

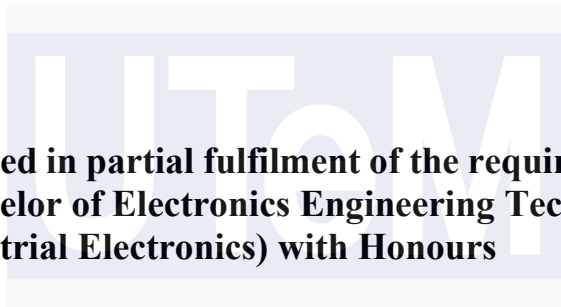
EEG-BASED ATTENTION MONITORING SYSTEM FOR CLASSROOM EVALUATION



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

EEG-BASED ATTENTION MONITORING SYSTEM FOR CLASSROOM EVALUATION

NUR ASHIKIN BINTI MUHAMMAD NASIR



**This report is submitted in partial fulfilment of the requirements for
the degree of Bachelor of Electronics Engineering Technology
(Industrial Electronics) with Honours**

اونيورسيتي تيكنيكل مليسيا ملاك

**Faculty of Electronics and Computer Technology and Engineering
Universiti Teknikal Malaysia Melaka**

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I declare that this project report entitled “EEG-BASED ATTENTION MONITORING FOR CLASSROOM EVALUATION” is the result of my own research except as cited in the references. The project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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I hereby declare that I have checked this project report entitled “EEG-BASED ATTENTION FOR CLASSROOM EVALUATION” and in my opinion, this project report is adequate in terms of scope and quality for the award of the degree of Bachelor of Electronics Engineering Technology (Industrial Electronics) with Honours.



Signature : _____

Supervisor Name : TS. KHAIRUL AZHA BIN A AZIZ _____

Date : _____

Signature : _____

Co-Supervisor : _____

Name (if any) : _____

Date : _____

DEDICATION

*To my beloved mother, Anisah binti Talib, and father, Muhammad Nasir bin Manadi,
and my beloved family.*

To my supervisor, Sir Khairul Azha bin A Aziz,

*This project is dedicated to all of you and to God Almighty who is my creator, my
strong pillar, my source of inspiration, wisdom, knowledge, and comprehension.
They have been a source of strength for me throughout this effort, and on His wings I
have soared. They have also supported me along the way to ensure that I give it
everything I must finish what I have started. God's blessing on you.*



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ABSTRACT

The project of EEG- Based Attention Monitoring System for Classroom Evaluation come up with an inventive method of monitoring student engagement and attention levels during classes is the EEG-based attention monitoring system. In modern educational environments, monitoring student engagement is critical for effective learning, yet traditional methods are often subjective and insufficient. This project addresses the need for objective, real-time attention monitoring by developing an EEG-based system using Mind Link sensors connected via HC-05 Bluetooth modules to Arduino Uno microcontrollers, capturing data through a MATLAB GUI. The primary objectives are to read real-time data from the MindLink brain sensor and process acquire through MATLAB GUI, accurately interpret the detected EEG waveforms, and monitor student attention levels. The methodology involves setting up the hardware to collect EEG data, processing signals via Arduino, and analyzing them with MATLAB levels. The outcome is instructional effectiveness and personalized learning experiences through timely interventions based on accurate attention and meditation data. The conclusion, aims to revolutionize classroom evaluation by providing objective measures of student engagement of attention and meditation, ultimately leading to improved educational outcomes. Students wear EEG sensors that track electrical brainwave activity in a classroom. Supervisor and students receive real-time data on their attention or meditation levels through a dashboard or alerts, which are analyzed by developing algorithms.

ABSTRAK

Projek Sistem Pemantauan Perhatian Berasaskan EEG untuk Penilaian Bilik Darjah menghasilkan kaedah inventif untuk memantau penglibatan dan tahap perhatian pelajar semasa kelas ialah sistem pemantauan perhatian berasaskan EEG. Dalam persekitaran pendidikan moden, pemantauan penglibatan pelajar adalah penting untuk pembelajaran yang berkesan, namun kaedah tradisional selalunya subjektif dan tidak mencukupi. Projek ini menangani keperluan untuk pemantauan perhatian masa nyata yang objektif dengan membangunkan sistem berasaskan EEG menggunakan penderia Mind Link yang disambungkan melalui modul Bluetooth HC-05 kepada mikropengawal Arduino Uno, menangkap data melalui GUI MATLAB. Objektif utama adalah untuk membaca data masa nyata daripada penderia otak MindLink dan proses memperoleh melalui MATLAB GUI, mentafsirkan bentuk gelombang EEG yang dikesan dengan tepat, dan memantau tahap perhatian pelajar. Metodologi ini melibatkan penyediaan perkakasan untuk mengumpul data EEG, memproses isyarat melalui Arduino, dan menganalisisnya dengan tahap MATLAB. Hasilnya ialah keberkesanan pengajaran dan pengalaman pembelajaran yang diperibadikan melalui intervensi tepat pada masanya berdasarkan data perhatian dan meditasi yang tepat. Kesimpulannya, bertujuan untuk merevolusikan penilaian bilik darjah dengan menyediakan ukuran objektif penglibatan perhatian dan meditasi pelajar, akhirnya membawa kepada hasil pendidikan yang lebih baik. Pelajar memakai penderia EEG yang menjejaki aktiviti gelombang otak elektrik di dalam bilik darjah. Penyelia dan pelajar menerima data masa nyata mengenai tahap perhatian atau meditasi mereka melalui papan pemuka atau makluman, yang dianalisis dengan membangunkan algoritma.

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My highest appreciation goes to my parents, and family members for their love and prayer during the period of my study. An honorable also for all the motivation and understanding.

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LIST OF SYMBOLS

α	-	Alpha
β	-	Beta
θ	-	Theta
δ	-	Delta
γ	-	Gamma



LIST OF ABBREVIATIONS

EEG	- Electroencephalogram
HC-05	- Bluetooth Module
GUI	- Graphical User Interface



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CHAPTER 1

INTRODUCTION

1.0 Background

One of the most challenges in today's educational environment is maintaining students' attention and concentration in the classroom. The creation of exciting and engaging learning environment has made it more crucial than ever for lecturers to recognize and keep an eye on student's attention levels. Conventional techniques for evaluating attention, like self-reporting and behavioral observation, frequently fail to provide accurate, up-to-date information. Development in neurotechnology provide intriguing ways to reduce this gap.

Implementing electroencephalography (EEG) to monitor attention levels in real time is one such modern method. EEG is a non-invasive method that captures brain electrical activity and offers information on different cognitive states, such as focus and attention. Brain wave patterns are captured and analyzed by EEG, which makes it a valuable tool for evaluating and improving student engagement in classrooms. By giving teachers immediate feedback on their student's attentional states, the development of an EEG-based attention monitoring system aims to completely transform the evaluation of learning in the classroom.

This system accurately measures attention levels by utilizing machine learning algorithms, advanced signal processing techniques, and contemporary EEG sensors. By better understanding each student's needs, teachers can adjust their teaching methods and create a more conducive learning environment with the use of this technology. Acquiring the right EEG hardware, developing data collection and signal processing programs,

and developing user interfaces with real-time feedback are only some of the crucial parts of this project.

1.1 Project Justification and Organization

Effective learning and academic performances depend heavily on lecturers being able to keep students' attention and concentration in the classroom. Although conventional approaches to measuring students' attention, such as lecturer observations and student self-reports, are frequently undefined, unreliable and lacking of immediate feedback. There may be lost opportunities for rapid intervention and individualized education as a result of this inefficiency in measuring and evaluating students' attention levels.

1.2 Problem Statement

Effective learning and academic performances depend heavily on lecturers being able to keep students' attention and concentration in the classroom. Although conventional approaches to measuring students' attention and meditation, such as lecturer observations and student self-reports, are frequently undefined, unreliable, and lacking of immediate feedback. There may be lost opportunities for rapid intervention and individualized education as a result of this inefficiency in measuring and evaluating students' attention and meditation levels while monitoring their EEG brainwaves.

1.3 Project Objective

The main objective of this project is to develop an EEG-based attention monitoring system that can assess students' attention levels in the classroom. This system aims to provide

a real-time data representation into the student's attention, allowing to read the obtained EEG waveform.

Specifically, the objectives are as follows:

- a) To develop an EEG-based attention monitoring system for classroom evaluation that can accurately and reliably measure student attention levels in real-time.
- b) To develop the capability to read and display real-time EEG data from Mind Link sensors through the MATLAB GUI. Ensure seamless data transmission via HC-05 Bluetooth modules connected to Arduino Uno microcontrollers.
- c) To implement signal processing techniques within the MATLAB environment to accurately save and analyze the detected EEG waveforms.

1.4 Scope of Project

The scope of this project are as follows:

- a) Monitor student attention level in a classroom.
- b) Develop software for data acquisition, signal processing, and real-time visualization of attention levels.
- c) Capture brainwave data of attention and meditation indicative of student attention and engagement.
- d) Used real-time data to analyze teaching strategies for educators
- e) The primary users include educators, students, educational researchers, and school administrators.

CHAPTER 2

LITERATURE REVIEW

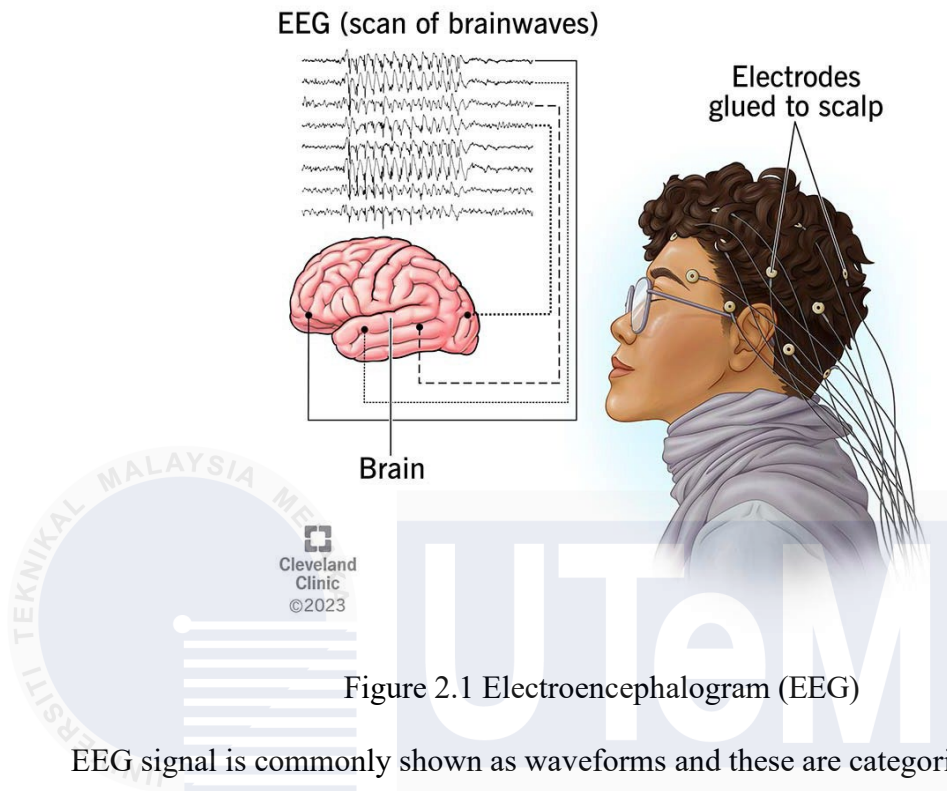
2.0 Introduction

The previous chapter explained about the background of this project for the development of EEG-Based Attention Monitoring System for Classroom Evaluation. It also explained about the problem statement, objective, and scope of the project. This chapter will explain the research of literature related project. It contains of some work that already done by other student or institutes. They have also described several concepts of this project in this chapter. This is because the understanding between theory and work will help much in preparing this project.

2.1 Electroencephalography (EEG)

EEG is an important clinical method that allows recording of the electrical activity of the brain. This is the process of applying electrodes to the patient's scalp to record the electrical activity in the neurons of the brain. For diagnosis of various neurological disorders including epilepsy, sleep disorder and tumors. EEG is widely used in clinical practice [1]. It can also be used in research to examine how the brain communicates or functions when it is presented with a certain stimulus or when performing a particular task [1].

Electroencephalogram (EEG)



EEG signal is commonly shown as waveforms and these are categorized dependent on the frequency as delta waves, theta waves, alpha waves, beta waves and the gamma waves. Essentially, each of these frequency bands is said to relate to particular states of consciousness, cognition, and brain activity [2].

Lesser of drawbacks of EEG includes less invasiveness, high-temporal resolution (it can differentiate relatively fast changing signals from the brain), cost effectiveness as compared to other imaging modalities such as fMRI or PET [3]. However, it is not without its drawbacks including lower spatial resolution that prevents users from getting exact locations of activity within the human brain and high sensitivity to artifacts from muscle movements and other electrical interferences.

2.2 Brain Wave

Neural oscillations or brain waves are electrical patterns of neural activity in the human brain that are recurrent or rhythmic. They can be studied by methods such as electroencephalography (EEG) and are divided into several types according to the frequency at which they occur, and each state corresponds to a certain level of brain activity. Here's a brief overview of the main types of brain wave which is Delta waves, Theta waves, Alpha waves, Beta waves, and Gamma waves [2].

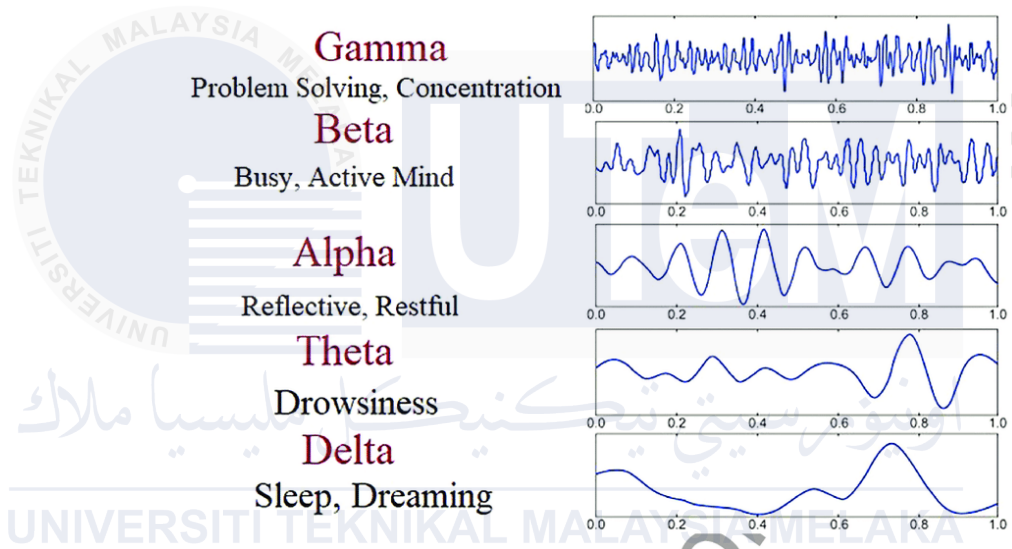


Figure 2.2 Brain waves

2.2.1 Delta waves

Delta waves frequency range is from 0.5 to 4 Hz. Delta waves are the slowest type of EEG waveforms and the most frequent during deep, dreamless sleep, or non-REM sleep. They are also linked to brain abnormalities if present during wakefulness [2].

2.2.2 Theta waves

Theta waves frequency range is from 4 to 8 Hz. Theta waves are slower than alpha and beta waves and are often associated with drowsiness, light sleep, and some meditative states [2]. They can also be seen in children and young adults during cognitive tasks.

2.2.3 Alpha wave

Alpha waves frequency range is from 8 to 14 Hz. Alpha waves are most associated with light sleep and occur during wakefulness with the eyes closed or when the individual is fully awake and resting. They are most times said to cause the receiver to be more relaxed, calm and even end up feeling meditating [2].

2.2.4 Beta waves

Beta waves frequency range is from 14 to 30 Hz. They are faster and have lower amplitude as compared to alpha waves and are related to associative phase of consciousness, wakefulness, and active analytical thinking. They are most noticeable during wakeful states, which include thinking, reasoning, and concentrating activities [2].

2.2.5 Gamma waves

Gamma waves frequency range is from 30 to 100 Hz. The last and most frequent band of EEG waveforms which are faster than other waves and are related to perception and cognitive awareness of the environment as well as information processing. This is true when they are recognized at task that involves attention, memory, and sensory perception [2].

2.3 Suitable brain waves

Beta waves are useful for attention monitoring in classroom evaluations because they range from 14 to 30 Hz and are linked with thinking, problem-solving, concentrating, and being conscious. These fast-frequency waves are at the highest when students are doing knowledge-related activities such as listening to the lectures, note-taking, or interacting in the class. Electroencephalography is used to observe beta wave activity to get real-time information about the level of attention of students [4].

The beta wave data indicate that the amount of beta waves is directly proportional to the level of learning hence educators can easily track the students' attention span to ensure that they remain interested in the lesson being taught. Also, gamma waves, usually ranging from 30 to 100 Hz, which are associated with high cognitive operations, can provide a better picture of cognition. Alpha waves (8-13Hz), connected with a subject's relaxed, non-sleeping state of mind, and beta waves might mean optimal levels of attentiveness [4].

Wearable, non-implanted EEG devices can record characteristics of brain waves and offer information in a timely, noninvasive manner. These data can then be used to look for trends in student attention and engagement, which can make it easier for teachers to appropriately adjust their strategies to enhance the classroom experience. Beta waves, therefore, play a crucial role in evaluating and promoting attention in learning environments [4].

