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Hybrid Human Interface System for Stress Level Monitoring: Integrating EEG and HRV Sensors

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ABSTRACT

This study addresses the pressing need for advanced stress monitoring systems by proposing a Hybrid Human Interface System. Currently, the accurate assessment of an individual's stress levels is a critical aspect of healthcare, wellness and performance optimization. However, existing stress monitoring approaches often lack the precision required for comprehensive evaluations. To bridge this gap, our study leverages Electroencephalogram (EEG) and Heart Rate Variability (HRV) sensors to create a sophisticated hybrid system. The EEG sensor captures intricate brainwave patterns, offering valuable insights into cognitive responses, while the HRV sensor measures the variability in heartbeat intervals, reflecting autonomic nervous system activity. The integration of these physiological data sources aims to provide a comprehensive and accurate assessment of stress levels, addressing the limitations of current methodologies. By combining these two sources of information, our proposed system enhances the precision and reliability of stress level assessments. The study concludes by highlighting the promising potential of the hybrid approach for advancing stress monitoring systems, with broad applications in healthcare, wellness and performance optimization.

1. Introduction

The exploration of stress and its impact on human well-being is increasingly important [1-3]. Researchers are actively investigating methods to detect and monitor stress levels, with a particular focus on leveraging Electroencephalogram (EEG) signals and self-reported data. This paper delves into the advancements and challenges within stress detection research, emphasizing the complexities of the human brain and potential applications of stress monitoring systems. The

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utilization of EEG signals stands out as a primary avenue for progress in stress detection. EEG, being non-invasive, records brain electrical activity, providing valuable neurological insights into stress. Sophisticated algorithms have been developed to analyse EEG patterns associated with stress, enabling more accurate and real-time detection.

Moreover, the integration of self-reported data has improved the reliability of stress detection systems [4-6]. The combination of objective physiological measures with subjective information from individuals offers a more comprehensive understanding of stress triggers and responses. This dual approach contributes to a holistic perspective on an individual's stress levels, enhancing the overall effectiveness of stress monitoring. Therefore, it is crucial to implement a stress monitoring system to analyse and display captured signals for an alert system. The next section outlines related work that can be undertaken for the development of a stress monitoring system.

2. Related Work

In the realm of stress detection, Healy *et al.,* [7] groundbreaking work has laid a formidable foundation, initially demonstrating success within controlled laboratory environments. Recognizing the considerable gap between stress experiences induced in laboratories and those encountered in real-world settings, the researchers shifted their focus to confront challenges inherent to authentic scenarios. Notably, Al-Shargie *et al.,* [8] employed a mental arithmetic task, uncovering heightened difficulty in EEG signals at the third level. Simultaneously, Arsalan *et al.,* [9] embarked on stress level classification by analysing participant presentations, grappling with challenges associated with the accuracy of the Perceived Stress Scale and relying on self-reported data.

While Villarejo *et al.,* [10] achieved a commendable 76% success rate in classifying stress states using Electrodermal Activity (EDA) induced by mentally demanding tasks, the translation to real-life applications witnessed a decline to 70-80%. This drop in accuracy can be attributed to factors such as unknown contexts, data quality issues, limb movement interference, sensor placement challenges and battery constraints. Shifting the focus to the intricacies of the human brain, the cerebrum, cerebellum and brainstem emerge as key players orchestrating various bodily functions. Within the cerebrum, two hemispheres govern opposite sides of the body, with the corpus callosum facilitating communication between them. Notably, a right-side stroke can result in left-side weakness. Functionally, the left hemisphere manages speech, comprehension, arithmetic and writing, while the right oversees creativity and spatial skills. Interestingly, approximately 92% of individuals exhibit left hemisphere dominance in hand use and language [11].

Beyond these fundamental functions, the cerebrum is responsible for higher cognitive processes, the cerebellum coordinates balance and movement and the brainstem control automatic bodily functions and sleep-wake regulation. This intricate interplay underscores the complexity of the neurological mechanisms involved in stress detection and highlights the challenges researchers face when translating their findings from controlled environments to real-world applications. At the cellular level, the brain, a network of billions of neurons, processes information through intricate electrical and chemical signals. Glial cells support and protect these neurons, forming the basis for the brain's remarkable capabilities as the body's control centre. The cerebrum, divided into two hemispheres, comprises four lobes—frontal, parietal, temporal and occipital. The cortex, the cerebrum's surface, folds to increase surface area, accommodating more neurons for higher function. Beneath the cerebrum lies the brainstem, with the cerebellum positioned behind it. The frontal lobe, the largest, handles memory, decision-making, executive functions, emotions and planning. The parietal lobe is responsible for handwriting, sensation and orientation. The temporal lobe facilitates distinguishing smells and sounds, sorting new information and contributes to short-term memory.

The left temporal lobe is mainly involved in verbal memory, while the occipital lobe processes visual information [12].

The EEG serves as a diagnostic test to detect abnormalities in brainwaves. Partridge *et al.,* [13] groundbreaking experiment in the 18th century showcased the impact of electrical stimulation on frog muscles, leading to violent tonic convulsions. This experiment underscored the significance of measuring neural function in both physics and physiology. In the late 1800s, Hans *et al.,* [14] developed electroencephalography, a method for recording brain activity, which revolutionized psychiatric research and influenced modern medicine. Similar to the electrocardiogram for the heart, EEG involves electrodes attached to the head, detecting electric fields associated with neural impulses. The resulting voltage, measured in the time domain, constitutes the EEG signal, providing insights into brain activity morphologies. Free running EEG captures continuous brain activity, offering an indicator of the user's state through fluctuations in power within specific frequency bands [15].

