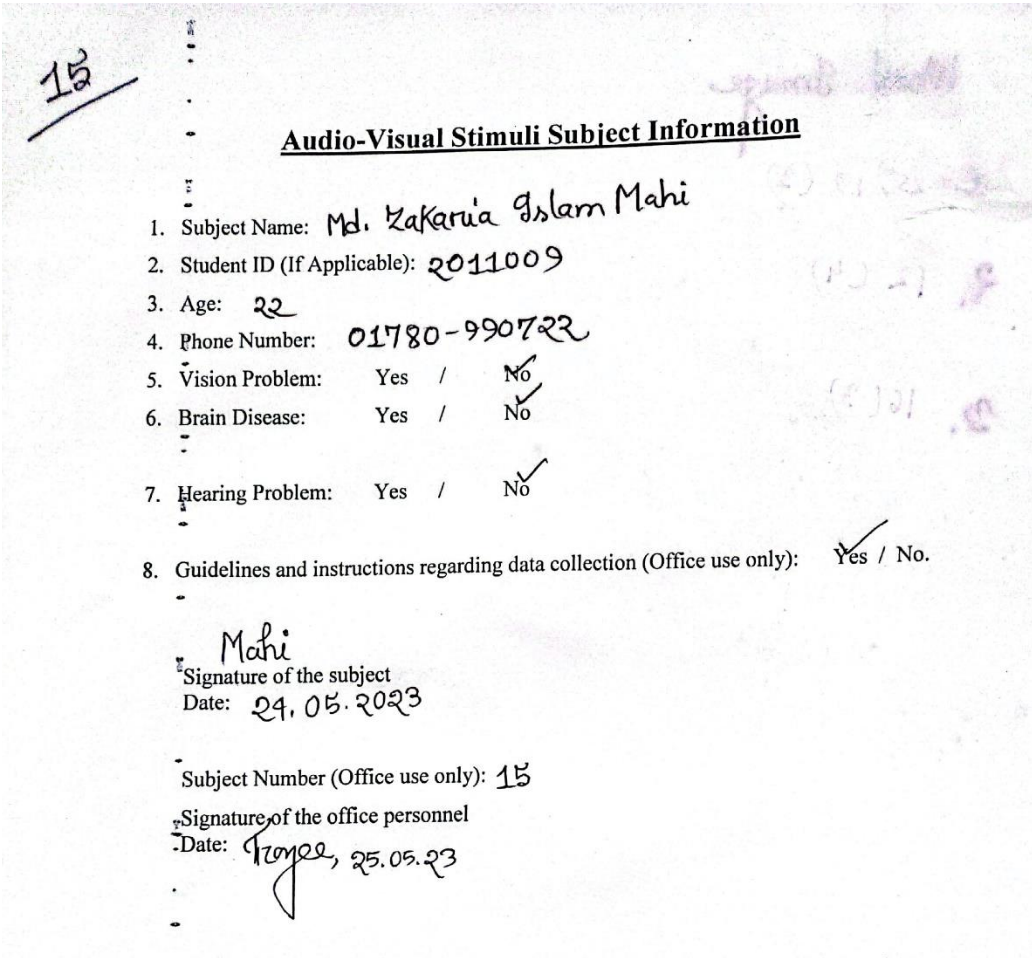
Preference by Analysis and Classification EEG Signals," *Front. Hum. Neurosci.*, vol. 14, no. January, 2021, doi: 10.3389/fnhum.2020.604639.

[138] M. S. Rahman *et al.*, "Average Power Based EEG Channel Selection Method for Emotion Recognition," The International Conference on Innovations in Computing Research, pp. 270–280, 2022, December 2023, doi: 10.1007/978-3-031-14054-9_26.

APPENDICES

APPENDIX A: DATA COLLECTION

One example of consent form used during data collection period:



15

Audio-Visual Stimuli Subject Information

1. Subject Name: Md. Zakaria Islam Mahi
2. Student ID (If Applicable): 2011009
3. Age: 22
4. Phone Number: 01780-990722
5. Vision Problem: Yes / No
6. Brain Disease: Yes / No
7. Hearing Problem: Yes / No
8. Guidelines and instructions regarding data collection (Office use only): Yes / No.

Mahi
Signature of the subject
Date: 24.05.2023

Subject Number (Office use only): 15

Signature of the office personnel
Date: Trayee, 25.05.23

Fig. A1 Consent paper collected from the subjects before data collection

Stimuli used during data collection period:

Mathematical word problems having three difficulty levels were selected to induce different level of stress.

