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MENEADY: Mental Readiness Alert System using BCI

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Abstract

Digital platforms have been utilized in teaching and learning sessions especially during the Covid-19 pandemic. However, sessions that are too long can reduce concentration due to lack of mental readiness. Because of this, the efficiency of the learning session may be impacted. Although electroencephalogram (EEG) signals may provide the overview of various mental states, no online application has been developed to detect mental readiness when students are learning online. Therefore, this paper aims to describe the design and development of MENEADY (MENtal rEADiness alert system), a EEG-based BCI that detects mental readiness and provides alert to users using the NeuroSky MindWave Mobile 2 headset. MENEADY is developed using Python. The mental readiness states are measured using the Neurosky attention eSense meter algorithm. The back-end is handled by the Flask framework, while the front-end is managed by Bootstrap. The design of MENEADY can also be adapted for an automated neurofeedback performing intervention neural activation states.

Keywords: *Electroencephalograms (EEG), Brain-Computer Interface, COVID-19, Online Learning, Mental Readiness.*

1. Introduction

The world is struggling to overcome the COVID-19 outbreak with a SARS-CoV-2 novel coronavirus which was first discovered in Wuhan, Hubei, China near the end of 2019 (Huang et al., 2020). People with psychiatric problems are more likely to experience worse COVID-19-related outcomes because they frequently co-occur with physical conditions that have a negative impact on COVID-19 outcomes. Immune system dysfunction is linked to severe mental disorders like childhood adversity (Danese & J Lewis, 2016; Fries et al., 2019), chronic stress (Dhabhar, 2014), sleep problems (Cohen et al., 2009), negative attitudes (de Hert et al., 2011), and cognitive dysfunction (Sheffield et al., 2018; Tempelaar et al., 2017). People have undergone isolation to break the chain of COVID-19. All industries have made their working mode work from home. People feel depressed, and stress while they are following a long period of social distancing. This becomes worse for children and students because all the educational institutions moved to distance learning. Their performance was reduced because of the long period of online learning through Zoom, Google Meet, and Microsoft Teams. One might become mentally exhausted from spending a lot of time online and in front of a computer (Halupa & Bolliger, 2020). As a result, mental fatigue impacts mental readiness for attending online teaching and learning sessions through lower motivation, energy exhaustion, diminished self-performance, and a sense of accumulated stress (van Cutsem et al., 2017).

Mental readiness refers to attentional control, relaxation, activation, self-confidence, and self-talk that creates a balanced psychological condition in which someone can perform at his best. It has become a very important issue to understand students' brain activation state in these historic times and beyond. Different brain states can be understood through brain signal analysis. Electroencephalogram (EEG) signals allow us to measure brain waves. Thanks to researchers from all around the world have contributed to the development of the modern technological period. An EEG-based Brain-Computer Interface (BCI) is one of the advanced technologies to address different brain states.

An EEG-based brain-computer interface enables direct communication between the electrical activity of the brain and a computer system (Vidal, 1973; Wolpaw et al., 2002). EEG signals are non-invasive brain waves and categorized into five frequency bands: (i) delta (0.3-4 Hz), (ii) theta (4-8Hz), (iii) alpha (8-13 Hz), (iv) beta (13-30 Hz), and (v) gamma (> 30 Hz) (Subha et al., 2008). This non-invasive method tracks brain activity using external sensors to avoid the intrusion of artificial objects into the subject's brain (Steyrl et al., 2016).

Based on advancements in EEG data processing, several approaches for identifying cognitive disorders such as mental stress, exhaustion, ADHD, and PTSD have been reported (Krepel et al., 2020; Noohi et al., 2017; Roy et al., 2014). However, there is no BCI that measures mental readiness state and alerts students while they are studying online. Therefore, the purpose of this study is to create a web-based MENEADY, a BCI application that can assess students' mental readiness for online classroom and learning sessions. EEG signal acquisition can be done using Neurosky Mindwave Mobile 2 headset. EEG signal processing involves a built-in ThinkGear chip and ThinkGearASIC module. Then, mental readiness will be evaluated by measuring attention values through the eSense meter in Neurosky. An alert system is designed to improve their level of focus by informing their mental attention level.