Delving into the intricate workings of the human brain reveals a captivating realm of brainwaves. The research explores Delta, Theta, Alpha, Beta and Gamma waves, each characterized by distinctive frequencies and associated with various states of consciousness. Delta waves [16,17], ranging from 0.5 to 4 Hz, play a vital role in sleep and abnormal processes, crucial for the body's rejuvenation and the brain's revitalization during deep sleep and infancy. Adequate delta wave production is integral to promoting immune system health and facilitating natural healing [18]. Theta waves, with frequencies from 4 to 8 Hz, signify slow activity linked to deep relaxation, meditation and sleep. Inducing a state of unique deep relaxation while maintaining consciousness, theta brainwave activity is marked by vivid imagery, creative thinking and heightened intuition. Practices like meditation, yoga and deep breathing exercises induce theta activity, contributing to cognitive processes and memory formation [9]. The human brain operates through distinct brainwaves—Delta for sleep, Theta for relaxation, Alpha for well-being, Beta for alertness and Gamma for high-level cognition. These waves, characterized by specific frequencies, impact various states of consciousness. Neurons, the nervous system's building blocks, transmit information through electrical impulses in a process called neurotransmission [19,20].

The nervous system, comprising the Central Nervous System (CNS) and Peripheral Nervous System (PNS) [21-23], is vital for influencing bodily functions. The CNS, consisting of the brain and spinal cord orchestrates physiological processes, while the PNS involves neurons synchronizing electrical signals for communication. A collaboration of afferent, efferent and interneurons integrates information and orchestrates responses. Monitoring heart rate, blood pressure and EEG signals offers a comprehensive approach to understanding our body's dynamics. These vital signs serve as windows into cardiovascular health and brain activity. Heart rate, measured in beats per minute (BPM), is a fundamental cardiovascular indicator. Modern wearable devices provide continuous monitoring for insights into fitness levels, stress responses and medical diagnosis.

Blood pressure, expressed as systolic and diastolic pressures, offers crucial insights into cardiovascular well-being. Stress, a significant influencer, triggers hormonal responses affecting heart rate and blood vessels, contributing to the "fight or flight" response [24,25]. Chronic stress can elevate blood pressure, emphasizing the link between mental well-being and cardiovascular health. Stress management techniques, like relaxation and exercise, play pivotal roles in maintaining optimal blood pressure. EEG signal recording, a non-invasive method for diagnosing neurological disorders and studying brain activity, involves placing electrodes on the scalp. Despite limitations, such as poor spatial resolution, scalp electrodes are widely used for their accessibility. EEG recordings reveal cognitive states, extending to Brain-Computer Interface (BCI) technology, allowing device control through brain activity [26,27].

The above highlighted work emphasizing the link between mental well-being and cardiovascular health, stressing the importance of stress management techniques and highlighting EEG signal recording as a valuable tool for diagnosing neurological disorders and studying brain activity. In navigating through the intricate workings of the human brain, the essay sheds light on its remarkable capabilities and the challenges researchers faces in translating findings to real-world applications.

In this research, a pioneering Hybrid Human Interface System designed for the purpose of Stress Level Monitoring is proposed. The system utilizes a combination of EEG and Heart Rate Variability (HRV) sensors to offer a comprehensive and sophisticated approach to stress assessment. The EEG sensor, measuring brainwave patterns, provides valuable insights into cognitive states, while the HRV sensor captures variations in heart rate, reflecting the activity of the autonomic nervous system. By integrating these two distinct sensor modalities, our proposed system seeks to achieve a more accurate and reliable method for monitoring stress levels. This holistic approach allows for a deeper understanding of the interplay between physiological and neural aspects of stress, providing a more nuanced and informative evaluation. The potential applications of this integrated system extend to various domains, including healthcare, well-being and performance optimization. The real-time and non-invasive nature of our approach holds promise for delivering timely and actionable insights into stress dynamics, contributing to a more comprehensive understanding of individual stress responses.

3. Methodology

In the pursuit of developing an innovative Stress Monitoring System, the project begins with the development of a Brainwaves Monitoring System (BMS) using the NeuroSky MindWave headset and Arduino technology. The foundational steps include establishing circuit connections and coding using the Arduino IDE. Rigorous testing ensures the functionality of the code, leading to either a successful pass or the identification of necessary refinements. The integration of Excel Data Streamer with the Arduino IDE enables real-time data streaming to Microsoft Excel, allowing for the visualization and recording of brainwave data. The project then focuses on monitoring brainwave signals in real-time, providing visual representations of various frequencies and amplitudes to gain insights into cognitive states.

3.1 Components of the System

Figure 1 serves as a visual guide to the key components that form the backbone of our system, each playing a crucial role in the seamless functioning and data processing capabilities of the overall setup.