Do the math and write down the answer on paper

Over a 3 days period, Susan ate 39 chocolates. Each day she ate 3 more than on the previous day. How many chocolates were eaten on the last day?

Fig. A2 Medium Mathematical word problem

Do the math and write down the answer on paper

Nur's present age is 20 years which is 6 years greater than his brother's age. After 5 years what would be both of their age?

Fig. A3 Easy Mathematical word problem

Do the math and write down the answer on paper

Siyan is 8 years older than Rifat. In four years Siyan will be twice as old as Rifat. How old is Siyan now?

Fig. A4 Hard Mathematical word problem

APPENDIX B: EMOTIV EPOC FLEX

EMOTIV is a neurotechnology company that builds hardware and software for **EEG (Electroencephalogram) acquisition**, brain-computer interfaces (BCI), and cognitive studies.

They create systems that make EEG more **portable**, **affordable**, and **user-friendly** compared to traditional, lab-based EEG setups.

EMOTIV EEG Systems

They mainly offer:

- **EPOC Series** (EPOC+, EPOC X) – 14-channel, high-resolution EEG headsets
- **INSIGHT** – 5-channel headset (more portable, quick setups)
- **MN8 Earbuds** – EEG integrated into earphones
- **Flex Cap** – a customizable, research-grade cap with 32+ channels

Builder Machine isn't the name of a headset; it often refers to their **software platform**, but people sometimes call their "complete system" a builder machine.

Hardware Components (for EEG acquisition)

- **Electrodes**
  - Saline-based or dry-contact depending on the model.
  - Placement mostly follows the **10-20 International System** for EEG.
- **Amplifiers**
  - Amplify microvolt-level EEG signals to readable levels.
- **ADC (Analog-to-Digital Converter)**
  - Converts raw EEG analog signals to digital form.
  - Sampling rates:
    - EPOC+ / X: **128 Hz** (default) or **256 Hz** (high-performance mode).

- **Wireless transmission**
  - Data sent via **Bluetooth** or **dedicated USB dongles** to a computer.

Software Ecosystem (Builder Part)

- **EMOTIVPRO**
  - Main EEG acquisition, visualization, and recording software.
  - Real-time display of EEG signals.
  - Event markers (triggers) can be placed during recordings.
- **EMOTIVBCI**
  - For training machine learning models based on user EEG (brain control).
- **Emotiv App Store**
  - Hosts additional apps for signal analysis, games, meditation tracking, and brain-training tools.
- **Developer SDK**
  - Provides APIs (Cortex API) for:
    - Real-time EEG data streaming
    - Cognitive metric tracking (stress, focus, excitement)
    - Brain command recognition (BCI)

Applications

- Neurofeedback training
- Brain-Computer Interface (BCI) development
- Cognitive load and emotional state research
- Meditation studies
- Sleep studies
- Clinical research (non-diagnostic)

Advantages of EMOTIV Systems

- Portable and lightweight
- Quick setup (no messy gels for some models)

- Good balance of research-grade quality and user-friendliness
- Active support for **MATLAB**, **Python**, **Unity**, **C++**, and **JavaScript** via SDKs.

Limitations

- Not as high-fidelity as medical-grade EEG (e.g., for epilepsy diagnosis)
- Saline electrodes need regular re-wetting for long recordings.
- Limited electrode density (compared to full 64/128-channel lab EEG).

Fig. B1 Emotiv headset during data collection period

APPENDIX C: TURNITIN REPORT

ORIGINALITY REPORT

12%	7%	9%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	braininformatics.springeropen.com Internet Source	1%
2	www.ncbi.nlm.nih.gov Internet Source	1%
3	Md. Fazlul Karim Khondakar, Trishita Ghosh Trovee, Mahmudul Hasan, Md. Hasib Sarowar et al. "A Comparative Analysis of Different Pre-Processing Pipelines for EEG-Based Preference Prediction in Neuromarketing", 2023 IEEE Pune Section International Conference (PuneCon), 2023 Publication	1%
4	Likun Xia, Aamir Saeed Malik, Ahmad Rauf Subhani. "A physiological signal-based method for early mental-stress detection", Biomedical Signal Processing and Control, 2018 Publication	<1%
5	Submitted to The University of Manchester Student Paper	<1%
6	www.mdpi.com Internet Source	<1%
7	Submitted to Aston University Student Paper	<1%
8	doctorpenguin.com Internet Source	<1%