2. Literature Review

There are several contributions to addressing different mental states. In (Hossan et al., 2017; Roy et al., 2014) papers reported drivers' mental fatigue detection. The major frequency components were identified using power spectrum analysis using MATLAB. For several epochs, the slow wave to rapid wave ratios of the EEG activity was evaluated to gauge the fatigue of the driver. For tracking, remote notification, and servomotor control, Arduino MEGA was equipped with GPS and GSM modules (Hossan et al., 2017). In (Roy et al., 2014) at first, the EEG signal is filtered in a certain frequency band. Then, based on Riemannian geometry picked 15 electrodes out of 32. Next, six common spatial patterns (CSP) filters are used in a spatial filtering phase. Finally, Fisher's linear discriminant analysis (FLDA) is used to achieve a binary classification.

Then, (Zaeni et al., 2019) addressed learning concentration while reading text. The subject's score after reading the reading content is evaluated by measuring the alpha and beta waves. The estimation model is created using an Artificial Neural Network (ANN). Another frequency- based EEG concentration detection was reported in the study (Purnamasari & Junika, 2019). In this study, frequency-based feature extraction and a Radial Basis Function (RBF) kernel SVM classifier was used to handle the EEG signal. The power spectral density (PSD) from the Fast Fourier Transform (FFT) and the energy from the Discrete Wavelet Transform were two compared features.

In (Vasiljevic et al., 2018) presented a system named Zen Cat which is a meditation game application based on BCI interaction for relaxation using neurofeedback. In the evaluation session, participants were required to be accommodated in a closed, quiet, and climatized room. Participants then have to play 4 consecutive games, fill up a set of questionnaires and answer sincerely regarding the game experience. It is measuring meditation levels over time and shows results in the form of a boxplot to the participants. The game theme is said to be satisfying and suitable for medication control.

An application run on smartphones called Morpheus alert is developed to solve the problem of drowsiness and microsleeps among drivers (Martinez-Maradiaga & Meixner, 2017). It is conducted in both normal and drowsy conditions requiring the participants to sit comfortably and the attention level of the brain signals is analyzed. To alert the user when drowsy is detected, the smartphone will vibrate and make a loud sound. It is very sufficient to prevent microsleeps that may be caused by sleeping disorders and some medications.

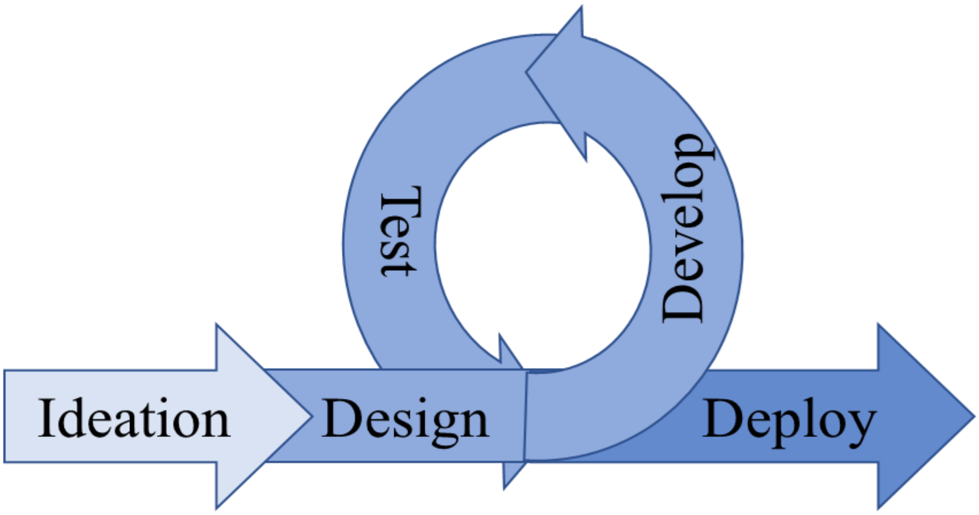

Figure 1: Methodology for MENEADY

In (Antle et al., 2018) presented Mind-Full, which is a neurofeedback BCI implementing a game application made especially for children in Nepal who suffered from complex trauma. The goal is to help them in self-regulation of different brain states such as anxiety, attention, pain, and cognitive load. The system comprises two Samsung Galaxy 10.1 touch tablets that ran a mobile game development engine which is known as Unity 3D. There are 3 games run in a single application on one tablet, two games for relaxation, and one game for attention while a real-time calibration application runs on the second tablet. A follow-up test is also done after completing the playing game session for more effectiveness. The data is analyzed and shared with the teachers so they could always monitor the children's momentum in the class.