(a) Arduino Nano (b) I^{2}C LCD 16x2

(c) NeuroSky MindWave Mobile 2 Headset

(d) Fitness Tracker Watch

Fig. 1. Components of the system

The Arduino Nano, depicted in Figure 1(a), is a compact and versatile microcontroller board based on the ATmega328 microcontroller. It offers similar functionality to the Arduino Uno but in a smaller form factor. Compatible with the Arduino programming environment, the Nano can be programmed using the Arduino Integrated Development Environment (IDE). Operating at 5V, it boasts 32KB of flash memory for program storage. The board features 14 digital input and output pins, six of which can be utilized as Pulse Width Modulation (PWM) outputs, along with eight analogue input pins.

In Figure 1(b), the I^2C LCD 16x2 module combines a 16x2 character Liquid Crystal Display (LCD) with an I^2C interface. The module includes a 16-character by 2-line alphanumeric display and an I^2C converter or input/output expander chip that interfaces with the LCD. This chip converts I^2C signals from the microcontroller into parallel signals required by the LCD. Additionally, the LCD incorporates a backlight that can be controlled through the I^2C interface, enabling users to adjust brightness or turn it on/off programmatically.

Figure 1(c) showcases the NeuroSky MindWave Mobile 2, a brain-computer interface (BCI) headset developed by NeuroSky. Designed to measure and monitor brainwave activity, this headset allows users to interact with various applications and devices using their mental state. Employing electroencephalography technology, the MindWave Mobile 2 features wireless connectivity via Bluetooth for easy cordless communication with compatible devices like smartphones and computers. The headset utilizes a single electrode sensor placed on the forehead to capture brainwave signals, measuring the electrical potential generated by the brain and sending them to the connected devices for processing and analysis.

As depicted in Figure 1(d), a fitness tracker is a wearable device designed to monitor various aspects of user health and fitness. Many fitness tracker watches include a built-in heart rate sensor that continuously monitors heart rate. Typically, able to connect to a companion mobile app on smartphones, the application allows users to view and analyse fitness data and track their progress.

3.2 Coding

This section serves as a link between the hardware explanation and the coding specifics. It helps readers seamlessly grasp how the components function together in a practical context. Figure 2 illustrates the detailed coding for this project.

The coding for this project has been designed using the Arduino IDE Software, which serves as the primary platform for programming. The Arduino IDE is a free software application that enables users to write, upload and execute code on an Arduino board. It offers a straightforward and user-friendly interface for programming and interacting with the board, supporting various programming languages, including C and C++.

Code	Explanation
#include <Wire.h>	Include the Wire library for I2C communication
#include <LiquidCrystal_I2C.h>	Include the LiquidCrystal_I2C library for LCD
LiquidCrystal_I2C lcd(0x27, 16, 2);	Initialize the LCD with the given I2C address and dimensions
const int len = 60;	Define the maximum length of character arrays
char my_str[len];	Declare a character array to store received data
char my_str2[len];	Declare another character array for the second line of the LCD
int pos = 0;	Initialize a variable to track the position in the character array
bool newData = false;	Flag to indicate new data received
bool noData = true;	Flag to indicate no data received
void setup() {	Setup function that runs once at the beginning
lcd.init();	Initialize the LCD
lcd.backlight();	Turn on the LCD backlight
lcd.begin(16, 2);	Set up the LCD's number of columns and rows
lcd.setCursor(2, 0);	Set the cursor position for printing on the LCD
lcd.print("Stress Level");	Print a test message on the LCD
lcd.setCursor(3, 1);	Set the cursor position for the second line
lcd.print("Monitoring");	Print a test message on the LCD
delay(5000);	Delay for 5 seconds
Serial.begin(38400);	Configure serial communication with a baud rate of 38400
lcd.clear();	Clear the LCD display initially
}	
void loop() {	Loop function that runs continuously
if (newData) {	Check if new data is available
lcd.clear();	Clear the LCD display
noData = false;	Reset the noData flag
lcd.setCursor(0, 0);	Set the cursor position for printing on the LCD
lcd.print(my_str);	Print the received string on the LCD
if (pos > 13) {	Check if the string is longer than the first line of the LCD
for (int i = 0; i < pos; i++) {	Iterate through the characters to get the second line of the LCD
my_str2[i] = my_str[i + 16];	Copy characters for the second line
}	
lcd.setCursor(0, 1);	Set the cursor position for the second line
lcd.print(my_str2);	Print the second line of text on the LCD
}	
newData = false;	Reset the newData flag
}	
if (noData) {	Check if no data is received
lcd.setCursor(3, 0);	Set the cursor position for printing on the LCD
lcd.print("Enter Data");	Print a message on the LCD
lcd.setCursor(0, 1);	Set the cursor position for the second line
lcd.print(" ");	Print a space on the LCD to clear the second line
}	
}	
void serialEvent() {	Serial event function triggered when new data is available
if (!newData) {	Clear the previous text when new data is received
lcd.clear();	Clear the LCD display
}	
while (Serial.available()) {	Read incoming bytes from the serial port
char incomingByte = Serial.read();	Read the incoming byte
if (incomingByte == '\n') {	Check if the end of the line is reached
my_str[pos] = '\0';	Null-terminate the received string
pos = 0;	Reset the position for the next iteration
newData = true;	Set the newData flag
noData = false;	Reset the noData flag
} else {	If end of line not reached
if (pos < len - 1) {	Check if there is space in the character array
my_str[pos] = incomingByte;	Store the incoming byte in the array
pos++;	Increment the position for the next character
}	
}	
}	
}	

Fig. 2. Coding

In principle, the flowchart of the circuit development can be seen in Figure 3. Within the Arduino IDE, there is a built-in library of functions and sample code, with the flexibility to add additional libraries as needed. To commence the coding process, the LiquidCrystal_I^{2}C library is required. This specific library allows the control of I^{2}C displays using functions that closely resemble those in the LiquidCrystal_I^{2}C library. Installing the library is a straightforward process. First, Open the Arduino IDE and navigate to the library manager. Second, search for the LiquidCrystal_I^{2}C library. Finally, download the library index and update the list of installed libraries. This installation ensures that the necessary functions for controlling I^{2}C displays are readily available in the coding environment, streamlining the development process for the Stress Level Monitoring System project.