2.4 Research on Attention Monitoring for Classroom Evaluation Article

2.4.1 Multimodal Approach to Identify Attention Level of Student using Jetso Nano

The article discusses a research paper on "A Multimodal Approach to Identify Student Attention Levels Using the Jetson Nano." This study conducted by a team from PSG

College of Technology, India aimed to assess students' attitude in class based on their physiological state, using biochemical and electrical signals in the brain. The proposed method uses Deep Convolution Neural Network (DCNN) with Histogram of Gradient (HoG) for face recognition. Attention is tested using facenet algorithms for face recognition, which convolution neural network model implemented in Jetson Nano. The study also observed existing work in facial expression recognition and similar techniques, and focused on potential applications in academic and other fields such as medical research, video games, autonomous vehicles, state offices and retail[5].

The paper delves into the challenges of traditional methods such as EEG and ECG for measuring physiological signals, and the potential distractions introduced by scalp extraction of EEG signals. In addition, the paper describes the experimental design, the proposed design framework, and the Jetson Nano developer kit to be used for effective project development in embedded systems and artificial intelligence [5].

The study also presents the results of the proposed algorithm, which includes training the model with student facial images and carefully testing it through eye position recognition, yawning detection, and facial position prediction. Test results seeing perfect care in individual and group photos, with 100% work accuracy [5].

2.4.2 EEG-Based Closed-Loop Neurofeedback for Attention Monitoring and Training in Young Adults

The paper introduces an improved attention monitoring and training method using an IRF algorithm with closed-loop neurofeedback for young adults. It demonstrates higher accuracy in attention monitoring and significant performance improvements in attention training, proving the method's reliability and efficiency. The research paper utilizes two main modules: EEG-based attention monitoring and EEG-based training. For EEG-based

Attention Monitoring Module, the attention monitoring workflows are initiated based on EEG signals. EEG data processing and feature extraction are performed to prepare the data for analysis. The Improved Random Forest (IRF) algorithm is employed for classification to enhance monitoring accuracy. Next is EEG-based Training Module, which is the principle of attention training is illustrated, focusing on sustained attention, selective attention, and focus attention. Serious games with closed-loop neurofeedback are implemented for effective training. The study also involves the use of the IRF algorithm for five-level attention monitoring and the design of serious games targeting different aspects of attention. Additionally, a self-control method with four indicators is applied to validate the training effect, ensuring the effectiveness of the proposed method [6].

2.4.3 Using Electroencephalography to Determine Student Attention in the Classroom

This paper discusses the demanding situations confronted by using educators in enticing college students' interest inside lecture room and proposes a technological answer using wearables. The research is based totally on data amassed from a workshop with engineering educators, where they brainstormed the important thing demanding situations they faced of their classrooms and designed solutions the usage of wearables. The workshop emphasized the importance of pupil interest and engagement as crucial elements for successful mastering results. The paper explores the capacity of the use of electroencephalography (EEG) records analytics to detect and screen pupil attention. It additionally highlights the various technology that may be used for interest detection, inclusive of eye monitoring, facial recognition, and coronary heart fee monitoring. The studies questions generated from the workshop form the idea for future work in this are [7].

2.4.4 Electroencephalography-Based Attention Level Classification Using Convolution Attention Memory Neural Network

Attention is a cognitive system of that specialize in important records in the situation for gaining knowledge of and memory. Attentive is crucial because it will give a good to the studying experience and may potentially make a contribution to tremendous mastering consequences. Most professions along with lecturer, physician, and students need an excessive percentage of attention to entire the work efficaciously. Other than that, growing a system that may correctly display the interest percentage lead to a significant absorption of studies. The related publisher who oversaw this manuscript's evaluation and gave it permission for publication became Sung Chan Jun [8].

The researcher develops an attention awareness system that uses eye tracking software to detect students' attention in the classroom. Although eye movement can provide information related to attention, it can only respond to obvious visual attention shifts, which may not be enough to determine the student's attention level. Due to the reasons, most of the research studies explored the relationship between Electroencephalogram (EEG) and attention level [8].

List the researcher used pattern classification to conclude that the EEG signals can be used to predict attention states. Liu et al. used a wireless mobile EEG headset to record the EEG signals of the frontal cortex and adopted a Support Vector Machine (SVM) to classify student's attention state [8]. Similar EEG headsets, feature selection methods, and classifiers were used by Gunawan et al. to detect the early drop of attention and Peng et al. designed an attentiveness recognition system. Typically, most research studies rely heavily on handcrafted EEG spectral features to perform classification, and there is a lack of research on the use of deep learned features and neural networks in this field. Hence, a deep learning model is applied in the research [8].

2.4.5 Implementation Artificial Neural Network on Microcontroller for Student Attention Level Monitoring Device Using EEG

Learning concentration is an interesting subject matter to observe. A take a look at has been carried out to take a look at the impact of mastering hobby on the concentration of studying of college students who are requested to study within the study room. Research shows that low mastering hobby causes a decrease awareness of learning. Attention is essential for people to shield them from interference. Attention is crucial for humans once they observe, together with analyzing or listening. Attention, while a person is reading, can be measured using an electroencephalograph (EEG). There are many types of EEG wave signals dependent on the frequency spectrum, inclusive of alpha, beta, theta, delta, and gamma [9].

Study approximately detecting attention degree primarily based on EEG sign via the usage of ANN has been carried out by way of a few researcher. The study about imposing ANN on attention detection has the EEG sign. A PC has been used as a method to detect the person attention even as the problem read a text. The scholar have a tendency to examine on any region this is snug for them to examine. Using a PC make the device can not be carried to any places. A system with a microcontroller will be greater green to be applied for attention detection [9].

The EEG a good way to be used to measure is NeuroSky Mindwave Mobile as it has a lower rate, loads of packages, simple approaches to use, and supports diverse virtual media. NeuroSky Mindwave Mobile is also geared up with electrodes at the forehead and noise filters inside the form of ear clips established at the left ear to examine and report brain waves. The mind wave graph in the EEG adjustment depending at the circumstance of the human brain on the time of recording. This can arise due to inner stimuli such as intellectual hobby and external stimuli. The output of the signal can be labeled into the bad sign, eSense

Attention, meditation, wave delta, theta, alpha, beta, and gamma. Then the output of the sign will be identified Attention conditions the use of Artificial Neural Networks (ANN) with a Backpropagation set of rules for training [9].

2.4.6 EEG Data Quality in Real-World Setting: Examining Neural Correlates of Attention in School-Aged Children

Here are two studies from one school and children aged 5 to 10. EEG data were collected at the initial assessment when children participated in two lab-based tasks individually with the experimenter in the field laboratory. A wireless EEG system, and a semi-natural second Use data collected simultaneously from children for analysis Intervention in classroom activities using a wireless EEG system. They first examine the feasibility and limitations of the archive High-quality EEG data of young students in nature Comparative characterization of data from different school settings. Two examples of children frequently participating in activities Experience in school but varies in nature of the context (e.g. field laboratory or classroom) in which these. Various activities were held. They conclude with insights EEG data collection with young children in schools [10].

2.4.7 Real-Time Attention Monitoring System for Classroom: A Deep Learning Approach for Student's Behaviour Recognition

Effective classroom instruction requires monitoring student participation and interaction in class, insert clues to simulate concentration. Teachers ability to analyze and evaluating students' classroom practices is an important aspect of quality instruction. Behaviour recognition system can helps student reflect on their attention in classroom by using Artificial Intelligence (AI). Consequently, the global education system is rapidly introducing new emerging technologies including; AI, the Internet of Things, and others. advanced IT systems like big data analytics to enhance education programs. Modern

Classrooms in Educational Institutions the systems are fitted with the most modern technology to make it more interactive, refined and student oriented [11].

Still, it is hard to monitor students' favor for teachers. Attention level even with this technology. The research has been introduced using modern technology a classroom based on student emotions, attendance, and real-time intelligent feedback for. Machine learning are used to train us patterns of student behavior recognition, including facial expression recognition, are presented to students reflection/learning in the classroom. The conscious/unconscious inventory is compiled on nine bases various paragraphs. The dataset is given YOLOv5 pretrained weights for training. For testimonials. The work of different types (v5m, v5n, v5l, v5s, and v5x) of the YOLOv5 model is different Based on their analytical metrics (accuracy, recall, mAP, and F1 score). The outcomes show that as all dataset show convincing work with an average accuracy of 76%. Implementation of the design the model should enable teachers to visualize the student [11].

2.4.8 EEG Cross Validation of Effective Mobile Technology by Analyzing Attention Level in Classroom

The abstract discusses the use of EEG technology to measure students' attention levels in classrooms where mobile devices are utilized, along with statistical analysis to validate the acceptability of mobile technology. It highlights the growth of mobile devices in classrooms and the importance of overcoming challenges like visibility and interaction through the integration of mobile technology. Mobile technology has become prevalent in daily activities, including education, addressing challenges like visibility and interaction in large classrooms. This study focuses on the cognitive aspect of mobile device usage in classrooms, utilizing EEG technology to measure students' attention levels. The integration

of EEG technology, specifically a single-channel Mind Wave EEG headset, allows for the assessment of brain signals and attention levels of students during classroom activities. Statistical analyses, such as Bayesian t-tests and regression models, were employed to validate the data collected through surveys on the acceptability of mobile devices in educational settings. Electroencephalography (EEG) was employed using a single-channel Mind Wave EEG headset to measure the power spectrum from brain signals, providing insights into students' attention levels in the classroom. Data collected through surveys was statistically modeled to assess the acceptability of mobile devices in the classroom, utilizing Bayesian t-test and various regression analyses for validation [12].

2.4.9 Design of an Attention Evaluation System with 16-Channel Differential Signal Acquisition

The paper introduces an attention evaluation system utilizing 8-channel differential prefrontal EEG signals and a 16-channel neural signal acquisition module with various components like chopper LNAs, programmable gain amplifiers, and SAR ADC. The system incorporates a digital attention evaluation algorithm implemented on FPGA, including IIR filters, calculation of filtered neural signal strength indicator, and an SVM-based classifier. The introduction of the paper highlights the development of an attention evaluation system that utilizes 8-channel differential prefrontal EEG signals acquired from the forehead. It introduces a 16-channel neural signal acquisition module designed in TSMC 180nm CMOS process, comprising chopper LNAs, switched-Capacitor programmable gain amplifiers, and a 12-bit SAR ADC [13]. The system's digital attention evaluation algorithm, implemented on FPGA, includes components such as IIR filters, calculation of the filtered neural signal strength indicator, and an SVM-based classifier. The focus is on enhancing attention assessment through advanced signal processing techniques and neural signal analysis. The

paper utilized a 16-channel neural signal acquisition module fabricated in TSMC 180nm CMOS process, incorporating chopper LNAs, switched-Capacitor programmable gain amplifiers, and a 12-bit SAR ADC for signal acquisition. An attention evaluation algorithm was implemented on FPGA, involving the use of IIR filters for signal processing. The algorithm also included the calculation of the filtered neural signal strength indicator to assess attention levels [13].

Additionally, a SVM-based classifier was employed in the system to classify and evaluate attention based on the processed neural signals. The paper presented an attention evaluation system utilizing 8-channel differential prefrontal EEG signals and a 16-channel neural signal acquisition module designed in TSMC 180nm CMOS process. Through the implementation of advanced signal processing techniques and neural signal analysis, the system aimed to enhance attention assessment accuracy and reliability. The use of chopper LNAs, switched-Capacitor programmable gain amplifiers, and a 12-bit SAR ADC in the signal acquisition module demonstrated the system's capability for precise neural signal acquisition. The integration of an attention evaluation algorithm on FPGA, incorporating IIR filters, neural signal strength indicator calculation, and an SVM-based classifier, showcased a comprehensive approach to attention assessment. Overall, the study's findings suggest that the developed system holds promise for effective and efficient attention evaluation, offering a potential avenue for further research and application in cognitive assessment and related fields [13].

2.4.10 Predict Students Attention in Online Learning Using EEG Data

The article focuses on a work that was in the course of conducting a study that sought to determine the likelihood of students' attention in a distance learning environment using EEG data, so as to improve the quality of distance learning. In the study, the researcher

designed a brain computer interface (BCI) that uses electroencephalography (EEG) signals to identify the attention levels of the students during online classes. These are aimed to help teachers make objective evaluation of students staying and paying attention to the lesson [14].

The study conducted experiments on a public dataset, extracted power spectral density (PSD) features using fast Fourier transform, calculated different attention indexes, and built three different classification algorithms: Some of the top ML algorithms include K-nearest neighbors (KNN), support vector machine (SVM), and random forest (RF). Thus, using the proposed RF classifier we received 96% accuracy, which indicates the applicability of the approach in identifying the attention state of the user rather effectively as compared to KNN and SVM. The structure of the document also entails background information, related work, methodology and results of the study, as well as a comparison between the proposed model and the conventional models adopted for experiments similar to this one [14].

Thus, in line with the general significance of evaluating students' attention, the study is especially relevant in the context of the COVID-19 pandemic and the necessity to realistically evaluate students' attention during online learning. From EEG data and the application of machine learning, the research proposes a viable method to identify and categorise the level of students' attention [14].

The results show that the proposed random forest classifier in predicting the attention state of a user can work fine though it is more effective than the regular classification algorithms like KNN and SVM. The in-depth approach of the study and comparison with other related work highlights the contribution of this research in the enhancement of knowledge on online learning and identifying attention through EEG data [14].

2.4.11 Electroencephalogram Data Collection for Student Engagement Analysis with Audio-Visual Content

Monitoring students' attention during learning is crucial for successful knowledge acquisition, influencing cognitive function and enabling interactive learning systems to improve outcomes. The research involves collecting EEG data from 20 participants exposed to various visual stimuli, using a 40-channel wet electrode system, and providing the data for research community use. The introduction emphasizes the importance of monitoring students' attention during learning to enhance cognitive function and improve learning outcomes. It highlights the significance of tracking students' mental states in computer-based learning environments and the potential benefits of utilizing active learning to enhance student engagement index. The research aims to investigate the feasibility of using active learning to improve student engagement when exposed to various visual stimuli, focusing on EEG data collection from participants under different conditions. By collecting EEG data using a 40-channel wet electrode system and providing raw and pre-processed data, the study aims to contribute valuable insights to the research community for further analysis and utilization. EEG data was collected from 20 participants (ten males, ten females) using the Allengers Neuro PLOT, a 40-channel wet electrode system, while they were at rest and exposed to various virtual infotainment/educational content. The study included recording raw and pre-processed EEG data under quiescent and audio-visual continuous cues to analyze the participants' brain activity patterns. A development of EEG data pre-processing pipeline was employed to handle the collected data, ensuring its quality and reliability for further analysis. The research focused on investigating the impact of different visual stimuli on student engagement index and aimed to provide valuable EEG data for the research community to utilize in similar studies [15].

The study aimed to investigate the feasibility of enhancing student engagement through active learning when exposed to various visual stimuli, utilizing EEG data collection from participants. By collecting EEG data using a 40-channel wet electrode system and analyzing brain activity patterns under different conditions, the research provided valuable insights into monitoring students' mental states during learning. The findings suggest that tracking EEG data can offer a precise picture of a learner's mental state, enabling interactive learning systems to adapt tutoring content and improve learning outcomes. The availability of raw and pre-processed EEG data, along with a sophisticated data pre-processing pipeline, contributes to the research community for further analysis and utilization in similar studies. Overall, the study highlights the importance of monitoring student engagement through EEG data collection and the potential benefits of utilizing active learning strategies to enhance learning experiences in computer-based environments [15].

2.4.12 School-Based Neurofeedback Training for Sustained Attention

The study explores using neurofeedback training in schools to enhance sustained attention in students. Results suggest that classroom-based neurofeedback can improve attention, work habits, and learning skills in students. The study explores using neurofeedback training in schools to enhance sustained attention in students. Results suggest that classroom-based neurofeedback can improve attention, work habits, and learning skills in students. The study employed a one-group pretest-posttest quasi-experimental design to assess the impact of in situ neurofeedback training on sustained attention in students. Students participated in attention training through game-based neurofeedback sessions conducted in the classroom, with each session lasting 25 minutes, for a total of 35 sessions. The main focus was on building sustained attention in the general student population and

evaluating whether the improvements in attention could lead to enhanced work habits and learning skills [16].

The methods aimed to investigate the effectiveness of classroom-based neurofeedback in developing sustained attention and translating these gains into observable behaviors related to planning and organization. The research design and implementation of neurofeedback training in the school setting were geared towards exploring the potential of neurofeedback as a tool for enhancing attentional capacities in students, beyond its established use in treating Attention Deficit Hyperactivity Disorder (ADHD) [16].

The study supports the effectiveness of classroom-based neurofeedback training in improving sustained attention in students, leading to observable enhancements in work habits and learning behaviors such as planning and organization. While neurofeedback has demonstrated specificity in treating Attention Deficit Hyperactivity Disorder (ADHD), this research highlights its potential in developing attentional capacities in the general student population. The promising results of this exploratory investigation suggest that further applied research is warranted to delve deeper into the use of neurofeedback as a tool for enhancing attention and related skills in students [16].