However, Morpheus alert is the only system that has a notification system with sounds along with vibration to alert the user when drowsiness is detected. In addition, Zen Cat and Mind-Full provide three to four game applications causing some users more stress as stated in (Antle et al., 2018; Vasiljevic et al., 2018). Therefore, there are no BCI applications intended to focus on mental readiness alerts for online learning students.

3. Method

Figure 1 shows the Agile software development lifecycle that is adapted for developing MENEADY. It consists of 5 phases including ideation, design, develop, test and deploy. The ideation phases involves the selection of the scope by focusing on important and current concerns. The topic of mental health has been widely explored. This study focused on mental readiness for remote learning students. Then, related existing study helps to understand the MENEADY deployment requirements (Antle et al., 2018; Hossan et al., 2017; Ko et al., 2015; Martinez-Maradiaga & Meixner, 2017; Purnamasari & Junika, 2019; Vasiljevic et al., 2018; Zaeni et al., 2019). The ideation outcomes were functional requirements, tools, identifying MENEADY functional pipeline, and alert system, those described in the following sections.

The design phase involves the architectural design and user interface design. The architectural design consists of a logical view, process view, development view, physical view, and user view from the user's perspective. Details of the user interface are explained in the next section. In the development phase, MENEADY is mainly developed using Python.Then, MENEADY is tested in the trial process. Through Agile software development lifecycle, every segment of MENEADY was tested after coding. Therefore, the design, development, and testing processes are executed in iterative. If any changes are made to any section of projects, then updated on time. This made the development and improvement of the system very fast.

Figure 2: Neurosky Mindwave Mobile 2 Headset

4. MENEADY: Mental Readiness Alert System

MENEADY is a BCI application that helps students measure their mental readiness during online learning by measuring EEG signals. MENEADY is referring to “mental” and “ready”.

4.1 Requirements Analysis

The MENEADY system's requirements are investigated and divided into functional requirements and non-functional requirements, depicted in Table 1.

Table 1: Functional and Non-Functional Requirements

Functional Requirements	Non-Functional Requirements
Users should be able to connect the mobile device with the Neurosky Mindwave Mobile 2 headset	The user interface should be simple and understandable for users to use.
Brain signals could be read and illustrated in real-time graphs.	The real-time graph should start immediately after the start button is clicked.
A notification with sound should be popped up if the attention value is less than 50.	The alert system should be triggered within 10 minutes regardless if the user opens another software.

4.2 Tools

Neurosky Mindwave Mobile 2 headset is among the most comfortable EEG headsets which have a flexible arm of rubber sensor with a circular shape of forehead sensor tip, T-shaped headband, and ear clip sensor as indicated in Figure 2. The ground of this device was located in an ear clip, and its sensors were positioned at the FP1 position on the forehead. It is powered by a AAA battery with 8-hour battery life. Using a sample rate of 512 Hz, this device outputs 12 bytes of unprocessed brain waves (3-100 Hz) (Berith Olam et al., 2014).