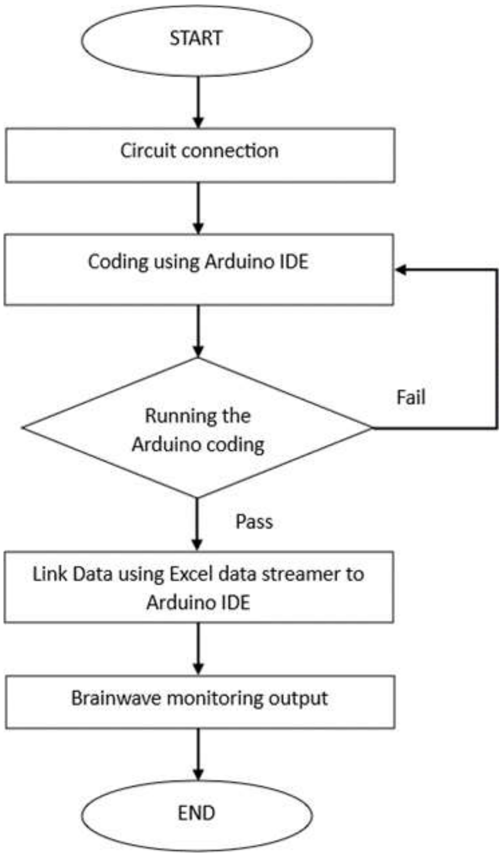


Fig. 3. Flowchart for circuit development

3.3 Monitoring System Process

Figure 4 illustrates the diagram of the data transmission process from the human to the monitoring system, representing the culmination of the prototype, coding and software development stages. The input for this system is the brainwave frequency originating from the subject's head. To capture this frequency, the NeuroSky Mind Wave Mobile headset is utilized, detecting readings from the contact of the metal to the skin. This headset is attached to the subject's head to capture real-time brain signals while they engage in assigned tasks to fulfil the project objectives.

The extracted brainwave signal data is then transmitted from the brainwave device to the Brainwaves Monitoring System, which has been coded as part of the software development process. The raw output of brainwave data is displayed for further analysis. Simultaneously, a fitness tracker is worn by the subject to record heart rate ratings during the assigned activities. Subsequently, this heart rate data is transferred to a health application. Both the brainwave and heart rate readings are stored on a computer, where comprehensive analysis takes place before the readings are displayed on the monitoring system. This integrated approach ensures a comprehensive understanding of the subject's physiological responses, combining brainwave and heart rate data for a more holistic monitoring system.

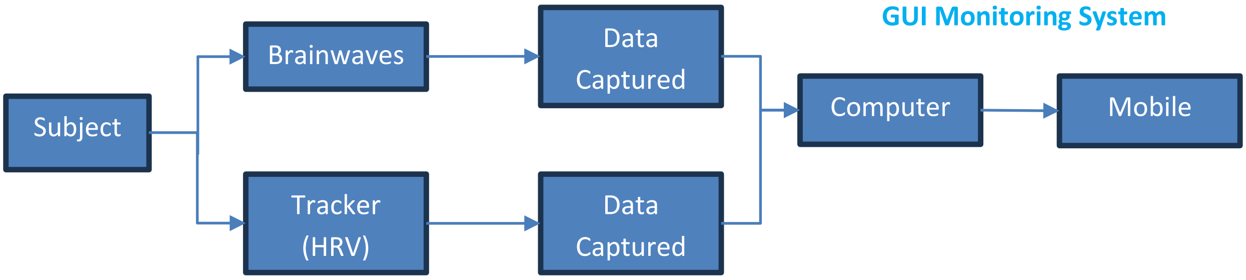


Fig. 4. Monitoring system block diagram

3.4 Link Arduino Code with Microsoft Excel

To link the Arduino code with Microsoft Excel (Figure 5) for storing data from the MindWave headset and fitness tracker, the Data Streamer add-ins are necessary. Data Streamer facilitates two-way data transfer, streaming live data from a microcontroller to Excel and sending data from Excel back to the microcontroller. Connecting a sensor to a microcontroller linked to a Windows 10 PC is the initial step. The Excel Data Streamer add-ins must be enabled and the workbook needs to be open. To initiate real-time data streaming in Excel, enable the Data Streamer add-in by opening Excel options, navigating to add-ins, selecting COM add-ins and enabling "Microsoft Data Streamer for Excel." This ensures a seamless flow of data between the Arduino and Excel, enhancing the capabilities of the stress monitoring system. Note that the use of excel is of primary importance to handle the streaming data obtained from Heart Rate Variability (HRV) sensor.