2.4.13 An Online Teaching Video Evaluation Scheme Based on EEG Signals and Machine Learning Predict Students Attention in Online Learning Using EEG Data

The abstract outlines a study using in situ neurofeedback training to improve sustained attention in students through game-based sessions in the classroom. Results indicate that classroom-based neurofeedback can effectively enhance sustained attention and translate these improvements into better work habits and learning behaviors, emphasizing the need for further research in this area. The introduction of the paper discusses the use of neurofeedback training to enhance sustained attention in students within the school

environment. It highlights the existing research on the specificity of neurofeedback in treating Attention Deficit Hyperactivity Disorder (ADHD) but notes the lack of focus on its efficacy in improving attention in the general student population. The introduction sets the stage for the study by emphasizing the potential of neurofeedback to improve attentional capacities and learning skills in students, leading to the need for further investigation in this area. The study employed a one-group pretest-posttest quasi-experimental design to assess the impact of attention training game-based neurofeedback on sustained attention in students. Students participated in 35 sessions of 25 minutes each, engaging in neurofeedback training within the classroom setting [17].

The neurofeedback training aimed to enhance sustained attention and translate these improvements into observable work habits and learning behaviors, such as planning and organization. The methods focused on investigating the effectiveness of classroom-based neurofeedback in building sustained attention in the general student population, highlighting the potential of neurofeedback as a tool for improving attentional capacities and learning skills. Neurofeedback training can build sustained attention in students and can improve work habits and learning skills [17].

2.4.14 Measuring Brain Waves in the Classroom

In their article "Measuring Brain Waves in the Classroom," published by NEUROSCIENCE on 11 August 2020, Nienke van Atteveldt, Tieme W.P. Janssen and Ido Davidesco address the use of portable electroencephalography (EEG) devices as an instrument to measure brain activity in educational settings. In this post by authors at the Vrije Universiteit Amsterdam and the University of Connecticut, they talk about the science of brain waves, which are cycles of electrical currents generated by groups of neurons firing

in synchrony. One way to track these waves is with an EEG, which detects electrical activity via electrodes placed on the scalp [18].

Human brain waves correspond to various mental states: as an example, brain waves in the delta frequency band (1-4 Hz) are representative of deep sleep. It also presents event-related potentials (ERPs), which are the activity of the brain in response to the events such as the reading of a word or control of an impulse. ERPs are isolated from the EEG signal by averaging responses to repeated events [18].

The researcher further suggest that tissue samples taken from autopsies may not be in their true resting state and point out that overactive neural cells may manifest in cell culture experiments as they did in the laboratory experiments used by previous researchers (which measured methodological brain activity in unnatural settings that do not replicate natural circumstances). Here, they all have a story to tell, a research on portable EEG devices they used to measure brain activity in a high school biology classroom during lessons. In the study, students' brain waves were found to be more in tune with the brain waves of their classmates and to a greater extent the more engaged students were [18].

Portable EEG devices not only enhance research but also offer educational opportunities, as seen in the "BrainWaves" neuroscience high school program, where students use EEG to design their own research projects. However, the authors caution that portable EEG data is not as precise as laboratory data and that the natural environment introduces variables that can complicate interpretation [18].

The article concludes by addressing concerns about mind reading, asserting that current technology cannot decode thoughts. The authors also critique the idea of using EEG to monitor students' attention, emphasizing the need for more research and the importance of allowing the brain to rest and wander for effective learning [18].

Overall, the article presents portable EEG as a valuable tool for studying brain activity in natural environments, enhancing education, and providing insights into social interactions, while also acknowledging the ethical and practical considerations of such technology [18].

2.4.15 EEG Emotion Classification Network Based on Attention Fusion of Multi-Channel Band Features

The document presents a study on EEG-based emotion classification, focusing on learning emotions such as boredom, neutrality, and engagement. The authors, Xiaoliang Zhu and colleagues from the National Engineering Research Center of Educational Big Data, Central China Normal University, introduce the EEG Emotion Classification Network Based on Attention Fusion of Multi-Channel Band Features (ECN-AF). This network is designed to improve emotion recognition by extracting and fusing multi-channel band features using attention units [19].

The study utilizes two datasets: the open-access SEED dataset and a self-collected dataset, LE-EEG, which includes physiological signals from 45 subjects during learning activities. The proposed ECN-AF model demonstrates higher accuracy than baseline models, achieving 96.45% on the SEED dataset and 95.87% on the LE-EEG dataset. The model outperforms existing methods by focusing on specific frequency bands and channels, using an attention mechanism to fuse features effectively [19].

The authors highlight the importance of physiological signals in emotion recognition, as they are more objective than external behavior-based methods. They also discuss the challenges of recognizing learning emotions due to the subtlety and short duration of facial expressions. The ECN-AF model addresses these challenges by leveraging EEG signals, which provide a more direct measure of brain activity related to emotions [19].

The study's methodology includes constructing a learning emotion EEG dataset (LE-EEG), proposing the ECN-AF model, and validating the model's performance across different datasets. The ECN-AF model consists of three modules: frequency band division and channel selection, frequency band attention feature extraction, and feature fusion and classification. The model employs a multi-channel convolutional backbone network and an attention fusion unit to enhance classification accuracy [19].

The experimental results show that the ECN-AF model not only outperforms baseline models but also demonstrates robustness across different datasets. The authors suggest that future work will focus on expanding the LE-EEG dataset and exploring multimodal learning emotion recognition, as well as optimizing the combination of EEG channels for emotion recognition [19].

The document concludes with acknowledgments of funding support and a statement on the availability of the SEED dataset. The authors also provide a list of references and an appendix detailing methods for careless/insufficient effort (C/IE) detection in questionnaire data [19].

2.4.16 Generalizability of EEG-based Mental Attention Modeling with Multiple Cognitive Tasks

The document titled "Generalizability of EEG-based Mental Attention Modeling with Multiple Cognitive Tasks" discusses a study on measuring and quantifying attention levels using electroencephalogram (EEG) data. The study involved three cognitive tests and collected data from ten subjects. The researchers used different cross-validation options to evaluate the performance of attention classification among different tasks. The results showed that EEG-based attention recognition can generalize across subjects and cognitive tasks. This research also emphasizes the role of mindfulness on cognitive performance, and

offers insight regarding the possibilities of using passive Brain-Computer Interface (BCI) to assess cognitive status and task enhancements. In the study, the researchers noted that the findings needed additional validation yet, and a lot more testing to improve the quality of this study [20].

In relation to selective and sustained attention, the work employed three cognitive tests to measure selective and sustained attention. The most frequently used tests were the Stroop test, the Eriksen Flanker test, and the Psychomotor Vigilance Task (PVT). Such tests were administered in random fashion in several runs to capture outcome from the subjects. Assessment of the attention classification's performance was also a part of this study among these different cognitive tasks [20].

The study's findings have significant implications for the generalizability of EEG-based mental attention models. The results suggest that EEG-based attention recognition can generalize across subjects and cognitive tasks. This indicates that EEG-based mental attention models have the potential to be applied across different individuals and cognitive tasks, demonstrating a broader applicability and reliability of these models in measuring and quantifying attention levels. This generalizability is crucial as it implies that the EEG-based mental attention models can be used effectively in various real-world scenarios and applications, such as improving learning efficiency, vigilance detection while driving, attention training, and rehabilitation [20].

2.4.17 Real-Time Learner Classification Using Cognitive Score

The document titled "Real-Time Learner Classification Using Cognitive Score" discusses a system designed to monitor students' learning progress using brainwave data. The system collects brainwave readings, evaluates attention levels, and sends the data to a server. It aims to enable dynamic adjustments to instructional methods and materials in a

fast learning environment. The document explains the theoretical background, the need for learner classification, and the proposed system architecture. It also outlines the workflow, classification engine, and experimental results. The study emphasizes the importance of understanding students' learning abilities and the potential benefits of personalized e-learning systems [21].

The proposed method for real-time assessment of students' intelligence and learning skills involves the use of brainwave data. The system is designed to collect brainwave readings from students of different age groups while they are learning. These brainwave readings are then used to classify the students' instant learning skills using a cognitive score. Based on this classification, the system suggests suitable learning materials to maintain the learner in an overall state of optimal learning. The main focus is on constructing cognitive state estimators from a multimodal array of physiological sensors to assess the intelligence and knowledge adapting abilities of the students [21].

The conclusion of the document emphasizes the importance of real-time learner classification using cognitive scores. It highlights the challenges faced in assessing students' attention and learning abilities in digital learning environments and the potential of brainwave data to address these challenges. The proposed system's ability to monitor students' attention levels and classify their learning skills in real-time is seen as a significant advancement in personalized e-learning. The document also discusses the experimental results and the potential impact of the proposed system on educational practices [21].

2.4.18 Real-Time Cognitive State Prediction Analysis using Brain Wave Signal

The document is a research paper that discusses the use of brain wave signals to predict cognitive states during learning tasks. It focuses on the analysis of cognitive states using EEG measurements and proposes a model that employs advanced deep learning

algorithms for classification. The paper outlines the methods used for data collection, preprocessing, and feature extraction from EEG signals. It also introduces the concept of Enhanced Convolutional Neural Network (ECNN) for classifying concentration levels based on the extracted parameters. Data Collection is EEG signals are captured using a 128-channel Emotive Epoch headset device. The document mentions that 20 healthy individuals (20-21 years) participated in the experiments. Next, Preprocessing is linear filtering is used to filter out artifacts prominent in raw EEG signals. other than that, Feature Extraction which is the document describes the use of Discrete Wavelet Transform (DWT) and fuzzy fractal dimension measures for feature extraction. These techniques are applied to the processed signals to extract spectral and statistical parameters such as entropy, energy, and mean. The last one, Classification that the paper introduces the use of an advanced deep learning technique called Enhanced Convolutional Neural Network (ECNN) to classify the extracted parameters into concentration levels (i.e., high and low). These methods and techniques collectively aim to analyze cognitive states during learning tasks by processing and classifying EEG brain signals. The research aims to improve online learning systems by analyzing brain signals during different learning tasks [22].

The document concludes by emphasizing the importance of maintaining the highest level of cognitive state during learning and decision-making processes. It highlights the significance of cognitive state analysis in critical decision-making and mentions that empirical methods of the brain are used to analyze the behavioral and physiological responses of learners. The paper also discusses the potential impact of changes in behavior on physiology and the working brain system. Furthermore, the document references a study titled "StressSense" that focuses on detecting stress in unconstrained acoustic environments using smartphones. This reference suggests a broader application of cognitive state analysis beyond the specific context of learning tasks. Overall, the conclusion underscores the

relevance of cognitive state analysis and its potential implications for various fields, including education, psychology, and human-computer interaction [22].

2.4.19 Enhancing the Learning Experience Using Real-Time Cognitive Evaluation

The document titled "Enhancing the Learning Experience Using Real-Time Cognitive Evaluation.pdf" presents a study on adapting the learning process in real-time based on the learner's cognitive and emotional states. It introduces a system called MENTOR, which uses electroencephalogram (EEG) signals to detect the learner's mental engagement and cognitive load. The system then adapts the learning strategy by selecting the best interaction approach, such as problem-solving or worked examples. The study evaluates the impact of this real-time adaptation on learning outcomes, emotional states, and satisfaction levels. The document also discusses the experimental results and the adaptive rules used by MENTOR. Overall, it highlights the potential benefits of dynamically adjusting the learning process based on the learner's mental and emotional states [23].

The method used in the document involves real-time monitoring of the learner's cognitive and emotional states using electroencephalogram (EEG) signals. These signals are processed to determine the learner's mental engagement and cognitive load. Based on this information, the system adapts the learning strategy by selecting the best interaction approach, such as problem-solving or worked examples. The study evaluates the impact of this real-time adaptation on learning outcomes, emotional states, and satisfaction levels. The conclusion of the study highlights the potential benefits of dynamically adjusting the learning process based on the learner's mental and emotional states, which could lead to an enhanced learning experience [23].

The conclusion of the document emphasizes the potential benefits of dynamically adjusting the learning process based on the learner's mental and emotional states. The real-

time monitoring of cognitive and emotional states using EEG signals, and the subsequent adaptation of the learning strategy, has shown positive impacts on learning outcomes, emotional states, and satisfaction levels. The study suggests that this approach has the potential to enhance the learning experience by providing tailored learning activities based on the learner's cognitive and emotional states [23].

2.4.20 EEG-Based Auditory Attention Detection via Frequency and Channel Neural Attention

The paper entitled 'EEG-Based Auditory Attention Detection via Frequency and Channel Neural Attention' focuses on a novel method of detecting auditory attention from EEG signals. The document shows proof showing the validity of the proposed system, with improved accuracy as compared to previous models. The proposed system is to facilitate new forms of human-machine cooperation by identifying the attended speaker based on biosignals obtained in complex auditory environment. The given document reports quantitative outcomes of experiments proving the enhanced performance of the proposed system compared to previous models [24].

It overviews different techniques employed to identify auditory attention from electrical signals in the brain. First, Stimulus Reconstruction which is This approach reconstructs the stimulus from EEG signals and then identifies the relationship between the reconstructed stimulus and the interval of the attended speech envelopes. Secondly, Linear and Nonlinear Decoders is an Algorithms for auditory attention detection can be categorized as either linear or nonlinear. Linear decoders use the concept of stimulus reconstruction, while postprocessing nonlinear decoders, including CNNs, connect the raw EEG data and speech stimulus to the attention detection decision. Thirdly, the proposed neural attention mechanism, Frequency and Channel Neural Attention Mechanism, dynamically allocates different weights to subbands and channels of EEG signals so as to capture discriminative

representations for the detection of auditory attention. Finally, Deep Neural Networks (DNN) which is the use of DNN models is highlighted in the document as nonlinear decoder baseline for detecting auditory attention using EEG. These methods are to demodulate the auditory attention from EEG signals, with the ability to identify the attended speaker in a multiple-speaker acoustic environment [24].

Overall, the document provides an extensive review on approaches for identifying auditory attention at the brain level, especially through EEG signals. The effectiveness of the proposed mechanism is confirmed analytically and with reference to the existing models. The study represents a significant progress toward online attention inference for neurocontrolled hearing aids. The results presented can be considered as the basis for further investigation of auditory attention in natural acoustic conditions and its potential use in human-voice interaction system [24].

2.4.21 EEG-Based measurement system for monitoring student engagement in learning 4.0

The document is a scientific report proposing a wearable system for personalized EEG-based detection of engagement in learning 4.0. It focuses on cognitive and emotional engagement detection during a learning task, using EEG signals acquired from the scalp. The system aims to improve the adaptability of intelligent teaching systems and is validated through experimental trials involving cognitive and motor skills. The study outlines the EEG instrumentation, data acquisition protocol, and data processing methods, emphasizing the use of standardized stimuli and self-assessment questionnaires to build a reliable metrological reference. Additionally, it discusses the architecture of the proposed system, including the feature extraction and selection process, baseline removal, domain adaptation, and classification methods. The study concludes by highlighting the potential applications

of the proposed system in automated teaching platforms and the need for further validation in real educational settings [25].

The document outlines a comprehensive methodology for the proposed wearable system. Firstly, Experimental Protocol which is the study involved 21 school-age subjects, and the experimental sample was extracted from the population of college students to mitigate the impact of age and educational attainment on performance. The ethical committee of the University of Naples Federico II approved the experimental protocol. Secondly, Data Acquisition that EEG signals were acquired using a wireless cap with dry electrodes and 8 data acquisition channels. The EEG signals were acquired with a 512 Sa/s sampling rate and sent via Bluetooth to a computation device. The document also details the EEG signal acquisition device and the process for assessing contact impedance to guarantee optimal signal-acquisition conditions. Thirdly, Stimuli and Feedback that Various stimuli were used to induce high and low levels of emotive and cognitive engagements. The Continuous Performance Test (CPT) was used to modulate cognitive engagement, and background music and social feedback were used to modulate emotive engagement levels. The social feedback effectiveness was improved by simultaneous music background effects. Next, Data Processing is the document details the data processing methods, including artifact removal, feature extraction, and classification stages. Independent Component Analysis (ICA) was used to filter out artifacts from the EEG signals, and EEG data were divided into epochs for feature extraction. Then, Validation Procedures when the study employed standardized engagement assessment procedures, including a performance index and the Self Assessment Manikin questionnaire (SAM) to ensure a well-founded metrological reference. Lastly, Experimental Results which is the document discusses the experimental results obtained in within- and cross-subject cases, highlighting the effectiveness of the proposed signal processing pipeline in detecting both cognitive and

emotional engagement. These methods collectively form the basis for the development and validation of the proposed wearable system for personalized EEG-based detection of engagement in learning 4.0[25].

The conclusion of the document emphasizes the potential applications of the proposed system in automated teaching platforms. It also highlights the need for further validation in real educational settings. The study concludes by discussing the limitations and future directions of the research, including the lack of a prototype demonstration in an operational environment and the need for standardized engagement assessment procedures in real educational situations. Additionally, the document underscores the importance of the proposed system in improving the adaptability of intelligent teaching systems. It suggests that adaptive strategies could be aimed at improving learner engagement, and the effectiveness of the learning process mainly depends on the engagement level of the learner. The study also points out the potential impact of the ongoing Fourth Industrial Revolution on human learning and the increasing mediation of man's relationship with knowledge by technology [25].

2.4.22 EEG- System for monitoring and adjusting the learning process of primary school children based on EEG data analysis

Information and Control Systems describe a framework for detecting and adapting the learning process of primary school children based on EEG data. Supervision entails the process of assessing mental functions such as memory and attention through EEG analysis. The purpose is to make the educational process individualized which is to contribute to the increase of learning efficiency. It also entails EEG analysis, wavelet analysis, and feedback control for varying the level of task difficulty. Outcomes confirm the fact that feedback based on alterations in the brain activity rhythms leads to enhanced learning effectiveness. It also briefly mentions that EEG systems can be used for objective analysis and customization in

education, stating that there should be solutions for schools to use on the spot. Application value is to improve the educational quality and efficiency of learning new material. Specifically, the article focuses on analyzing the EEG signal, evaluating the amount of cognitive resources, as well as designing individual learning experiences for primary school children. It enlightens the restrictions of EEG system integration in school and introduces compact EEG devices and dry electrode solutions [26].