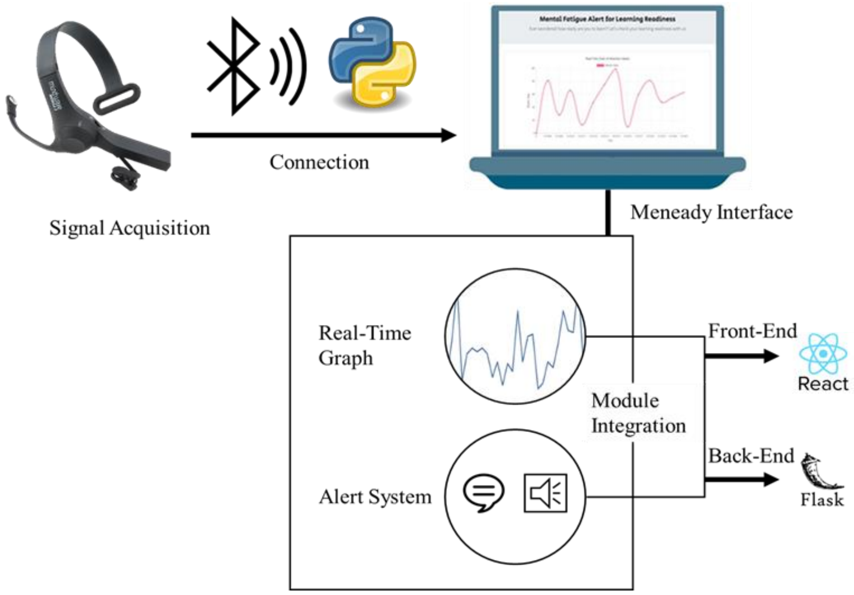

Figure 3: System Integration between Python, Flask and Bootstrap

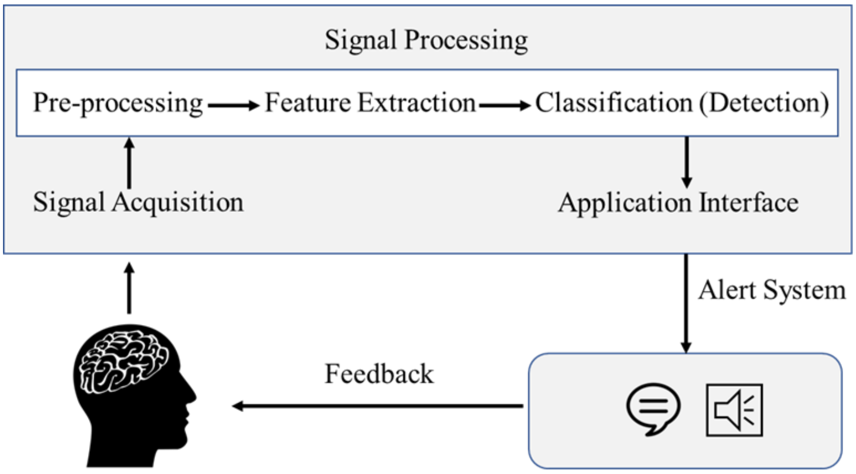

Figure 4: MENEADY Implementation Design

Python programming language has been used with the Flask framework in developing the intended system. Python is easy to use, versatile, contains numerous third-party modules, and provides extensive support libraries. Furthermore, Python works well with the Neurosky Mindwave Mobile headset regarding the connection and acquiring raw data. In addition, a Flask framework is used due to its extreme flexibility, minimalism, ease to handle and it is small core, and easily extensible. Bootstrap is also used together with the Flask framework to handle the front-end interface while Flask is responsible for the back-end process. The integration of Python programming language, Flask framework, and Bootstrap is demonstrated in Figure 3.

4.3 MENEADY Functional Pipeline

The application of BCI in MENEADY is depicted in the form of a system design or block diagram as in Figure 4 which involves the signal acquisition, signal processing, and alert system as feedback.

4.3.1 Signal Acquisition

EEG signal acquisition is a complex process because EEG signals are very sensitive. At first, students need to wear a Neurosky headset. Then need to connect it to a computer using Bluetooth. There are 2 channels that can analyze brain signals an electrode attached to the forehead sensor tip and an electrode on the ear clip sensor. The electrodes collect the user's brain activity and help to analyze it. The signals are categorized into different frequency bands known as Delta, Theta, Alpha, Beta, and Gamma. However, the majority of clinical and physiological research targets the frequency range that is between 0.5Hz and 30Hz (Yildirim & Varol, 2016). The characteristics of EEG frequency bands (0.5-30) are depicted in Table 2 (van Atteveldt et al., 2020).