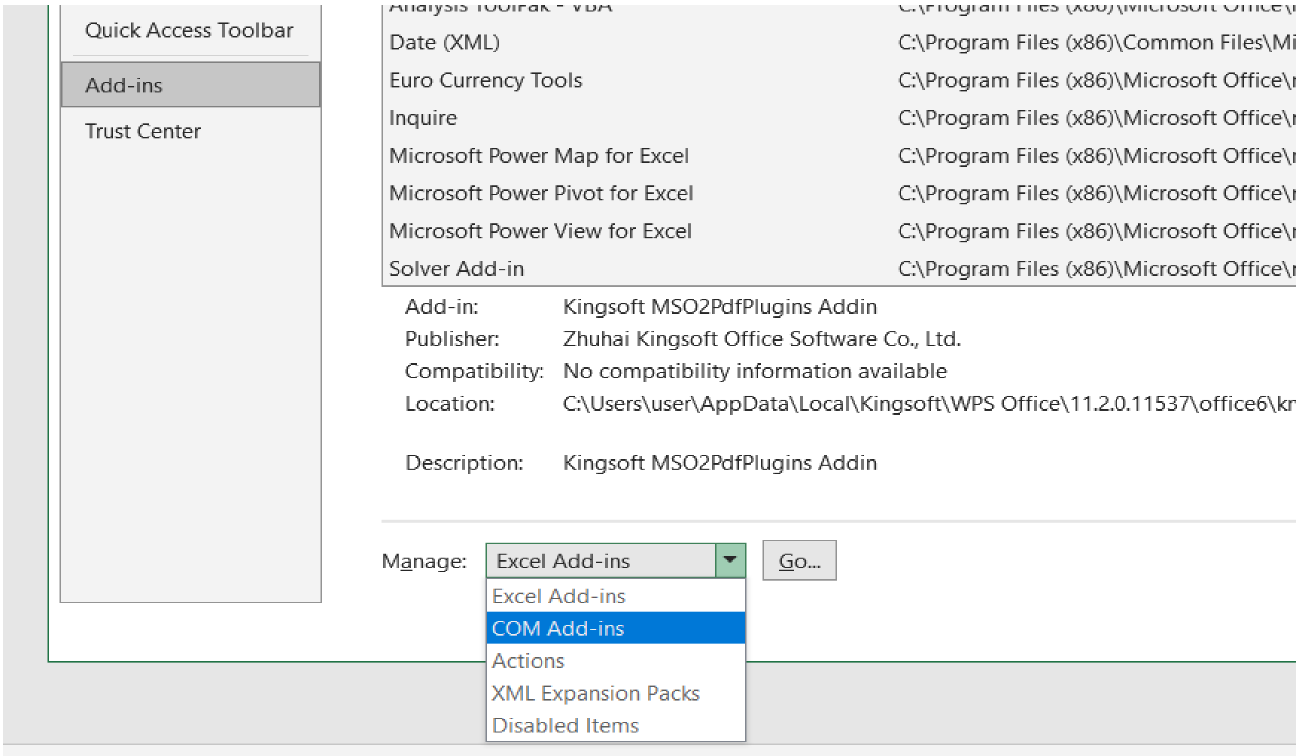


Fig. 5. Enable data streamer in Microsoft Excel

3.5 Subject Test

To meet the project's objectives, participants must wear the designated devices and perform assigned tasks. The brainwave device captures data, which is then transmitted to the brainwave monitoring system for analysis. Raw brainwave data is displayed on a monitor. Simultaneously, a fitness tracker records the participant's heart rate during the activity and this data is transferred to a health application. The collected brainwave and heart rate readings are stored on a computer for in-depth analysis before being displayed on the monitoring system. In the specific experiment (Activity 1: Meditate), participants use a Mindwave headset and a fitness tracker watch to explore brainwave activity during relaxation. To ensure data accuracy, participants are instructed to close their eyes and engage in a 5-minute meditation session, minimizing external disturbances that could affect brainwave signal measurements.

4. Results

4.1 Hybrid Brainwaves Monitoring System

The implementation of the Hybrid Brainwaves Monitoring System (HBMS), as depicted in Figure 6, marks a significant milestone. This system acquires data specifically from the NeuroSky MindWave headset, focusing on the EEG Sensor and meticulously manages and processes various brainwave signals, including Delta, Theta, Low Alpha, High Alpha, Low Beta, High Beta, Low Gamma and High Gamma waves. A noteworthy feature of the HBMS is its capability not only to interpret these intricate neural signals but also to measure the user's attention and meditation levels on a scale from 0 to 100. This comprehensive approach provides a sophisticated understanding of the user's cognitive state. It's important to note that, at this stage, the data collection from the Heart Rate Tracer is monitored separately. For the correlation study, data obtained from the EEG sensor and Heart Rate Variability (HRV) are tracked in an Excel spreadsheet, as briefly explained in Section 3.4. Despite the separate monitoring processes, the correlation study can still be investigated, as discussed in subsection 4.3.