Algorithms of the developed system include system tuning, mandatory test analysis, identification of cognitive characteristics, tuning of the tasks' level of difficulty, and feedback, which improve the learning process enhancement and customization. It also offers a detailed explanation of how the system is equipped with EEG recording equipment and an educational environment that is engaging. The EEE uses tasks such as Schulte tables and logic problems to measure the cognitive assets and the adjustability of the tasks. The options available include test outcomes, assessment of cognitive capabilities, and personalized instructions. The text is focused on the testing of Schulte tables with regards to work efficiency and capacity amongst school children. The outcome measures include work efficiency and working capacity ratios and these provide an understanding of the level of consistency of attention and productivity in the primary school children [26].

It can be stated that the development of a system for monitoring and management of primary schoolchildren's learning process based on the analysis of EEG data is vital for creating individual learning strategies. It allows providing feedback and increasing the effectiveness of learning tasks by analyzing the data received from the EEG signal of brain activity. EEG systems' implementation into the process of learning allows for a better comprehension of a student's cognitive processes and the provision of individual feedback to enhance learning results. The system is designed to enhance the quality of education by providing the system with objective measures of the subject's characteristics and modifying

the learning process based on those characteristics. In light of these technological developments in the field of neuroscience, EEG systems can play a crucial role in augmenting the learning process and improving the efficiency of knowledge acquisition [26].

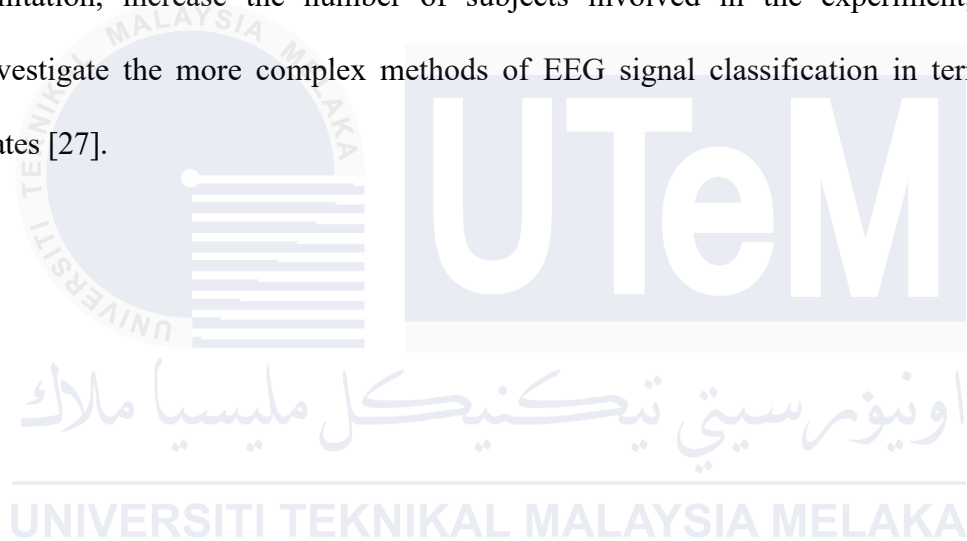
2.4.23 EEG-Based Tool for Prediction of University Students' Cognitive Performance in the Classroom

A study adopted neuroengineering and machine learning to assess the cognitive performance of university students across six learning modes. The video EEG data were collected, and the findings indicated that the video instruction was more effective than the text instruction. The results showed that the theta/alpha ratio and delta power were negatively related to performance suggesting fatigue. The designed tool made an 85% accuracy in the prediction of performance and estimated that video group was the most efficient media. The reported research indicated that the discussed approach can be useful when assessing learning approaches and promoting learning outcomes while acknowledging the small number of subjects [27].

The technique applied entailed observing and analyzing the EEG signals in order to extract the facial or cognitive characteristics. These features include skin temperature, electrodermal activity, and heart rate, which were mentioned by the study as ways to improve the accuracy of the model. Furthermore, the authors highlighted one other application of a P300-inducing protocol to measure the amplitudes and latencies caused by cognitive impairment. The study revealed that the group of students exposed to videos outperformed the group that was exposed to texts despite a slight rise in perceived workload in the video group. However, the mentioned study was done with a small sample size, so they admitted that it could have some impact on accuracy of the results. Due to this limitation, it is advised

that future work be conducted to consider more complex algorithms for classifying mental states through the EEG signals [27].

The study determined that additional aspects of physiological responses such as skin temperature, electrodermal activity, and the heart rate could be included in the model to improve the model's reliability. Although the study has demonstrated improved performance the participants the study has some shortcomings one of which is a small sample size thus questioning the validity of the results. It is suggested that the future studies overcome this limitation, increase the number of subjects involved in the experiment, and further investigate the more complex methods of EEG signal classification in terms of mental states [27].



2.5 Sample of table when it takes more than 1 pages

Table 2.1 Comparison for all the related past project

No	Year	Method	Waveform and frequency	Accuracy	Advantages	Disadvantages
[5]	2022	1. The research paper utilizes a multimodal approach to identify the attention level of students in the classroom 2. Physiological signals like Electro dermal activity (EDA), Electroencephalography (EEG), and Electrocardiogram (ECG) are measured to monitor students' attention. 3. Deep Convolution Neural Network (DCNN) with Histogram of Gradient (HoG) is used for face detection, and the facenet algorithm is employed for face recognition 4. A Convolution Neural Network model is proposed to evaluate students' attentiveness, focusing on physical cues like head movement, eye state, and mouth state (open or closed). 5. The model is trained using CNN instead of traditional Machine Learning algorithms to improve accuracy in identifying students' attention levels.	Null	100%	1.Improved accuracy using CNN instead of traditional ML algorithms. 2.Monitoring physical state of face for identifying student attentiveness.	1. EEG headbands may distract students in class. 2.Physiological signals are hard to extract and analyze effectively.
[6]	2023	1. EEG-based attention monitoring with IRF algorithm for accuracy improvement 2. EEG-based training with serious	Beta (16Hz ro 32Hz)	79.34%	1.IRF algorithm for five-level attention monitoring with promising accuracy. 2.Serious games designed for	1.Existing studies have low accuracy and poor attention levels. 2.Inefficiency during attention training is a common issue.

No	Year	Method	Waveform and frequency	Accuracy	Advantages	Disadvantages
		games and closed-loop neurofeedback			sustained, selective, and focus attention training.	
[7]	2023	1. EEG data analytics 2. Face-to-face conference workshop data collection	Null	Null	1. EEG data analytics for student attention monitoring in classrooms 2. Empowers learners and teachers with real-time attention insight	1. EEG data analysis complexity 2. Cost of EEG equipment and training
[8]	2021	1. Convolution Attention Memory Neural Network (CAMNN) 2. Vector-to-Vector (Vec2Vec) modeling	Beta (up to 128Hz)	92%	1. CAMNN model achieves 92% accuracy and 0.92 F1 score. 2. Outperforms existing neural network models like RNN, LSTM, CNN.	1. Limited discussion on potential limitations of CAMNN model 2. Lack of comparison with non-neural network methods for classification
[9]	2020	1. Backpropagation Type Neural Networks used for concentration level detection. 2. EEG waves with Theta, Low Beta, and High Beta inputs utilized.	Theta, Low Beta, High Beta	Null	1. Portable device for real-time monitoring of student attention levels. 2. Implementation on Arduino Microcontroller for easy accessibility and usability.	1. Overfitting risk in training neural network model 2. Limited processing power of Arduino for real-time monitoring tasks
[10]	2022	Wired and wireless EEG technology Multilevel linear models for data analysis	Alpha (7Hz tp12Hz)	Null	1. Mobile EEG technology allows real-world neural process examination. 2. Alpha oscillations provide stable EEG data for attention assessment.	1. Data loss increased in classroom-based paradigm. 2. Concerns about data quality and artifact contamination in EEG recordings.
[11]	2023	1. Real-time vision-based classroom monitoring system 2. YOLOv5-based action behavior detection,	Null	76%	1. Real-time vision-based system monitors student behavior, emotions, and attendance.	1. Limited dataset size for training deep learning models 2. Dependency on facial expressions for attention recognition

No	Year	Method	Waveform and frequency	Accuracy	Advantages	Disadvantages
		emotion detection, and facial recognition system			2.AI-based behavior recognition enhances instructors' performance and student engagement.	
[12]	2023	1. EEG headset measures brain signals for attention level analysis. 2. Statistical modeling, Bayesian t-test, regression analysis validate the work.	Null	Null	1.Overcome classroom difficulties like visibility, audibility, and interaction. 2.Measure attention level using EEG for effective learning analysis.	1.Overcoming difficulties like visibility, audibility, and interaction in classroom. 2. Statistical modeling and validation of EEG data for acceptability assessment.
[13]	2021	1. 8-channel differential prefrontal EEG signals acquisition 2. Digital attention evaluation algorithm implemented on FPGA	Null	85%	1.16-channel neural signal acquisition for precise attention evaluation. 2.FPGA implementation of digital attention evaluation algorithm for accurate results.	1. Limited to 8-channel differential prefrontal EEG signals for attention evaluation. 2. Complexity in design with multiple components for signal acquisition.
[14]	2022	1. Signal preprocessing, feature extraction, and attention computation phases 2. Classification algorithms for attention detection (KNN, SVM, random forest)	128Hz	96%	1.Objective assessment of student attention and engagement in online classes 2.Higher accuracy achieved by proposed random forest classifier	1. Limited to detecting positive attention state, not negative states 2. Dataset used was small, limited to 5 subjects
[15]	2022	1.EEG data collection from 20 participants using 40-channel electrode system 2.Investigation of student engagement index with various visual stimuli	Null	Null	1.Enhances student engagement index with active learning and visual stimuli. 2.Provides EEG data for research community usage after sophisticated pre-processing.	Null

No	Year	Method	Waveform and frequency	Accuracy	Advantages	Disadvantages
[16]	2023	1.In situ neurofeedback training 2.35 sessions of attention training game-based neurofeedback	Null	Null	1.Classroom-based neurofeedback effective for sustained attention in students 2.Neurofeedback can improve work habits and learning skills in students	1.Limited research on efficacy in general population 2.Further applied research needed for conclusive results
[17]	2022	1.K-nearest neighbor regression for mental workload test 2.Random forest algorithm for concentration test	Null	Null	1.EEG signals and machine learning for objective video evaluation 2.Improved student satisfaction and teaching quality with 85% increase.	Null
[18]	2020	1.Portable EEG devices used to measure brain activity in classrooms 2.Students develop research projects using EEG for teaching purposes	Null	Null	1.Measures brain waves in classrooms 2.Provides insights into student brain activity and engagement	1.EEG cannot measure individual brain cells due to small currents. 2.Lab experiments measure brain activity in unnatural situations.
[19]	2022	1.Feature summation fusion 2.Feature multiplication fusion 3.Attention weight fusion	Null	96.45%	1.ECN-AF model outperforms baseline models on SEED dataset. 2.ECN-AF model achieves 21.49% increase on LE-EEG dataset.	1.Limited sample size in SEED dataset (N = 15) 2.Small sample size in LE-EEG dataset (N = 45)
[20]	2020	1.Leave-One-Test-Out Train on 2 tests, remaining as Test data. 2.Leave-One-Subject-Out Train on N-1 subjects, remaining as Testing.	Delta, Theta, Alpha, Beta, Gamma	74.1%	1.EEG advantages: low cost, high availability, convenient setup 2.EEG measures frontal lobe activities related to attention, emotions	1.Small sample size of 10 subjects 2.No optimal feature selection for EEG-based attention modeling

No	Year	Method	Waveform and frequency	Accuracy	Advantages	Disadvantages
[21]	2020	1.Real-time assessment of intelligence based on cognitive score 2.Constructing cognitive state estimators from physiological sensors	Beta (12-30 Hz), Alpha (8-12 Hz)	82.27%	1.Real-time assessment of intelligence based on instant learning skills. 2.Suggests suitable learning materials for optimal learning based on cognitive score.	Null
[22]	2021	1.Linear filtering for artifact removal in EEG brain signals 2.Feature extraction using fuzzy fractal dimension and Discrete Wavelet Transform	Null	Null	1.Improved online learning efficiency 2.Accurate cognitive state prediction using ECNN classifier	1.Artifacts in raw signals require filtering for accurate analysis. 2.Deep learning classification is highly accurate for cognitive state prediction.
[23]	2019	1.Adaptation of learning strategy based on mental state 2.Extraction of cognitive load and engagement indexes from EEG signals	Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-22 Hz)	Null	1.Problem solving activities avoid illusion of understanding and promote generalization. 2.Worked examples can lead to irrelevant focus and illusion of understanding.	1.Worked examples may lead to illusion of understanding. 2.Problem solving can cause mental overload and frustration.
[24]	2022	1.Neural attention mechanism assigns weights to EEG subbands and channels. 2.Incorporate neural attention into AAD system for improved performance.	Null	86.9%	1.Neural attention assigns weights to EEG subbands and channels dynamically. 2.Proposed system outperforms state-of-the-art reference baselines significantly.	Null
[25]	2022	1.Filter bank, Common Spatial Pattern, Support Vector Machine 2.Transfer Component Analysis (TCA) for Domain Adaptation	Null	76.9%	1.Cross-subject approach reduces time for initial calibration procedure. 2.Domain Adaptation methods gaining	1.Nonstationarity of EEG signal leads to data variability between subjects. 2.Cross-subject approach challenging

No	Year	Method	Waveform and frequency	Accuracy	Advantages	Disadvantages
					attention for EEG signal classification.	due to EEG signal variability.
[26]	2020	1.EEG analysis 2.Wavelet analysis of recorded multichannel EEG data	Null	Null	1.Personalized learning process based on EEG data analysis 2.Continuous monitoring and adjustment of test task complexity	1.Lack of ready-made solutions for widespread use in schools 2.Scenarios for application need further development
[27]	2021	1.Neuroengineering-based machine learning tool 2.Correlation analysis to find relevant features for prediction	Theta, Alpha, Delta	85%	1.EEG tool predicts students' performance under different learning modalities 2.Video group showed better performance than text group.	1.Negative correlation between performance and (theta/alpha) ratio, delta power. 2.Users in fatigued, drowsy state performed worse during learning tasks.

2.6 Summary

The development of EEG-based attention monitoring systems has greatly enhanced the processes of classroom evaluation. Several authors have investigated the possibility of using EEG signals to track student attention levels, using devices such as Mind Link to give real-time data on attention and meditation modes. Past studies have demonstrated that employing EEG sensors can allow for accurate identification of student attention levels, which is essential to help interactive learning systems. Also, using EEG data, attention performance of university students can be predicted for the development of targeted learning methods. Research also shows the ability to read signals obtained from EEGs with higher degree algorithms and neural attention mechanism and determine student's auditory and visual attention. These projects demonstrate the possibility of putting Mind Link sensors in educational setting to monitor attention and meditation student achievement data.

CHAPTER 3

METHODOLOGY

3.0 Introduction

This chapter provided a precise and detailed description and justification of the component, theoretical techniques, project concept, and methodology. As a result, the evolution of the flow chart demonstrated that it could provide more straightforward and more precise explanations. Additionally, the materials utilized and the procedures for establishing the system connections in the project were provided. Finally, MATLAB software and Arduino coding was analyzed to create the system's algorithm and Graphical User Interface (GUI).

3.1 Project Overview

The workflow is the flow process for the entire system. Each of the different shapes in the flowchart describes the other procedure and has different meanings. Among the processes in the flowchart are decision, start, and termination. Refers to the Figure 3.1. The first process performed is research. Here, research is done based on the research paper used as a reference. The list of the software to be used is selected and needs to be understood in more depth. Numerous approaches and resources may be employed to gather as much information as possible as the system is developed and the project is understood. The algorithm here needs to be made to narrow down the work process and focus on one part. The required criteria and dimensions and the benefits and disadvantages are used in the following research stage. Finally, the implementation action was carried out when the preceding phase was accomplished. If there is an error, it needs troubleshooting. Then collect data from the project to obtain analysis and draw conclusions.



Figure 3.1 Project Overview

3.2 Methodology

This thesis presents a new and integrated analytical approach to monitor students attention level in a class. The essence of the approach used in this project is centered on the concept of EEG and attention. The selected approach is based on quantitative type, which aims to develop analytical model to calculate and analyze the attention level-based on the waveform occurs from the MATLAB GUI. The method (design) is experimental, which utilizes empirical modelling and statistical approach. Subsequently, Figure 3.1 shows the flowchart design of this thesis.

This flowchart explains the process of using a MindLink sensor in monitoring brainwave activity and analyzing the levels of attention and meditation. The process begins with the connection of the MindLink sensor to an HC-05 module that establishes the communication required. After that, the sensor scans the brainwave activity. The user then clicks the Run button to start the system, causing the brainwave data to appear in a GUI.

Next, the system performs a Human Interface Test on the brainwave data, evaluating attention and engagement for the student in a classroom environment. The obtained data is processed on MATLAB to figure out the extent of attention and levels of meditation that are experienced by the student. If the user clicks on Save, then that processed data can be stored as a local file for further references. This is the end of the process, and the data is safely saved and ready for further study. This flowchart clearly shows a systematic way of capturing, processing, and storing brainwave data in a user-friendly manner.