Table 2: Relationship between EEG Frequency and Brain States

EEG Frequency (Hz)	Activity (Mental state)
Delta δ (0.5-3)	Deep Sleep
Theta θ (4-7)	Drowsy
Alpha α (8-12)	Relaxed
Beta ß (13-30)	Focused

4.3.2 Signal Processing

The raw brain signals may contain interference such as environmental electrostatic noise, non-EEG biometric noise, and muscle movement. The ThinkGear chip inside the Neurosky headset will remove the interference to increase the reading of the raw brain signals to be transmitted to laptop devices via Bluetooth. The raw brain signals will undergo a calculation process of producing attention and meditation value that is considered as processed brain signals using inbuilt algorithms by the ThinkGearASIC module (Dinesh Anton Raja et al., 2020).

Among the brain signals, the attention value is the most closely related to mental readiness which indicates the level of engagement in the online learning session. If the participants have less attention, then it will be difficult to understand instructions, socialize with others, and have bad memory due to drained mental energy upon mental activity (Dinesh Anton Raja et al., 2020). It also demonstrates the measurement of mental focus and concentration either within or outside the control of mental activity through the attention eSense meter in Neurosky (Srimaharaj et al., 2021). The attention meter level may be declined because of distractions, wandering minds, less focus, or fear. Thus, attention value is chosen to be the measurement level for the project.

According to the eSense meter in the Neurosky headset, a user's attention value has a scale between 1 to 100 that is captured and transmitted every second. It is classified into 5 categories which are 1 to 20 indicates 'strongly lowered' levels and 20 to 40 indicates 'reduced' levels. The two categories imply the individual state of distraction, agitation, and abnormality. The value of 40 to 60 indicates that 'neutral' resembles "baseline" in traditional EEG measurement techniques. Moreover, the value from 60 to 80 indicates 'slightly elevated' by any chance higher than normal whereas 80 to 100 indicates 'elevated' showing the intense level of eSense. Nevertheless, the attention value can also be 0 if the sensor is not detecting any signal and it may be caused by excessive noise.

Hence, the threshold value for attention is set to 50 in order to determine mental readiness whereas the threshold value to identify the attention value that is less than 50 is set to only 10 seconds. In other words, the user with an attention value that is found below 50 within 10 seconds will be detected and considered as having less concentration.

4.3.3 Alert System

Based on the attention values obtained, it is visualized in the form of a real-time graph consisting of attention values against time in seconds. A start button needs to be tapped so the attention values begin to be captured. An alert system will trigger after 10 seconds finding the attention values less than 50. A notification with sounds will be popped up informing the poor mental readiness as well as offering a simple game application to enhance concentration level.

After the alert message is successful, it shows that the concentration level becomes stable, and the attention problem is resolved by controlling the brain waves.

4.4 User Interface

The user interface of MENEADY is displayed in Figure 5 and Figure 6 including a real-time chart of user's attention values against time and a popped-up notification window as an alert for students who are not mentally ready.