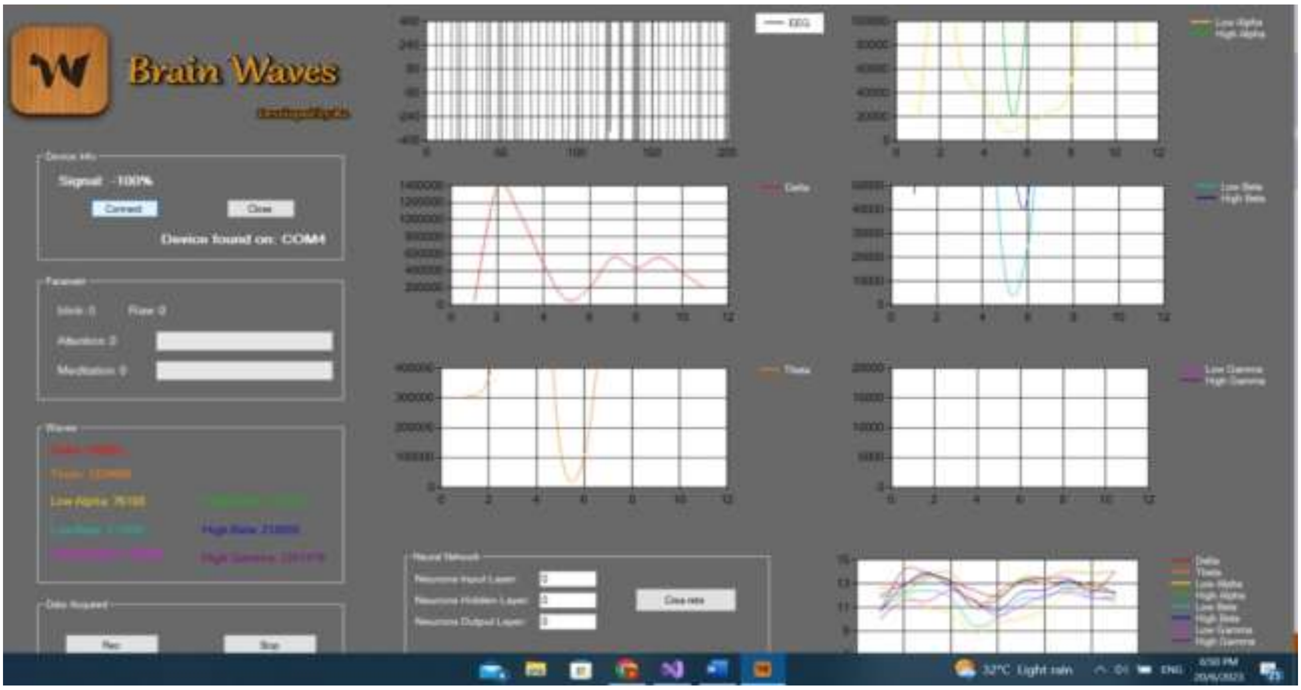


Fig. 6. Brainwaves Monitoring System (BMS) application interface

The real-time visualization aspect of the application adds an interactive dimension to the user experience. Each captured brainwave is dynamically displayed in graphical form, providing an instant and visually intuitive representation of the neural activity. This real-time feedback enhances the user's engagement and understanding of their cognitive patterns. Furthermore, BMS goes beyond immediate insights by incorporating a data recording function. All the gathered information is meticulously stored in numerical form, affording users the capability to archive and revisit the data for future analysis or reference. This not only adds a layer of convenience but also establishes BMS as a valuable tool for long-term cognitive monitoring and research purposes.

4.2 Capturing Data Attention and Meditation

The human brain exhibits dynamic patterns that adapt to the ongoing situation. When an individual focuses on a specific task or object, the brain generates measurable electrical activity, which is effectively captured through EEG. This cognitive phenomenon is denoted as "Attention," reflecting the intensity of mental focus, while "Meditation" signifies a state of mental calmness and relaxation.

To explore the intricate relationship between Attention and Meditation, an experiment was conducted using a Neuro experimenter. In this study, a numerical scale ranging from 0 to 1 was employed, where values falling between 0.4 and 0.6 were classified as neutral, akin to baseline levels. Values surpassing 0.6 were indicative of significantly heightened levels of cognitive performance, suggesting a state of pronounced focus and concentration.

Conversely, values below 0.4 were interpreted as representing lower levels of cognitive performance, suggesting a state of distraction or abnormality. This dual-scale approach provides a sophisticated understanding of the subject's cognitive state, allowing for the identification of optimal performance levels as well as instances of potential distraction or deviation from the norm. The integration of EEG technology and quantitative analysis adds precision to the evaluation, contributing to a comprehensive assessment of the interplay between attention and meditation in diverse cognitive states.

Figure 7 displays the attention and meditation values extracted from the Neuro Experimenter application. The meditation sense is linked to feelings of relaxation, calmness and an overall sense of well-being, while attention sense is tied to a state of alertness, focus and concentration. A discernible pattern emerges in the data, illustrating an inverse relationship between attention and meditation levels. As the attention level rises, the corresponding meditation level tends to decrease and conversely, when attention decreases, the meditation level tends to rise.