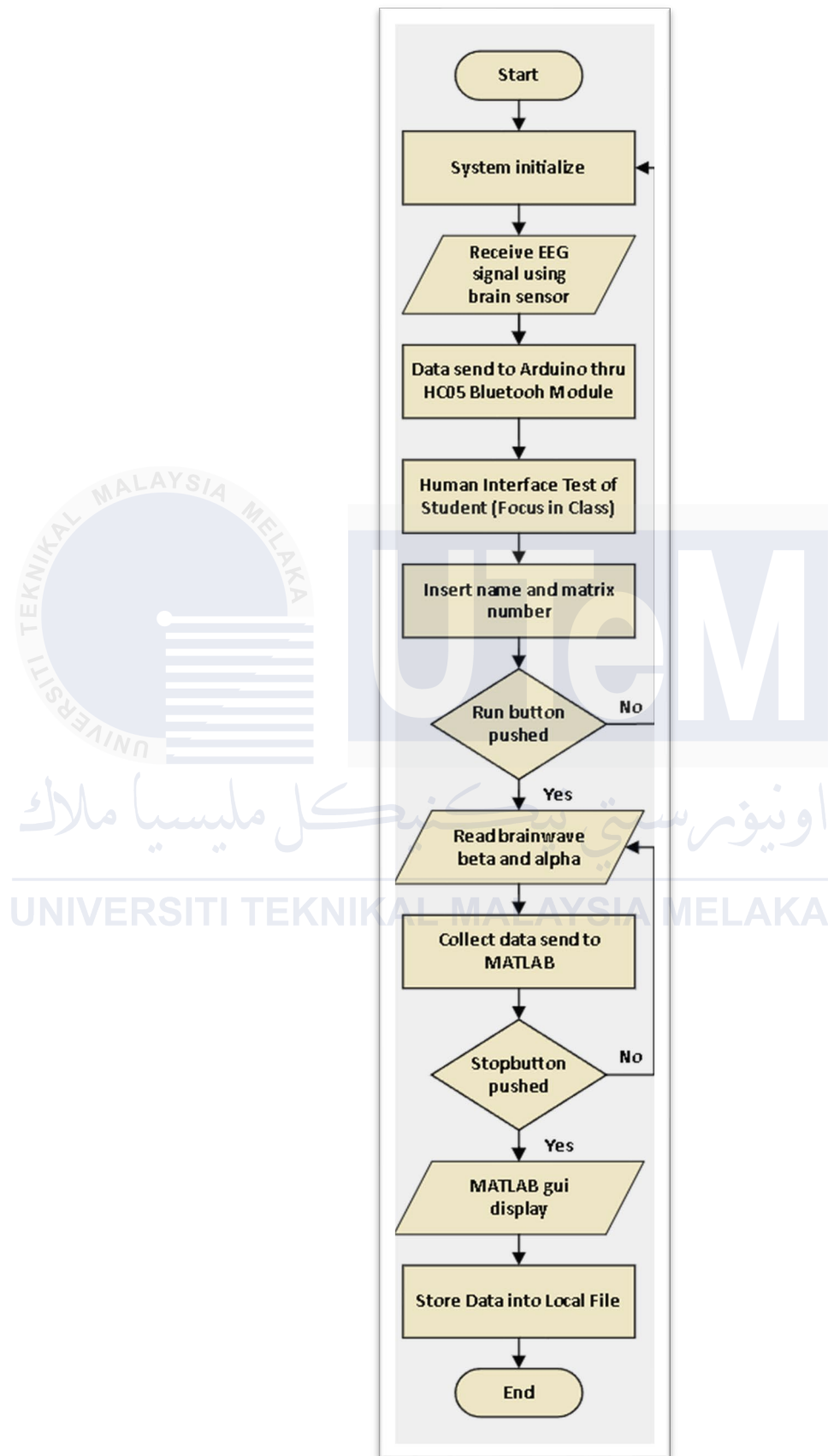


Figure 3.2 Attention monitoring system flowchart

3.3 Block diagram

This block diagram describes the realization of a system to monitor the attention and meditation level by using the brainwave data of a person wearing an EEG device as a Human-Machine Interface to record the activity of his brain while sitting in the classroom. The EEG device will capture his brainwave signals while sitting in the classroom and provide the real-time brain state data.

Noise is filtered and useful information of attention and meditation level is gathered from the raw brainwave data. The gathered processed data is now presented in a GUI-the simplest, friendliest interface-on which real-time visualizations about the activity of the brain can be viewed by a teacher or a researcher. Last but not least, the system saves this information to a file locally for any future review or analysis. This approach helps create a practical tool for understanding and improving student focus and engagement in the classroom.

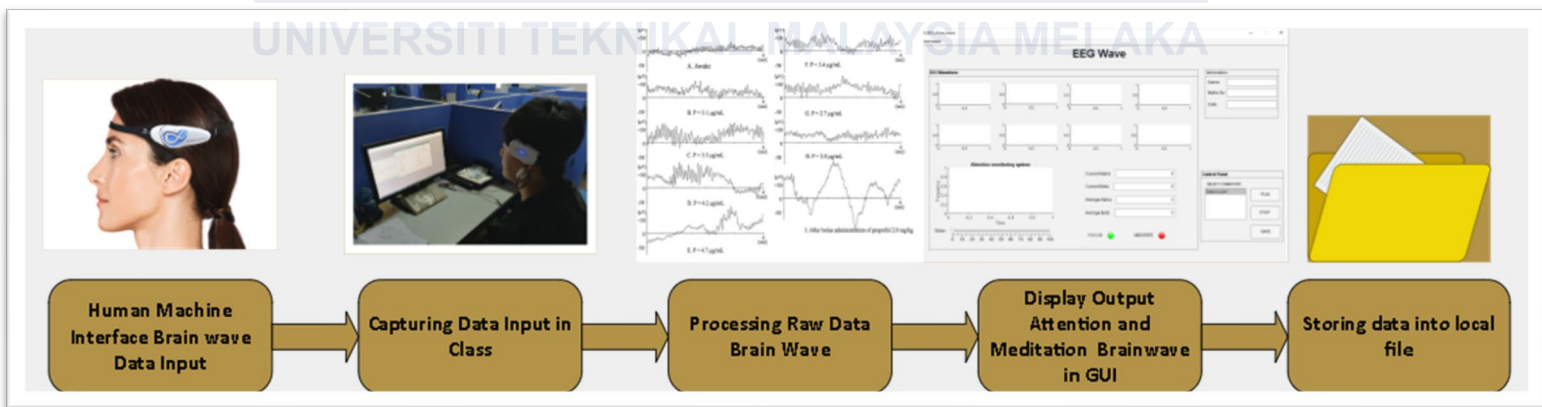


Figure 3.3 Block diagram

3.3.1 Experimental setup

Setting up an EEG-based attention monitoring system for classroom evaluation involves a combination of dependable hardware, strong software, and properly-designed experimental tactics. By following these tips, you could effectively monitor and analyze

student attention levels in a classroom.

3.3.1.1 Hardware Setup

- EEG device: Choose a reliable EEG device such as Mind Link that can measure attention and meditation.
- Computer or Laptop: A device to run the data acquisition and analysis software.
- Classroom Environment: Ensure the classroom is equipped with the necessary infrastructure to support EEG setup.

3.3.1.2 Software Setup

- Data Acquisition Software: Software to interface with the EEG device and collect data such as GUI
- Data Analysis Software: Software for processing and analyzing EEG data such as MATLAB

3.3.1.3 Experimental Procedure

- Participant Preparation: Explain the experiment to participants, obtain consent and fit the EEG device
- Baseline Recording: Record a baseline EEG signal for each participant when they are in a relaxed state.
- Classroom Activity: Conduct a normal classroom activity such as lectures while recording EEG data
- Post-Activity Recoding: Optionally record a post-activity baseline

3.3.1.4 Data Analysis

- Preprocessing: Read the real time data EEG from MATLAB GUI
- Feature Extraction: Extract from Arduino Uno to MATLAB GUI
- Statistical Analysis: Analyze the data to determine the attention and meditative levels.

3.4 Experimental procedure

In order to measure the student's attention levels in a classroom setting using an EEG based attention monitoring system, we were required to use the Mind Link sensor and Arduino Uno with the HC-05 Bluetooth module to connect with MATLAB and record real time data from a graphical user interface. Setting up the hardware required the attachment of the Mind Link sensor to the HC-05 Bluetooth module and the latter to the Arduino Uno. Arduino was to be involved in Bluetooth communication so that the EEG data may be sent to MATLAB GUI. The GUI, shown in Fig 3.5, provided real time EEG data, depicting student attentiveness as well as the duration of focus and meditation. This data was captured by the system and thus the ability to determine engagement level of students in successive periods. Applying the experimental procedure involved starting the sensor, data acquisition during class sessions and data save automatically that gives an integrated approach of monitoring and analyzing student attentiveness in real time in a classroom setting.

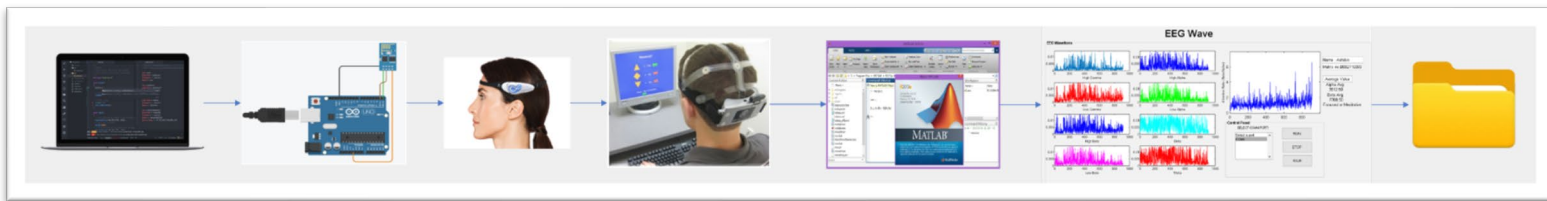


Figure 3.4 Project flow

3.5 Component selection

Component selection for EEG-based attention monitoring system for classroom evaluation.

3.5.1 Arduino Uno

The Arduino Uno is a microcontroller board that incorporates the ATmega328P to handle various Electric Circuit Projects because of its user-friendly feature. Some of the components that the board is fitted with include fourteen digital I/O pins, six analog inputs, sixteen MHz quartz Crystal, USB connection interface, a Power Jack, a Very high density ICSP header, and a RESET key. Based on the Arduino IDE, the board is programmable and supports diverse coding languages, which makes it suitable for students and experts. Another benefit due to its open-source origin and large community following is the limitless applicability in various fields.

The Arduino Uno is ideal for this EEG based attention monitoring project as described above. Since it can work with numerous sensors as well as modules such as the HC-05 Bluetooth module, the Mind Link sensor is suitable for connecting to read EEG data. Interfacing of Arduino Uno with MATLAB models can be done conveniently because of data acquisition and real-time data processing capabilities in the Uno board along with Bluetooth compatibility. Also, there are many Legos and it is very easy to program and

supporting it thus making the development and the troubleshooting much easier when it is used in monitoring of tendency of the students' attention in real time.

This process records the waves produced by an EEG sensor that measures activity inside the human brain that determines what is in one's focus or attentiveness. There is rudimentary pre-processing, which basically includes filtering and amplifying the signals, supplied by the Arduino Uno. This processed data, in turn, is transferred to a connected computer or system via HC05 Bluetooth modules for further analysis, which might include machine learning-based classification of attention states. The Arduino Uno is an ideal solution for connecting the EEG sensors with the software used for advanced signal processing and real-time feedback. Its affordability, ease of use, and compatibility with a wide range of sensors make it an ideal choice for prototyping and bringing this attention monitoring system into place.

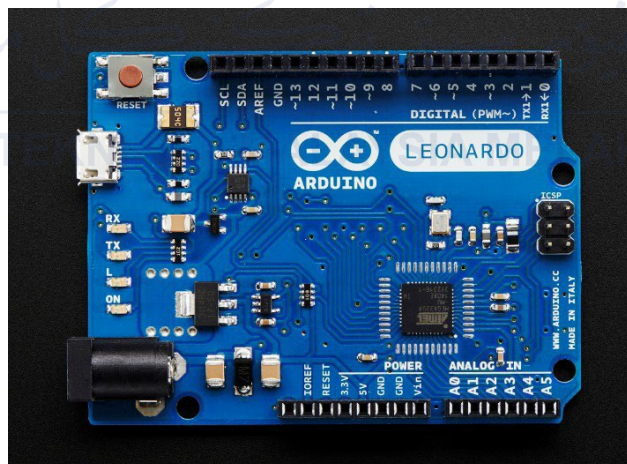


Figure 3.5 Arduino Uno

3.5.2 HC05 Bluetooth Module

The HC-05 Bluetooth module is a popular module commonly used in many practical applications in embedded systems. It works via the SPP and it is capable of creating a stable wireless connection that can exist between microcontrollers for instance the Arduino uno and any other Bluetooth devices. The module is easy to integrate with the main device, and has an accessible AT command set for configuration to allow it to be easily matched and used in communication. HC-05 is more energy efficient and less expensive as compared to many Bluetooth modules in the market and is compatible with a number of platforms that can be suitable in wireless data transmission applications like the EEG-based attention monitor.

The HC-05 Bluetooth module plays a crucial role in this project by enabling wireless communication between the EEG-based attention monitoring system and external devices, such as a teacher's computer or a mobile application. This module facilitates the real-time transmission of processed EEG data, such as attention levels, from the monitoring system to the user interface. HC-05 is an inexpensive and easy-to-operate module of serial communication; hence, very suitable for application in the system to operate with a microcontroller or another piece of hardware of it. With the application of HC-05, smoothness in the project regarding data transfer is assured; hence, the setting up of attention monitoring increases in efficiency and becomes user-friendly.



Figure 3.6 HC05 Bluetooth Module

3.5.3 Mind Link EEG Sensor

This technology would measure and interpret electrical activity in the brain by the detection of specific waveforms such as alpha, beta, delta, theta, and gamma waves. These waveforms will be useful in gathering valued information about different states of the mind, such as relaxation, being attentive, and deep sleep. It acquires real-time data on brain activity, such as user focus levels, emotional states, and relaxation patterns. Wireless data transmission-possibly by Bluetooth or other low-energy protocols-allows the feedback to be obtained in real time on MATLAB or receivers for changes in mental states.



Figure 3.7 Mind Link EEG Sensor

3.6 Software setup

3.6.1 Arduino IDE

The Arduino IDE will play an important role to do programming and controlling hardware parts for monitoring student's attention levels. It has given a proper software environment through which code may be written and compiled in order to be uploaded in a microcontroller for its interaction with the EEG sensors. Hence, using Arduino IDE, developers could configure their microcontroller for data processing and sensing, interaction with other systems, and further feedback to systems. This can easily be configured to ensure proper data intake and processing of signals due to the user-friendly interface and wide-ranging library support. This means that the system will be effective in running and forming the basis for easy integration of the machine learning models into a seamless attention monitoring solution.



Figure 3.8 Arduino IDE

3.6.2 MATLAB

MATLAB stands for Matrix Laboratory and is a high-level programming language coupled with an environment for both, numerical and symbolic computation. MATLAB is a high-level technical computing software, which is developed by MathWorks, focused on mathematical calculations, algorithms and modeling. It has simple commands and the program enables direct manipulation of matrices and arrays, making it ideal for engineering and scientific use. MATLAB has a wide range of functions and toolboxes that are inherent and some are extra specific for applications like signal processing, image processing, control systems and neural networks. It has a command prompt where you can type and execute commands, a console where you can store variables and manage them, and a script where the programmer can write scripts and functions. High documentation, strong community support, compatibility with other programming languages such as C/C++, Python, Java and continued development has made MATLAB ideal tool for researchers, engineers, and educators who need reliable solution to many computation problems.

The software of MATLAB will play a core role in this project: data processing of EEG, building the model of machine learning, and creating user-friendly interfaces. This versatile signal-processing toolbox filters and analyzes brain wave patterns to accurately extract attention-related features from raw EEG signals. Consequently, it also helps in developing algorithms with the aid of MATLAB's machine learning capabilities to classify the attention states in real time for adaptive feedback during classroom activities. Further, MATLAB App Designer enables the creation of an intuitive interface that will help teachers monitor the attention level and vary their teaching strategies. With its powerful integration of data analysis, visualization, and development of the user interface, the implementation of such an advanced EEG-based attention monitoring system becomes quite hassle-free and suitable for educational institutions.



Figure 3.9 MATLAB

3.6.3 Graphical User Interface (GUI)

A Graphical User Interface (GUI) is the method used within a device or a software in which the user is able to interact through pictures and icon and other visual methods rather than having to type in commands. GUIs offer clean interfaces where users are able to interact with and manage features using elements like push buttons, pull down menus, check boxes and scrolling bars. Using this type of map, information is easily arranged in a coherent structure, which helps to not only improve users' experience, but also make complex tasks easier to accomplish. It's hard to think of today's computing environment without referencing GUIs, which can be used in operating systems, applications, and embedded systems within mobile devices, tablets, PCs, and even complex industrial equipment. It allows the user to easily move through the software, adjust settings, and receive immediate feedback, which makes them irreplaceable for users of any level of proficiency, including experts who need to interact with various systems daily.

GUIDE (a Graphical User Interface Development Environment integrated within MATLAB) will be of great importance for the designing and realization of an interactive,

friendly interface for the user. GUIDE will ease the work of graphical interfaces by allowing users to drag and drop components like buttons, sliders, and plots directly onto a canvas, without complex or deep programming. This project could visualize real-time EEG data, visualize attention levels, and include interactive controls that would allow teachers to change the settings or monitor which students were not engaged. Due to the functionality in GUIDE, developers can link UI components to MATLAB scripts, thus seamlessly integrating advanced signal processing and machine learning algorithms and allowing the easy visualization of results and interaction with the system. This approach provides better usability but also offers a practical platform to test and improve the attention monitoring system in the classroom.