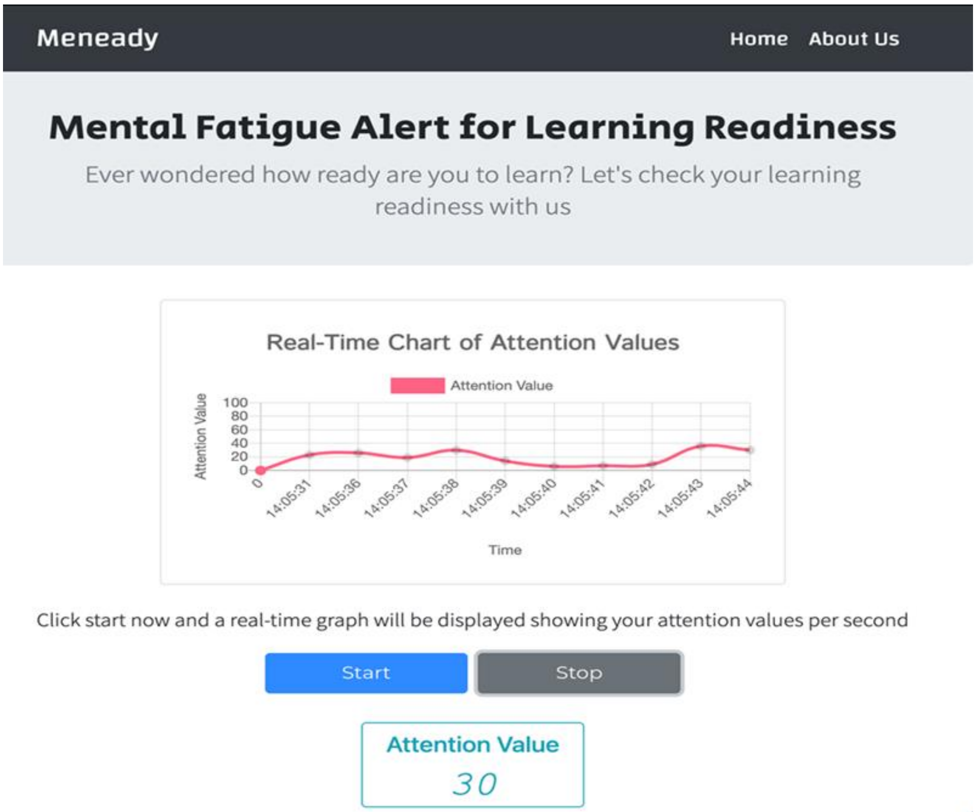

Figure 5: Main Page of MENEADY Showing the Teal-time Chart of Attention Value Against Time

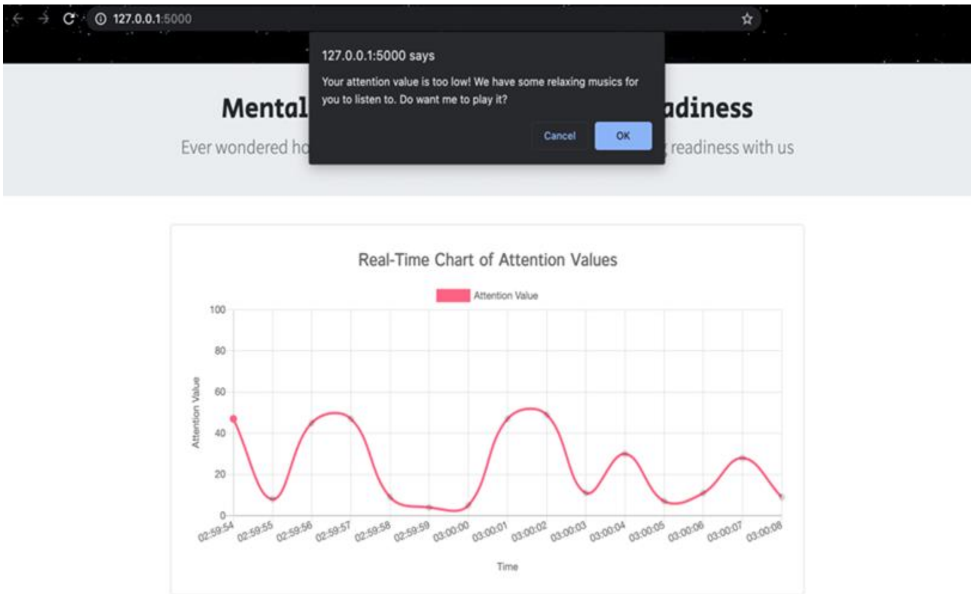

Figure 6: The Notification is Displayed when the User's Attention Level is Low

5. Conclusion

MENEADY is a tool that lets us determine a person's level of mental readiness. MENEADY is simple to use even for non-technical people. The modeling, classification, and analysis of user interfaces are straightforward, practical, and simple to use. MENEADY intends to assist in biomedical research because Neuro-Feedback treatment, a novel technique, can assist in identifying the fundamental emotional neural connections by instructing the brain to control its own movements. Thus, the MENEADY system provides benefits to students in obtaining effective online learning by staying focused.

However, MENEADY is only configured to be integrated with the Neurosky Mindwave mobile 2 headsets. For future works, the architectural design of MENEADY can be adapted for other automated neurofeedback applications, such as mental fatigue intervention and sleep disorder. This can be accomplished by providing MENEADY with increased control so that it can more precisely regulate the environment in response to the information received from the warning system.

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