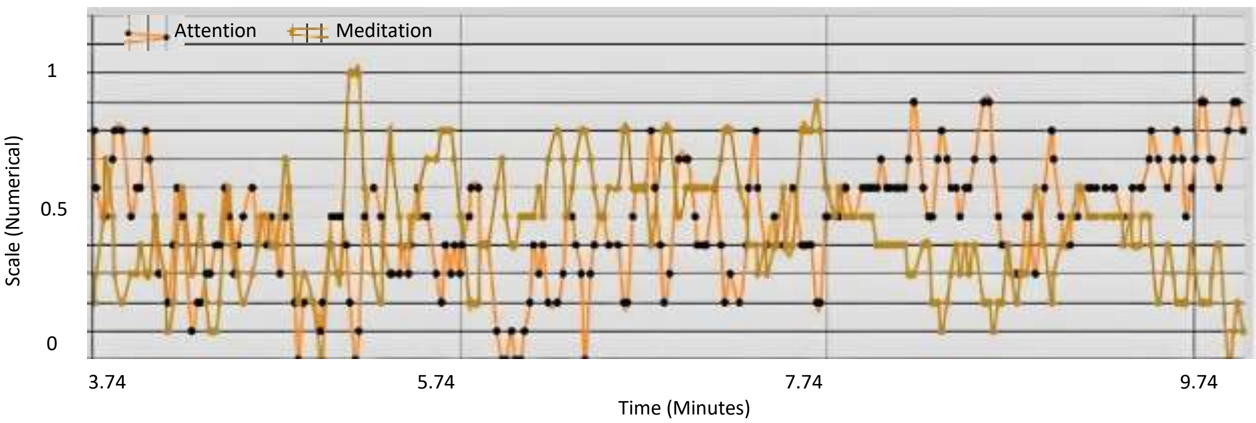


Fig. 7. The relationship between attention and meditation

This observed correlation is rooted in the inherent contradiction between concentration and relaxation. When an individual is deeply engaged in a task, directing heightened attention and focus, the mind tends to shift away from a relaxed state. Conversely, during moments of relaxation and calmness, the mind is less intensely focused, resulting in lower attention levels. The dynamic interplay between these cognitive states highlights the delicate balance between concentration and relaxation, shedding light on how the mind navigates these contrasting states in response to varying situations.

Meanwhile Figure 8 shows the ratios of average waveform outputs obtained from the Neuro Experimenter application for a 10-minute data segment. Each bar represents the performance ratio over the baseline for its respective wave type. The initial 5 minutes are designated as the baseline, during which the subject is engaged in some activity, while the subsequent 5 minutes are labelled as the performance phase, indicating a period of meditation. An attention value of 0.90 suggests that the average output for attention during the performance phase did not significantly differ from that during the baseline phase. This indicates a relative consistency in attention levels between the two segments of the session.

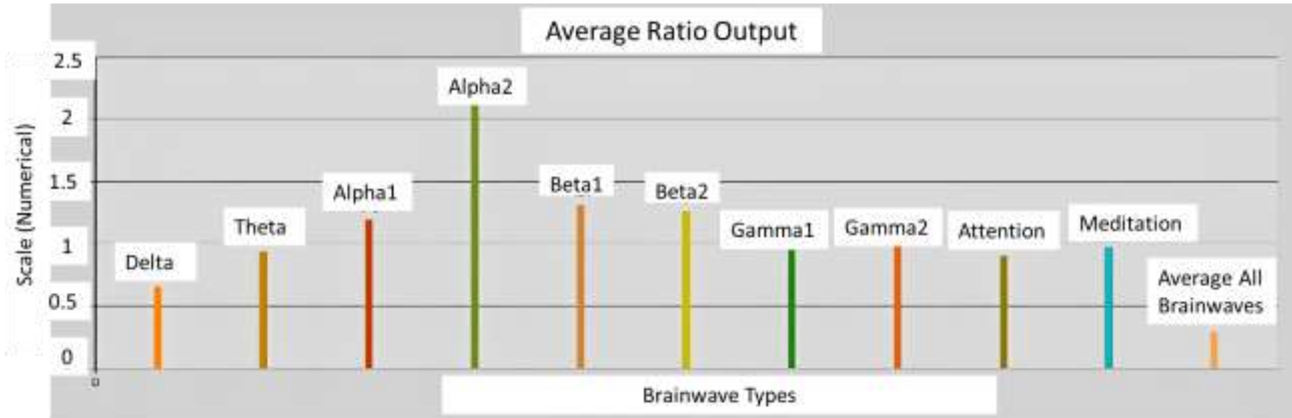


Fig. 8. The ratio of average output of different brainwaves

In contrast, the Alpha waves exhibit a robust performance ratio of 2.11, signifying a pronounced increase during the performance phase compared to the baseline. This notably high ratio suggests a strong meditation state during the latter half of the session, as Alpha waves are often associated with relaxation and meditative states. Additionally, the Gamma waves values of 0.95 and 1.01 indicate average attention levels during the activity, showcasing a moderate variation from the baseline. These values suggest that, on average, attention is maintained during the activity phase, with a relatively minor shift in performance compared to the baseline. The detailed analysis of these waveform ratios in Figure 7 provides a sophisticated understanding of the subject's cognitive dynamics, highlighting the specific wave types associated with attention, meditation and their variations across different phases of the experimental session.