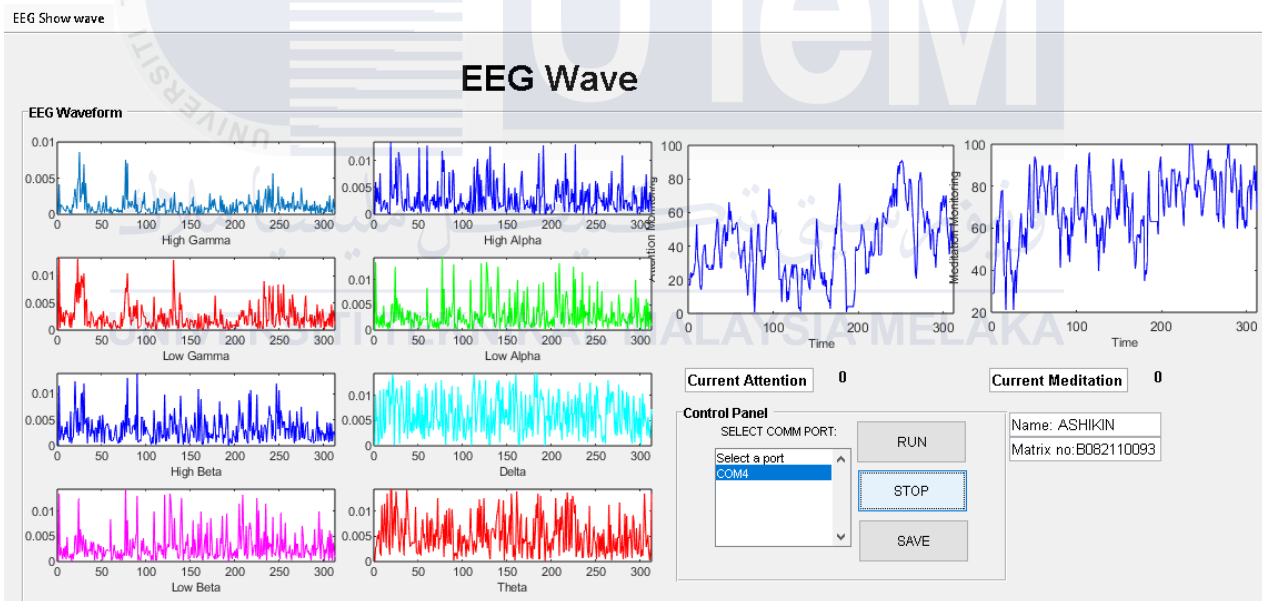


Figure 3.10 Graphical User Interface.

3.7 Summary

This chapter presents the methodology in order to develop a new, effective and integrated approach in estimating student attention level in a classroom. The system monitors student attention with brain sensor, and this has been developed to assist in monitoring the level of student's attention in a classroom. The Arduino Uno is connected to Mind Link brain sensor via an HC-05 Bluetooth Module. The process begins within Arduino IDE, where the necessary sketch is uploaded to the Arduino Uno. The installation complete, it wirelessly connects through Bluetooth to the brain sensor and then able to gather EEG data. That information is transmitted to MATLAB GUIDE, which processes and presents the real time data.

In MATLAB GUIDE, user need to select the correct Com port for the Bluetooth connection before running the program. When the program starts, it shows eight EEG wavelength bands which is high gamma, low gamma, high alpha, low alpha, high beta, low beta, delta, and theta. There are also two real time graphs that show the attention and meditation levels. The users are able to fill in the student's name and matrix number so it will be easier to tracked, and it also displays numerical values for attention and meditation based on to the graph. In order to enhance user interaction, a Stop button enable the user to terminate the program whenever required, while the Save button make sure the information can be saved for later. It is an easy to use system that helps in understanding how the students think during class.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.0 Introduction

The outcomes present the results and analysis on the development of EEG-Based Attention Monitoring System for Classroom Evaluation. Then, the Mind Link are used that connected through HS05 with MATLAB GUI to establish a methodology to monitor students level attention in a class. Case studies are performed to demonstrate the applicability of the proposed system using EEG method. The case study is based on a student's attention in a classroom. The case study located at classroom while having a lecture. It is important to note that, these case students' attention level is measured with a specific timing. The results are validated based on the time recorded in MATLAB GUI.

4.1 Prototype

The figure below shows an overview of the condition of the EEG-based attention monitoring system for classroom evaluation.



Figure 4.1 Prototype.

4.2 Average value data analysis for attention and meditation

Data analysis for the average value of attention and meditation within 10 students. The data is taken within 3 minutes for each student. From the average data for each student, it was found that majority students more attentive than meditative. This is due to the students tends to focus at beginning of the class start. From the data below, it shows that students are more attentive than meditative. The data can be collected through MATLAB application. There 7 out of 10 from the student's data has a higher attention level compare to meditation.

Table 4.1 Table average data analysis for 10 students.

NAME	AVERAGE VALUE ATTENTION	AVERAGE VALUE MEDITATION
AIMAN	40.04	37.87
AMER	53.85	43.43
IRFAN	60.40	53.18
ZULHILMI	69.43	60.23
SUNDRAM	25.68	56.68
FIRDAUS	43.10	58.75
AJIQ	55.37	24.78
DEENA	76.45	54.05
MUGILAN	39.71	70.57
ASHIKIN	55.43	39.07