4.3 Capturing Data Attention and Meditation and Heart Rate for Correlation Study

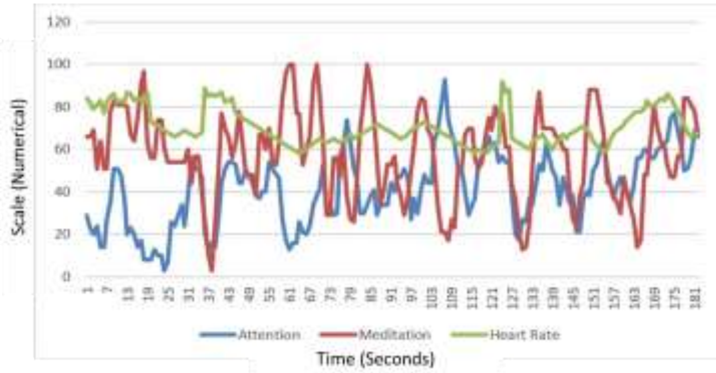
In this experiment, participants are involved in Activity 1, with the primary goal of exploring brainwave activity during a state of relaxation. It's worth noting that additional activities will be addressed in future work. To capture comprehensive data, subjects are equipped with a Mindwave headset and a fitness tracker watch. To ensure the accuracy of the recorded data, subjects are instructed to close their eyes and engage in a 5-minute meditation session. This intentional closure of the eyes aims to minimize external disturbances that could potentially affect the brainwave signals being measured. The focus of this activity is on Alpha waves, as these frequencies are commonly associated with a state of relaxed and wakeful awareness [28-30]. The Mindwave headset and fitness tracker watch work in tandem to record and monitor the relevant data during the meditation period.

This experimental setup allows for the in-depth analysis of Alpha wave patterns, providing insights into the subject's neurological responses during a relaxed state. The intentional inclusion of a fitness tracker enhances the overall understanding of physiological changes that may accompany the observed brainwave activity. The analysis of Figure 9 reveals the dynamic interplay of physiological and cognitive signals during meditation and relaxation phases. In Figure 9(a), the capturing signal of Heart Rate, Attention and Meditation is depicted, specifically when the subject is meditating. Figure 9(b) illustrates the Attention, Meditation and Heart Rate signals during relaxation.

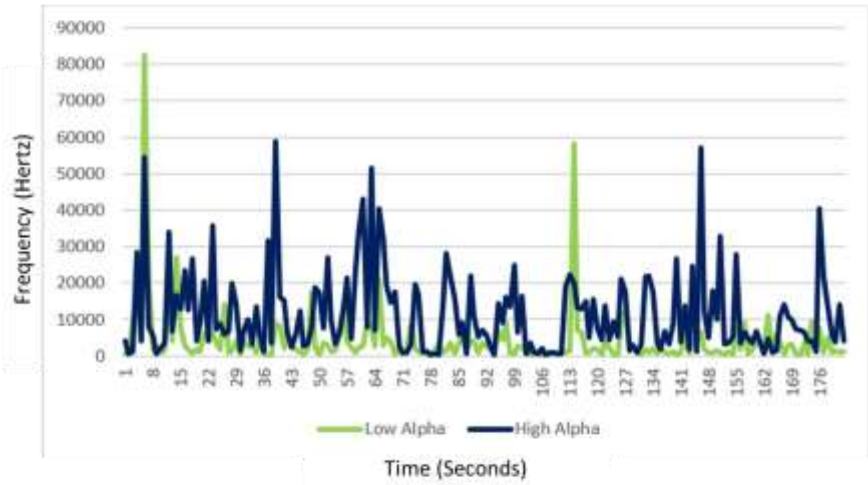
The activation of Alpha waves, shown in Figure 9(c), consistent with mental and physical relaxation, indicates a distinct pattern. Remarkably, instances of meditation, characterized by Alpha waves, consistently surpass attention, linked to Beta waves. This observation aligns with the subject's state of relaxation during meditation, as rising meditation values correspond to decreasing attention values.

An intriguing observation occurs at the 109th second, suggesting a potential interruption, possibly attributed to a wandering mind—an inherent aspect of meditation practices. The distinction between Low Alpha and High Alpha ranges provides further clarity on the subject's mental states. Higher power in Low Alpha indicates deeper relaxation (e.g., at the 113th second), while higher power in High Alpha suggests more focused attention or wandering (e.g., at the 148th second).

(a) Subject meditate and relax



(b) Heart rate, attention and meditation signal



(c) Alpha wave analysis

Fig. 9. Capturing signal of heart rate, attention and meditation (subject meditate)

5. Conclusions

The Hybrid Human Interface System, specifically the Hybrid Brainwaves Monitoring System, designed for stress level monitoring, successfully deploys and captures data from the NeuroSky MindWave headset. This system interprets and displays various brainwave signals, encompassing Delta, Theta, Low Alpha, High Alpha, Low Beta, High Beta, Low Gamma and High Gamma waves. It also effectively gauges levels of attention and meditation on a scale from 0 to 100. The application dynamically presents captured brainwave data in real-time graphical form, enhancing user engagement. Moreover, users can save and analyse information for future reference. The human brain exhibits dynamic patterns in response to different situations and EEG technology measures electrical activity, focusing on attention and meditation. The experiment, utilizing a Neuro experimenter, tests the relationship between Attention and Meditation, using a scale from 0 to 1. Values of 0.4 to 0.6 are considered neutral, above 0.6 indicative of high performance and below 0.4 suggesting lower performance or distraction. The inverse relationship between attention and meditation levels is attributed to the contrary nature of concentration and relaxation. In summary, the Hybrid Human Interface System provides a robust platform for real-time monitoring and analysis of cognitive states, with a specific focus on attention and meditation. The experimental data and visual representations offer valuable insights into the intricate dynamics of the human brain in different mental states. Due to some errors during the transfer of HRV data to the HBMS, advancements in the monitoring system will be carried out in the future.

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