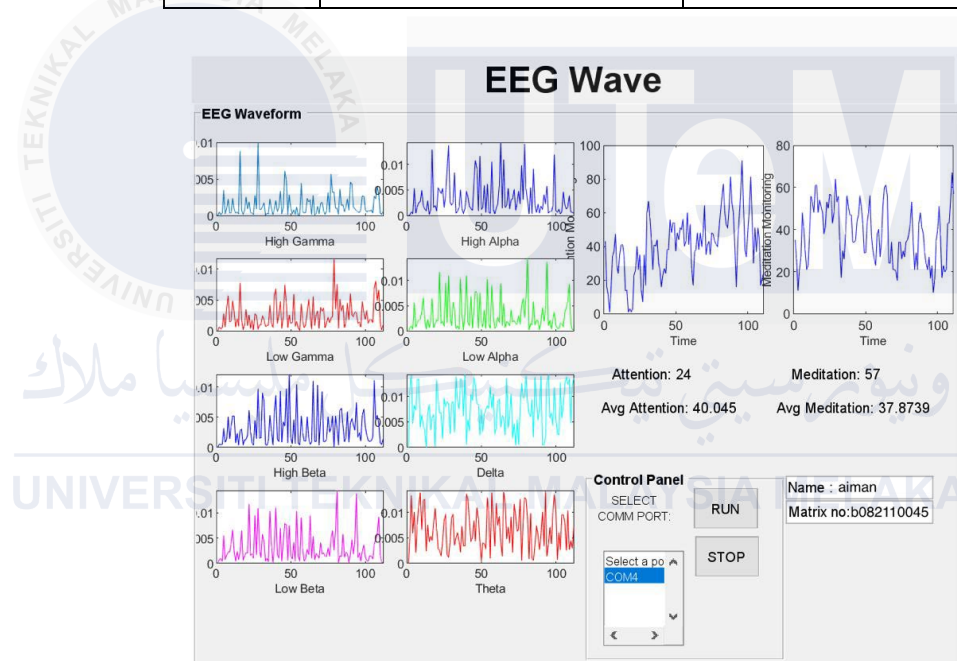


Figure 4.2 Data average Aiman

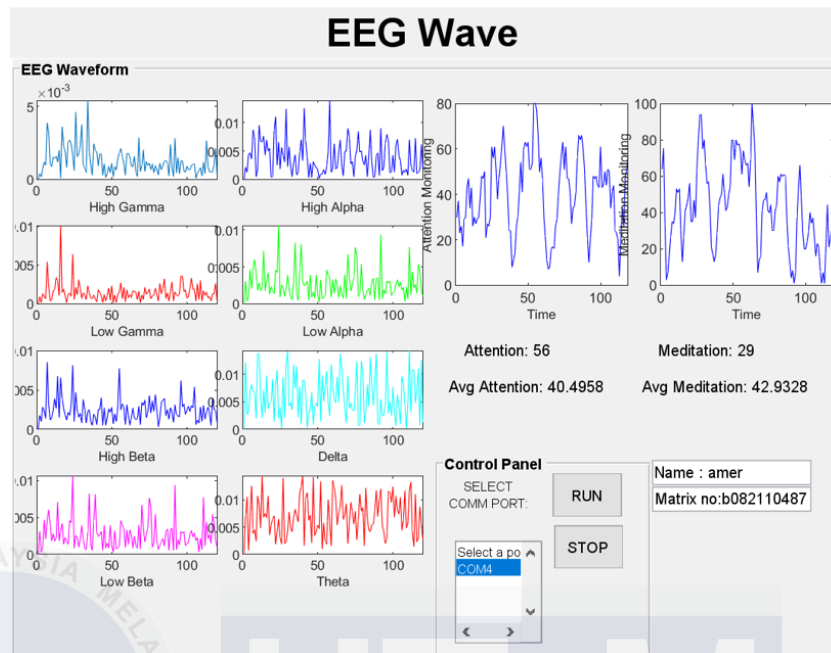


Figure 4.3 Data average Amer

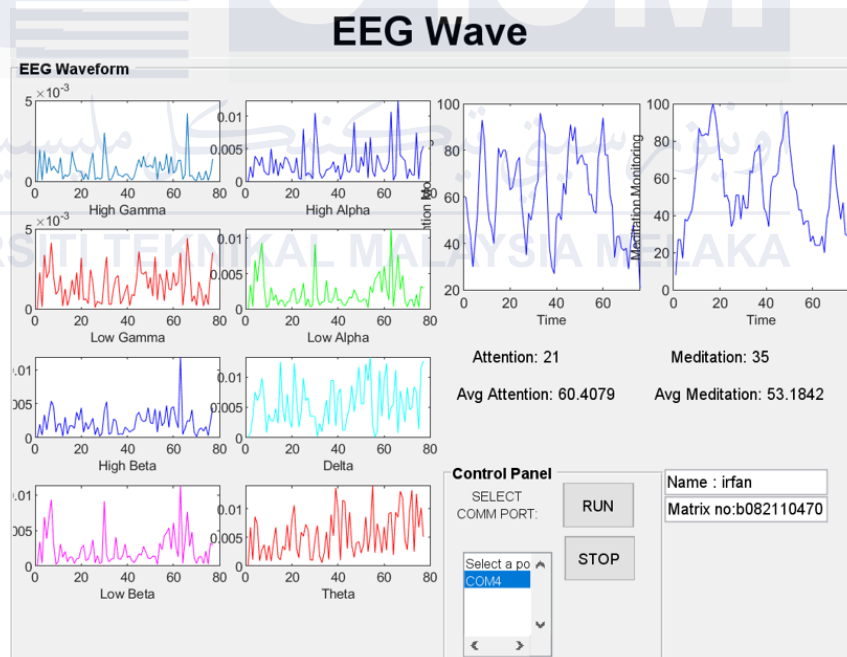


Figure 4.4 Data average Irfan

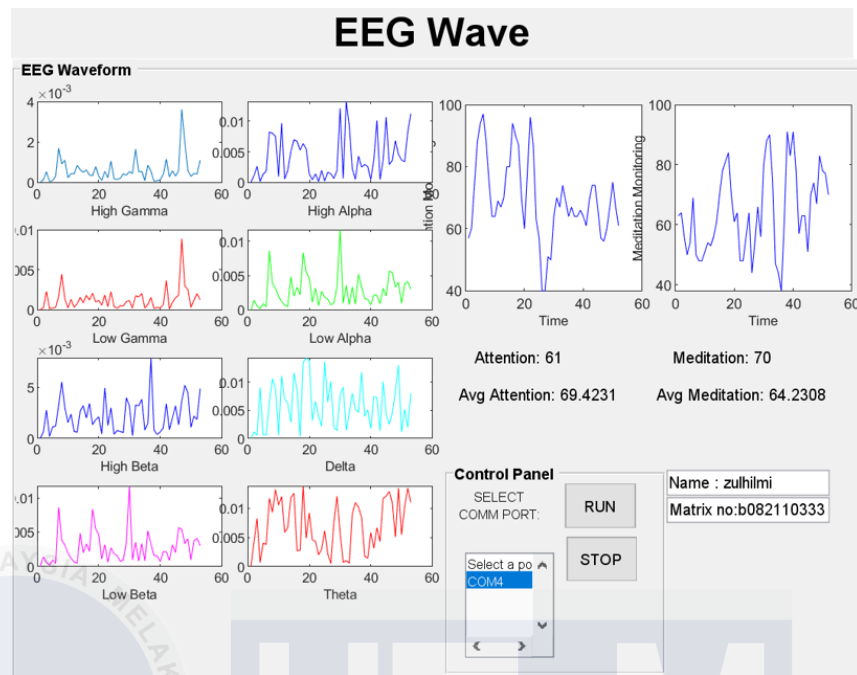


Figure 4.5 Data average Zulhilmi

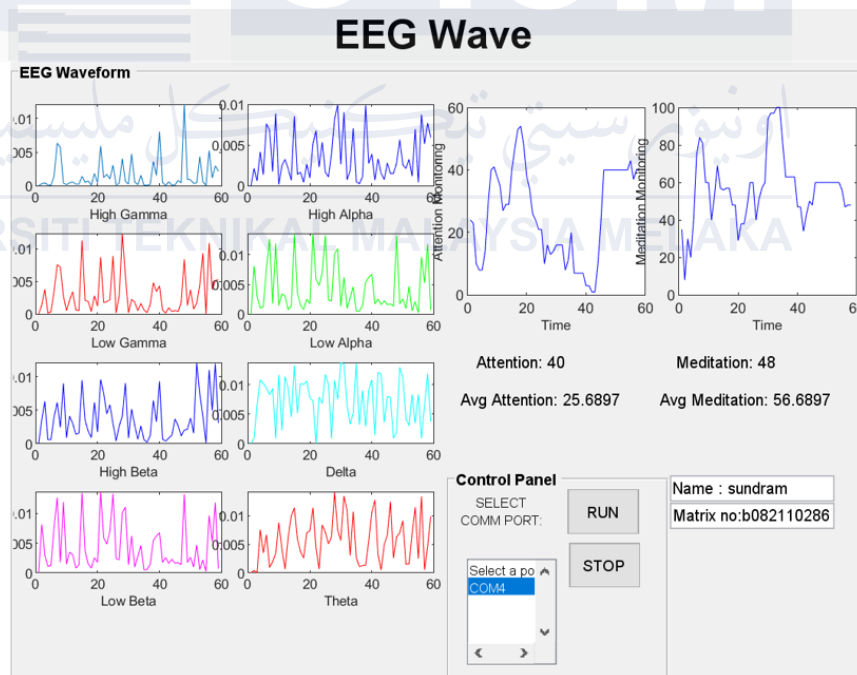


Figure 4.6 Data average Sundram

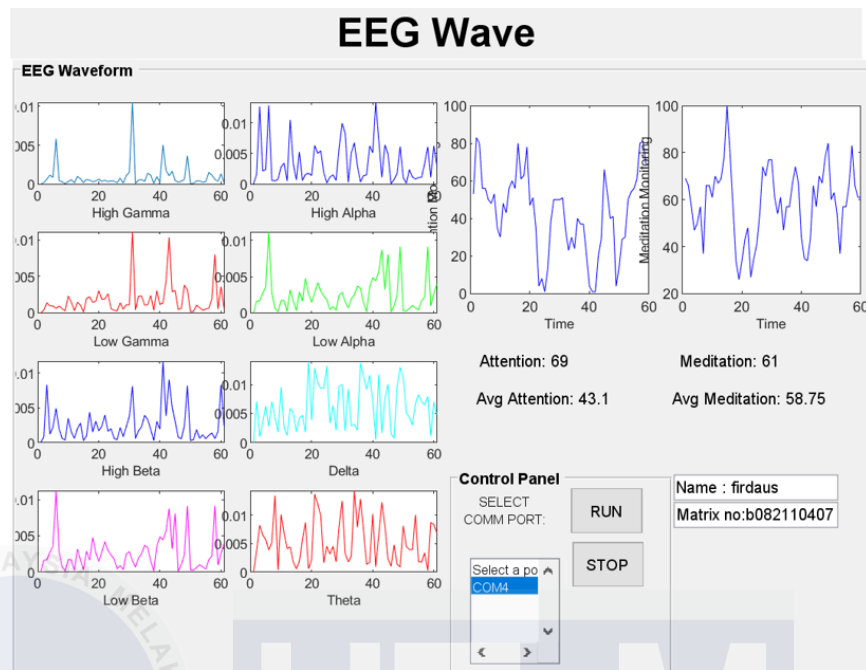


Figure 4.7 Data average Firdaus

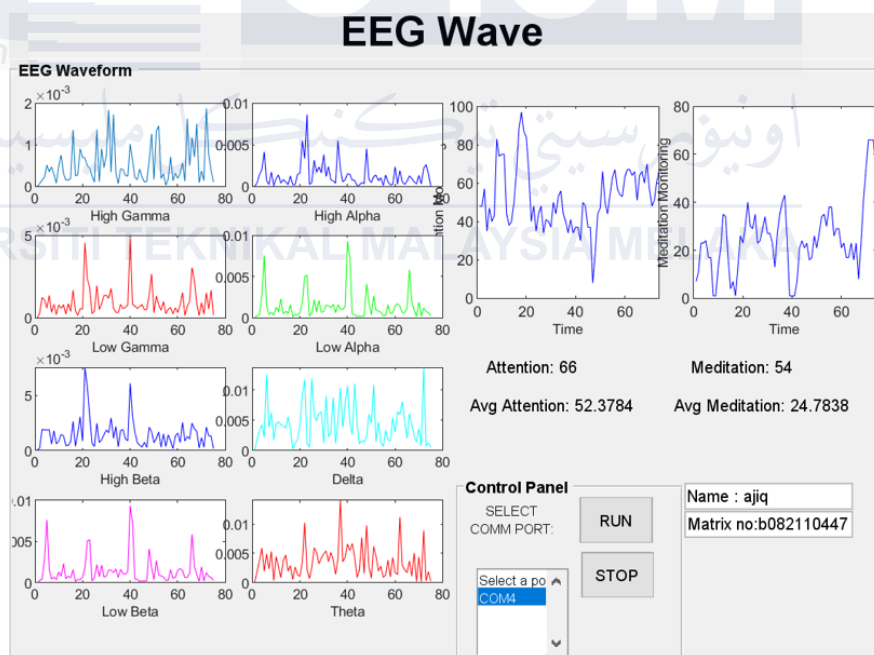


Figure 4.8 Data average Ajiq

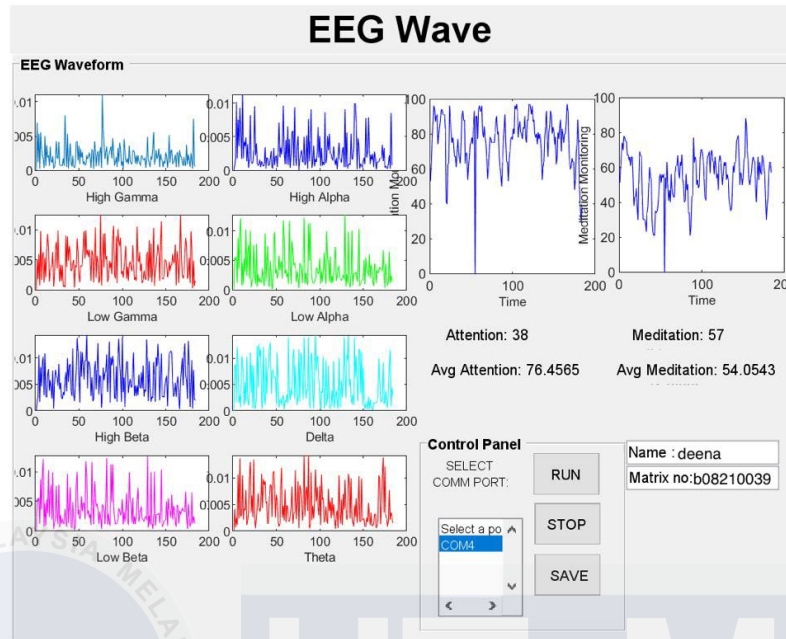


Figure 4.9 Data average Deena

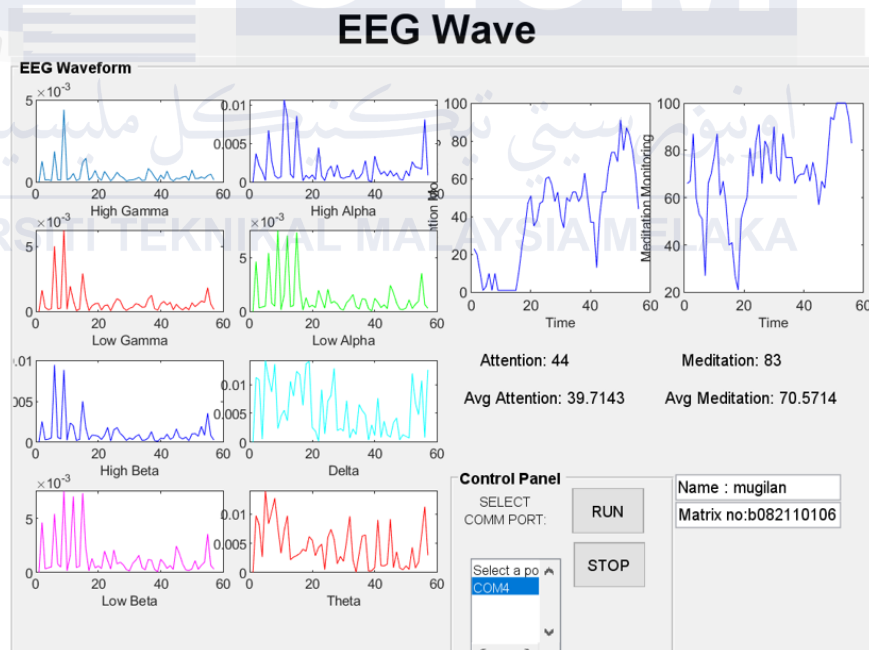


Figure 4.10 Data average Mugilan

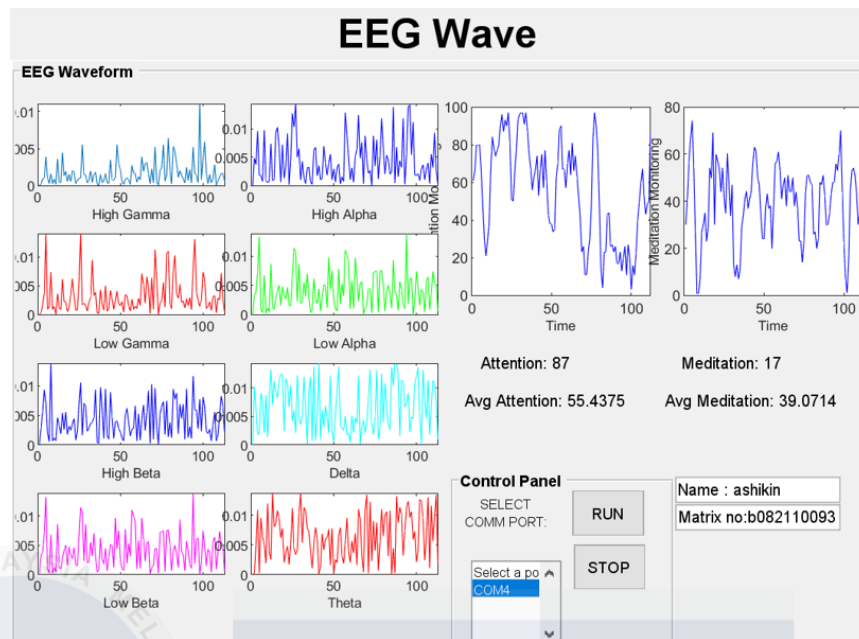


Figure 4.11 Data average Ashikin

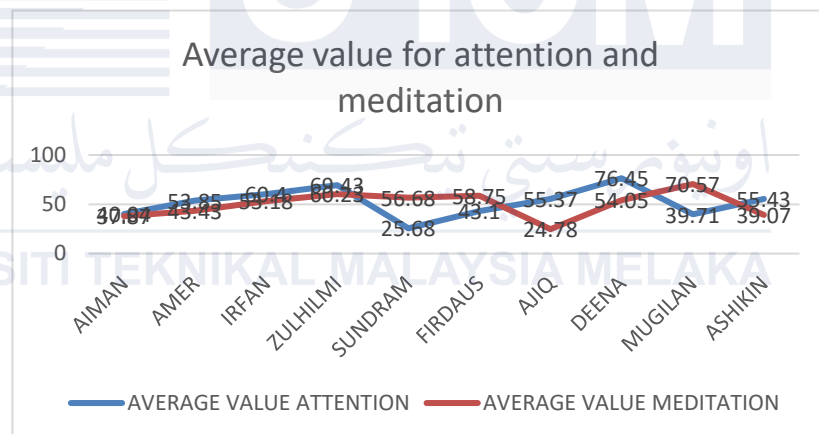


Figure 4.12 Graph for average value attention and meditation

4.3 Results and Analysis MATLAB GUI

The Figure 4.1 below shows an overview of the result for the EEG- based attention monitoring system for classroom evaluation. The MATLAB program successfully demonstrated its ability to monitor and visualize attention and meditation levels in real time through a user-friendly graphical interface. The displayed values were updated

dynamically and formatted clearly, ensuring they were easy to read and understand. The program handled live and efficiently, processing incoming information and updating the interfere smoothly. This makes it a suitable tool for applications like a biofeedback training, cognitive assessments, or experiments requiring immediate feedback.

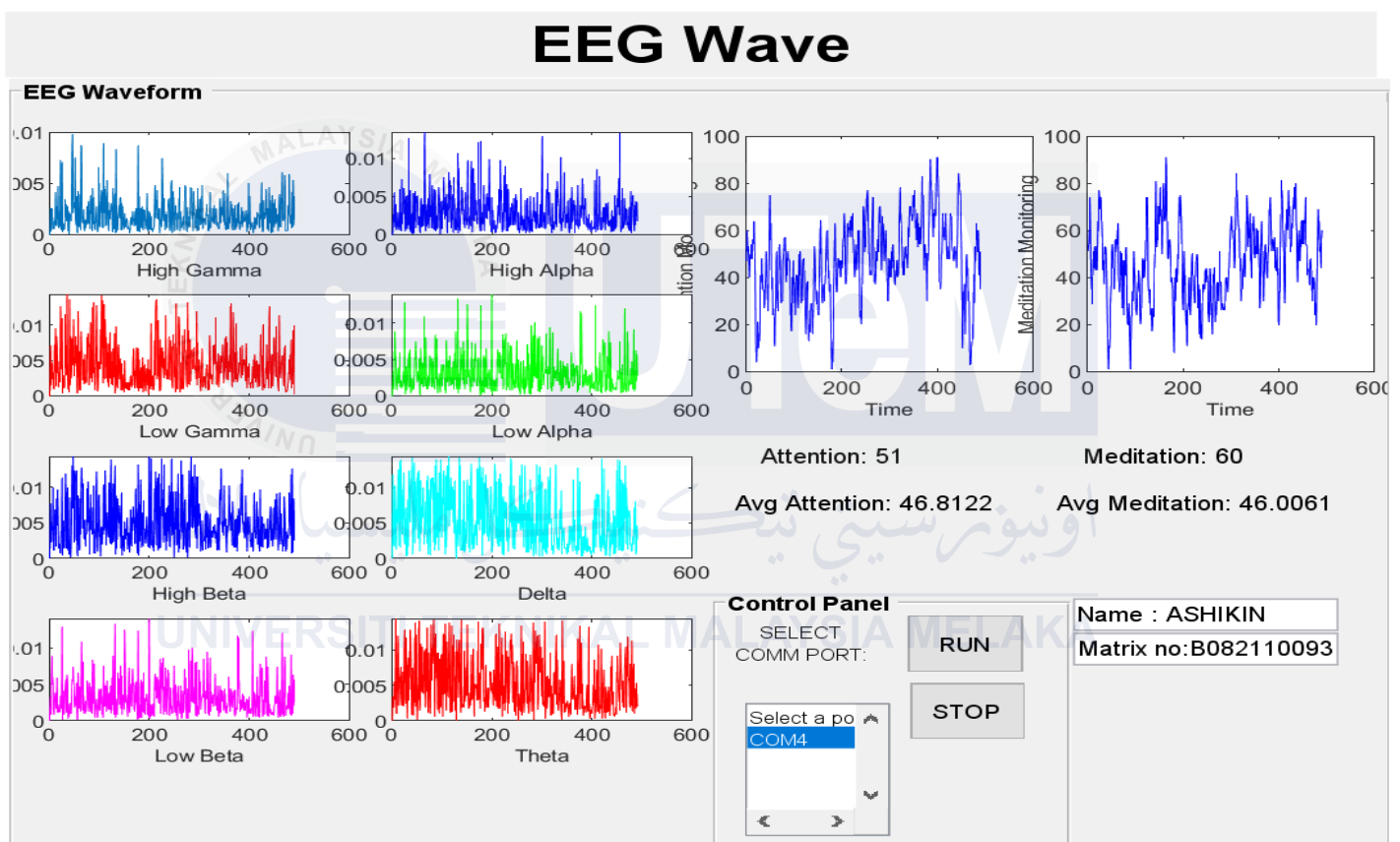


Figure 4.13 Layout MATLAB GUI

4.4 Summary

The MATLAB program successfully demonstrated its ability to monitor and visualize the attention and meditation levels in a real time through a GUIDE. The displayed values were updated dynamically and formatted clearly, ensuring they were easy to read and understand. The program handled live data efficiently, processing incoming

information and updating the interface smoothly. This makes it a suitable tool for applications like biofeedback training, cognitive assessment, or experiments requiring immediate feedback.

During testing, the attention and meditation levels were consistently and accurately displayed on a tally stopped. The continuous loop ensured the interface was always responsive, running seamlessly until the data might be missing or invalid, which is crucial for real-world usage. While the program performs well in displaying numerical values, adding graphical plots would make it easier to track trends and changes over time. Another useful addition would be a feature to log the data for later analysis. The interface could also benefit from more interactive options, like buttons to pause, reset, or customize display settings. Overall, the program provides a solid starting point for real-time data visualization tasks. With some added features and usability enhancements, it has the potential to become an even more versatile and user-friendly tool.

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.0 Conclusion

In conclusion, the project aims to monitor real-time EEG data, the system provides valuable insights into student's attention level with EEG-based attention monitoring system using Mind Link sensor that connected to MATLAB Guide. It can be used to show visualization, analysis data and storing data. The MATLAB program successfully achieved its goals of developing an EEG-based attention monitoring system for classroom evaluation. It reliably measures student attention and meditation levels in real time, seamlessly integrating Mind Link sensors with a MATLAB GUI via HC-05 Bluetooth modules and Arduino Uno microcontrollers. The program's signal processing capabilities ensure accurate interpretation of EEG waveforms which gamma, beta, alpha, delta, theta, attention, meditation and the data will be autosave to specific folder location, while its dynamic, responsive interface delivers clear and consistent data visualization. These achievements make it a reliable and practical tool for applications like biofeedback training, cognitive assessment, and real-time experiments. But such additional features as graphical plots of trends, data logging for future analysis, and interactive controls for personalization would go a long way in enhancing its usefulness and flexibility. This program thus sets a foundation for the monitoring and improvement of students' engagement but has considerable scope for development into a more comprehensive and user-friendly system.

5.1 Future Works

For future improvements, accuracy of the EEG-based attention monitoring system for classroom evaluation could be enhanced as follows:

- i) Develop advanced algorithms within MATLAB for more detail analysis of attention data to explore other learning techniques to predict attention pattern.
- ii) Adapt the MATLAB GUI for mobile phone to make it more flexible.
- iii) Explore integration with existing educational technologies like Ulearn that could automate data transfer.

5.2 Potential project

The EEG- based attention monitoring system for classroom evaluation presents a revolutionary idea that should replace traditional static (mostly subjective) data on class participation in real time. Integration within educational platforms means its potential use to increase the effectiveness of instruction, promote personalized learning and transform educational environment. The education level that can be useful such as:

- Primary school
- Secondary school
- University

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APPENDICES

Appendix A Gantt Chart PSM 1 and PSM2

WEEK	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Briefing														
Registration														
Gantt Chart														
Literature Review														
Introduction														
Objective														
Scope														
Project Background														
Methodology														
Preliminary Result														
Ready for Slide														
Finalised Slide														
Presentation														

PSM 1 GANTT CHART

اونيورسيتي تېكنيكل مليسيا ملاك
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

No.	Project Activity	2024												2025	
		October			November				December					January	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Development project														
	• Sketching														
	• Concept Evaluation & Selection														
	• Develop dummy sine wave														
	• Detail Design MATLAB GUI														
2	Development software design														
	• Coding for component														
	• Combined coding from MATLAB & Arduino														
	• Troubleshoot coding														
3	Combining system														
	• Integrate software														
	• Finishing Prototype														
4	Project deliverable (FYP2)														
	• Completing report PSM														
	• Presentation preparation														
	• Submission final report PSM														

PSM 2 GANTT CHART

Appendix B Costing

Product	Quantity	Price (RM)
Arduino Uno	1	39.90
HC05 Bluetooth Sensor	1	9.90
Mind Link EEG Sensor	1	341.40
Wire	3	3.60
Total		394.80

Appendix C Example of Appendix Coding Arduino Uno

```
6 int BAUDRATE = 57600;
7
8
9 // checksum variables
10 byte payloadChecksum = 0;
11 byte CalculatedChecksum;
12 byte checksum = 0; //data type byte stores an 8-bit
13 int payloadLength = 0;
14 byte payloadData[64] = {0};
15 byte poorQuality = 0;
16 byte attention = 0;
17 byte meditation = 0;
18 byte quality_C = 0; //ni tambah Sept 2021
19 byte kira_attention = 0; //kira berapa kali attention
20 byte blinks = 0; //kira berapa kali blinks
21
22 // system variables
23 long lastReceivedPacket = 0;
24 boolean bigPacket = false;
25 boolean brainwave = false;
26 void setup() {
27
28
29     Serial.begin(57600); // Bluetooth
30     delay(500);
```

```

35 }
36 byte ReadOneByte() {
37     int ByteRead;
38     // Wait until there is data
39     while(!Serial.available());
40     //Get the number of bytes (characters) available for reading
41     //This is data that's already arrived and stored in the serial
42     ByteRead = Serial.read();
43
44     return ByteRead; // read incoming serial data
45 }
46
47 unsigned int delta_wave = 0;
48 unsigned int theta_wave = 0;
49 unsigned int low_alpha_wave = 0;
50 unsigned int high_alpha_wave = 0;
51 unsigned int low_beta_wave = 0;
52 unsigned int high_beta_wave = 0;
53 unsigned int low_gamma_wave = 0;
54 unsigned int mid_gamma_wave = 0;
55
56 void read_waves(int i) {
57     delta_wave = read_3byte_int(i);
58     i+=3;
59     theta_wave = read_3byte_int(i);
60     i+=3;
61     low_alpha_wave = read_3byte_int(i);
62     i+=3;

```

```

63     high_alpha_wave = read_3byte_int(i);
64     i+=3;
65     low_beta_wave = read_3byte_int(i);
66     i+=3;
67     high_beta_wave = read_3byte_int(i);
68     i+=3;
69     low_gamma_wave = read_3byte_int(i);
70     i+=3;
71     mid_gamma_wave = read_3byte_int(i);
72 }
73
74 int read_3byte_int(int i) {
75     return ((payloadData[i] << 16) + (payloadData[i+1] << 8) + payloadData[i+2]);
76 }
77
78 void loop() {
79     // Look for sync bytes
80     // Byte order: 0xAA, 0xAA, payloadLength, payloadData,
81     // Checksum (sum all the bytes of payload, take lowest 8 bits, then bit inverse)
82     if(ReadOneByte() == 0xAA) {
83         if(ReadOneByte() == 0xAA) {
84             payloadLength = ReadOneByte();
85             if(payloadLength > 169) //Payload length can not be greater than 169
86                 return;
87             payloadChecksum = 0;
88             for(int i = 0; i < payloadLength; i++) { //loop until payload length
89                 payloadData[i] = ReadOneByte(); //Read payload
90                 payloadChecksum += payloadData[i];

```

```

91     }
92     checksum = ReadOneByte();
93     payloadChecksum = 255 - payloadChecksum;
94     if(checksum == payloadChecksum) {
95         poorQuality = 200;
96         attention = 0;
97         meditation = 0;
98     }
99     brainwave = false;
100     for(int i = 0; i < payloadLength; i++) { //
101         switch (payloadData[i]) {
102             case 02:
103                 i++;
104                 poorQuality = payloadData[i];
105                 bigPacket = true;
106                 break;
107             case 04:
108                 i++;
109                 attention = payloadData[i];
110                 break;
111             case 05:
112                 i++;
113                 meditation = payloadData[i];
114                 break;
115             case 0x80:
116                 i = i + 3;
117                 break;
118             case 0x83:

```

```

119         i++;
120         brainwave = true;
121         byte vlen = payloadData[i];
122         // Serial.print(vlen, DEC);
123         /// Serial.println();
124         read_waves(i+1);
125         i += vlen; // i = i + vlen
126         break;
127     }
128 } // switch
// for loop
129
130 if(bigPacket) {
131     if(poorQuality == 0){
132     }
133     else{ // do nothing
134     }
135 }
136
137 quality_C = (100-(poorQuality/2)); //kalau kurang dari 100
138
139 if(brainwave && attention > 0 && attention < 100) {
140
141     Serial.print("R");
142     Serial.print(attention, DEC);
143     Serial.print(",");
144     Serial.print(meditation, DEC);
145     Serial.print(",");
146     Serial.print(mid_gamma_wave, DEC);
147     Serial.print(",");
148     Serial.print(low_gamma_wave, DEC);
149     Serial.print(",");
150     Serial.print(high_beta_wave, DEC);
151     Serial.print(",");
152     Serial.print(low_beta_wave, DEC);
153     Serial.print(",");
154     Serial.print(high_alpha_wave, DEC);
155     Serial.print(",");
156     Serial.print(low_beta_wave, DEC);
157     Serial.print(",");
158     Serial.print(delta_wave, DEC);
159     Serial.print(",");
160     Serial.print(theta_wave, DEC);
161     Serial.println(",");
162     delay(100);

```

Appendix D Example of Appendix Coding MATLAB

```

1 % 10/11/22 jadik
2 function varargout = SATU(varargin)
3 % SATU MATLAB code for SATU.fig
4 % SATU, by itself, creates a new SATU or raises the existing
5 % singleton*.
6 %
7 % H = SATU returns the handle to a new SATU or the handle to
8 % the existing singleton*.
9 %
10 % SATU('CALLBACK',hObject,eventData,handles,...) calls the local
11 % function named CALLBACK in SATU.M with the given input arguments.
12 %
13 % SATU('Property','Value',...) creates a new SATU or raises the
14 % existing singleton*. Starting from the left, property value pairs are
15 % applied to the GUI before SATU_OpeningFcn gets called. An
16 % unrecognized property name or invalid value makes property application
17 % stop. All inputs are passed to SATU_OpeningFcn via varargin.
18 %
19 % *See GUI Options on GUIDE's Tools menu. Choose "GUI allows only one
20 % instance to run (singleton)".
21 %
22 % See also: GUIDE, GUIDATA, GUIHANDLES
23 %
24 % Edit the above text to modify the response to help SATU
25
26 % Last Modified by GUIDE v2.5 11-Jan-2025 23:48:27
27
28 % Begin initialization code - DO NOT EDIT
29 gui_Singleton = 1;
30 gui_State = struct('gui_Name', mfilename, ...
31 'gui_Singleton', gui_Singleton, ...
32 'gui_OpeningFcn', @SATU_OpeningFcn, ...
33 'gui_OutputFcn', @SATU_OutputFcn, ...
34 'gui_layoutFcn', [], ...
35 'gui_Callback', []);
36 if nargin && ischar(varargin{1})
37     gui_State.gui_Callback = str2func(varargin{1});
38 end
39
40 if nargin
41     [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
42 else
43     gui_mainfcn(gui_State, varargin{:});
44 end
45 % End initialization code - DO NOT EDIT
46
47
48 % --- Executes just before SATU is made visible.
49 function SATU_OpeningFcn(hObject, eventdata, handles, varargin)
50 % This function has no output args, see OutputFcn.

```

```

51 % hObject    handle to figure
52 % eventdata reserved - to be defined in a future version of MATLAB
53 % handles    structure with handles and user data (see GUIDATA)
54 % varargin   command line arguments to SATU (see VARARGIN)
55 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
56 serialPorts = instrhwinfo('serial');
57 nPorts = length(serialPorts.SerialPorts);
58 set(handles.portList, 'String', ...
59     [{'Select a port'} ; serialPorts.SerialPorts ]);
60 set(handles.portList, 'Value', 2);
61 % set(handles.history_box, 'String', cell(1));
62 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
63
64 % Choose default command line output for SATU
65 handles.output = hObject;
66
67 % Update handles structure
68 guidata(hObject, handles);
69
70 % UIWAIT makes SATU wait for user response (see UIRESUME)
71 % uiwait(handles.figure1);
72 global a; %mula edit di sini
73 |
74 % --- Outputs from this function are returned to the command line.
75 function varargout = SATU_OutputFcn(hObject, eventdata, handles)
76
77 % varargout cell array for returning output args (see VARARGOUT);
78 % hObject    handle to figure
79 % eventdata reserved - to be defined in a future version of MATLAB
80 % handles    structure with handles and user data (see GUIDATA)
81
82 % Initialize Static Text for Attention and Meditation
83 handles.attentionText = uicontrol('Style','text','Position',[604, 260, 200, 22], ...
84     'String','Attention: 0','FontSize',10);
85 handles.meditationText = uicontrol('Style','text','Position',[878, 260, 200, 22], ...
86     'String','Meditation: 0','FontSize',10);
87
88 % Add new text elements for average values
89 handles.avgAttentionText = uicontrol('Style','text','Position',[604, 230, 250, 22], ...
90     'String','Avg Attention: 0','FontSize',10);
91 handles.avgMeditationText = uicontrol('Style','text','Position',[878, 230, 250, 22], ...
92     'String','Avg Meditation: 0','FontSize',10);
93
94 % Update handles structure
95 guidata(hObject, handles);
96
97 % Get default command line output from handles structure
98 varargout{1} = handles.output;
99
100 % --- Executes on button press in simulate_button.
101 function simulate_button_Callback(hObject, eventdata, handles)
102 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
103 if ~isempty(instrfind)
104     fclose(instrfind);

```

```

102         delete(instrfind);
103     end
104     %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
105     % hObject      handle to simulate_button (see GCBO)
106     % eventdata    reserved - to be defined in a future version of MATLAB
107     % handles       structure with handles and user data (see GUIDATA)
108     global k;
109     k=0;%edit di sini
110     global SS; %serial port number
111     %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
112     %   VARIABLE UNTUK PLOT GRAF
113     %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
114     w = 0;
115     q=0;
116     z1 = 0;
117     z2 = 0;
118     z3 = 0;
119     z4 = 0;
120     z5 = 0;
121     z6 = 0;
122     z7 = 0;
123     z8 = 0;
124     z9 = 0;
125     z10 = 0;
126     %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
127     Baud_Rate = 57600;
128     Data_Bits = 16; %macam tak guna %asal 8
129     Stop_Bits = 1; %macam tak guna
130     %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
131     %   TAMBAH SERIAL LIST
132     %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
133     serPortn = get(handles.portList, 'Value');
134     if serPortn == 1
135         errordlg('Select valid COM port');
136     else
137         serList = get(handles.portList, 'String');
138         serPort = serList{serPortn};
139     end
140
141     arduino = serial(serPort);
142     set(arduino, 'BaudRate', 57600);
143     fopen(arduino);
144
145     x=linspace(1,500); % double check untuk apa
146
147     array1 = zeros(100,1);
148     array2 = zeros(100,1);
149     array3 = zeros(100,1);
150     array4 = zeros(100,1);%edit di sini

```

```

152         array5 = zeros(100,1);
153         array6 = zeros(100,1);
154         array7 = zeros(100,1);
155         array8 = zeros(100,1);
156 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
157 %   SETTING STOP
158 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
159 % Get default command line output from handles structure
160 varargout{1} = handles.output;
161 handles.stop_now = 0; %Create stop_now in the handles structure
162 guidata(hObject,handles); %Update the GUI data
163 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
164 global A;
165 while ~(handles.stop_now)
166     k=k+1;
167 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
168 %   SETTING STOP DALAM LOOP
169 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
170     drawnow %Give the button callback a chance to interrupt the loop
171     handles = guidata(hObject); %Get the newest GUI data
172     drawnow; % Allow GUI updates during the loop
173 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
174     data = fscanf(arduino);
175     panjang = length(data);|
176     kirakoma = count(data, ',');
177
178     if kirakoma == 10
179         RR = strfind(data,'R');
180         commas = strfind(data,',');
181         % Extracting data
182         Z1 = str2num(data((RR+1):commas(1)));
183         Z2 = str2num(data(commas(1):commas(2)));
184         % ... Extract other variables similarly
185
186         % Assuming attention value is the first value in the string
187         attention(k) = Z1; % Update the attention array
188         meditation(k) = Z2; % Update the meditation array
189         % Update the static text with new values
190         set(handles.attentionText, 'String', ['Attention: ', num2str(Z1)]);
191         set(handles.meditationText, 'String', ['Meditation: ', num2str(Z2)]);
192
193         % Calculate average attention and meditation
194         avgAttention = mean(attention(1:k));
195         avgMeditation = mean(meditation(1:k));
196
197         % Update average values in GUI
198         set(handles.avgAttentionText, 'String', ['Avg Attention: ', num2str(avgAttention)]);
199         set(handles.avgMeditationText, 'String', ['Avg Meditation: ', num2str(avgMeditation)]);
200         % Pause to update GUI
201         pause(0.01);
202

```

```

203 % Get the desktop path (works on most systems)
204 desktopPath = fullfile(getenv('USERPROFILE'), 'Desktop'); % For Windows
205 % If on macOS or Linux, use the following line:
206 % desktopPath = fullfile(getenv('HOME'), 'Desktop');
207
208 % Ensure the folder for saving exists
209 saveFolder = fullfile(desktopPath, 'Attention Monitoring');
210 if ~exist(saveFolder, 'dir')
211     mkdir(saveFolder); % Create the folder if it doesn't exist
212 end
213 %
214     disp(data);
215
216 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
217 array1(k) = str2num(data(RR+1:commas(1))); %DATA 1ST DARI ARDUINO....
218 array2(k) = str2num(data(commas(1):commas(2)));
219 array3(k) = str2num(data(commas(2):commas(3)));
220 array4(k) = str2num(data(commas(3):commas(4)));
221 array5(k) = str2num(data(commas(4):commas(5)));
222 array6(k) = str2num(data(commas(5):commas(6)));
223 array7(k) = str2num(data(commas(6):commas(7)));
224
225 array8(k) = str2num(data(commas(7):commas(8)));
226 array9(k) = str2num(data(commas(8):commas(9)));
227 % array10(k) = str2num(data(commas(9):end));
228 save aa.mat array1 array2 array3 array4 array5 array6 array7 array8 array9 data
    array10(k) = str2num(data(commas(9):commas(10)));
229
230
231
232 Z1 = str2num(data((RR+1):commas(1)));
233 Z2 = str2num(data(commas(1):commas(2)));
234 Z3 = str2num(data(commas(2):commas(3)));
235 Z4 = str2num(data(commas(3):commas(4)));
236 Z5 = str2num(data(commas(4):commas(5)));
237 Z6 = str2num(data(commas(5):commas(6)));
238 Z7 = str2num(data(commas(6):commas(7)));
239
240 Z8 = str2num(data(commas(7):commas(8)));
241 Z9 = str2num(data(commas(8):commas(9)));
242
243 % Z10 = str2num(data(commas(9):end));
244 save zz.mat Z1 Z2 Z3 Z4 Z5 Z6 Z7 Z8 Z9 data
    Z10 = str2num(data(commas(9):commas(10)));
245 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
246 % Darab Equation untuk Plot Graf
247 Z3=Z3*(1.8/4096)/2000;
248 Z4=Z4*(1.8/4096)/2000;
249 Z5=Z5*(1.8/4096)/2000;
250 Z6=Z6*(1.8/4096)/2000;
251 Z7=Z7*(1.8/4096)/2000;
252 Z8=Z8*(1.8/4096)/2000;
253 Z9=Z9*(1.8/4096)/2000;
254 Z10=Z10*(1.8/4096)/2000;

```

```

257 | z3=[z3,Z3];
258 | z4=[z4,Z4];
259 | z5=[z5,Z5];
260 | z6=[z6,Z6];
261 | z7=[z7,Z7];
262 | z8=[z8,Z8];
263 | z9=[z9,Z9];
264 | z10=[z10,Z10];
265 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
266 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
267 % Plot Attention monitoring
268 | plot(attention, 'Parent', handles.axes9, 'color', 'b')
269 | axes(handles.axes9);
270 | xlabel('Time', 'FontSize', 8);
271 | ylabel('Attention Monitoring', 'FontSize', 8);
272 | pause(0.01);
273 % Plot Meditation
274 | plot(meditation, 'Parent', handles.axes10, 'color', 'b')
275 | axes(handles.axes10);
276 | xlabel('Time', 'FontSize', 8);
277 | ylabel('Meditation Monitoring', 'FontSize', 8);
278 | pause(0.01);
279 %plot signal high gamma
280 | plot(z3, 'Parent', handles.axes1)
281 | axes(handles.axes1);
282 | xlabel('High Gamma', 'FontSize', 8);
283 | pause (0.01);
284
285 | plot(z4, 'Parent', handles.axes2, 'color', 'r')
286 | axes(handles.axes2);
287 | xlabel('Low Gamma', 'FontSize', 8);
288 | pause (0.01);
289
290 | plot(z5, 'Parent', handles.axes3, 'color', 'b')
291 | axes(handles.axes3);
292 | xlabel('High Beta', 'FontSize', 8);
293 | pause (0.01);
294
295 | plot(z6, 'Parent', handles.axes4, 'color', 'm')
296 | axes(handles.axes4);
297 | xlabel('Low Beta', 'FontSize', 8);
298 | pause (0.01);
299
300 | plot(z7, 'Parent', handles.axes5, 'color', 'b')
301 | axes(handles.axes5);
302 | xlabel('High Alpha', 'FontSize', 8);
303 | pause (0.01);
304
305 | plot(z8, 'Parent', handles.axes6, 'color', 'g')
306 | axes(handles.axes6);

```

```

307 xlabel('Low Alpha', 'FontSize', 8);
308 pause (0.01);
309
310 plot(z9, 'Parent', handles.axes7, 'color', 'c')
311 axes(handles.axes7);
312 xlabel('Delta', 'FontSize', 8);
313 pause (0.01);
314
315 plot(z10, 'Parent', handles.axes8, 'color', 'r')
316 axes(handles.axes8);
317 xlabel('Theta', 'FontSize', 8);
318 pause (0.01);
319
320 | assignin('base','bb',data); % masukkan variable ke dalam workspace
321
322 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
323 end
324 %edit di sini
325
326 % Autosave the attention plot
327 saveFilePath = fullfile(saveFolder, ['Attention_Monitoring_' num2str(k) '.png']);
328 saveas(handles.axes9, saveFilePath); % Save the current attention plot
329
330 % Autosave the attention plot
331 saveFilePath = fullfile(saveFolder, ['Attention_Monitoring_' num2str(k) '.png']);
332 saveas(handles.axes9, saveFilePath); % Save the current attention plot
333
334 % Update handles structure and GUI
335 guidata(hObject, handles);
336 drawnow; % Force GUI update after each iteration
337 pause(0.01);

```