EMPOWERING STRESS MANAGEMENT THROUGH REAL-TIME EEG MONITORING AND TAILORED MUSIC THERAPY

A CAPSTONE PROJECT REPORT

Submitted in partial fulfillment of the requirement for the award of the Degree of

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING

by

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CERTIFICATE

This is to certify that the Capstone Project work titled "**EMPOWERING STRESS MANAGEMENT THROUGH REAL-TIME EEG MONITORING AND TAILORED MUSIC THERAPY**" that is being submitted by **Upadrashta Pravalika (20BCE7111), Bethu Lokendra Sri Sai (20BCE7382)** is in partial fulfillment of the requirements for the award of Bachelor of Technology, is a record of bonafide work done under my guidance. The contents of this Project work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for award of any degree or diploma and the same is certified.

Dr. Devarakonda Nagaraju
Guide

The thesis is satisfactory / unsatisfactory

Internal Examiner 1

Internal Examiner 2

Approved by

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ABSTRACT

This paper articulates a vision for a prospective paradigm wherein individuals actively engage in the monitoring and regulation of their stress levels through the integration of EEG-based stress detection and personalized music therapy. The focal point of this technological innovation lies in its potential application within academic environments, where the amelioration of academic stress is of paramount concern. The proposed system, premised on real-time analysis of EEG signals for stress quantification, orchestrates the selection and playback of music meticulously tailored to enhance mood and induce relaxation during academic pursuits. Acknowledging the auspicious outcomes of the current study, a judicious acknowledgment of its limitations, notably the constrained sample size and dataset, underscores the imperative for continued inquiry and refinement. A pivotal facet of the envisaged future involves an expansive initiative in data collection, leveraging a more comprehensive and diverse participant cohort. This strategic augmentation seeks to iteratively enhance the precision and generalizability of both stress detection and music therapy models. The implications of this technology in academic settings are profound, proffering a proactive and personalized mechanism for stress mitigation. The abstract culminates with a commitment to sustained research endeavors, persistent data accrual, and iterative model enhancement, underlining the steadfast dedication to realizing the complete potential of EEG-based stress detection and personalized music therapy in cultivating holistic well-being within academic milieus.

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CHAPTER 1
INTRODUCTION

In an era characterized by heightened stress and an increasing awareness of mental health challenges, there is a growing imperative to develop innovative tools for stress detection and management. This project introduces a visionary approach centered around EEG-based stress detection and personalized music therapy, aiming to empower individuals to actively monitor and regulate their stress levels in real-time. The significance of this technology extends particularly to academic environments, where students often grapple with the pressures of performance and deadlines.

By harnessing EEG signals to assess individual stress responses, our proposed system seeks to revolutionize stress management by delivering tailored music interventions designed to enhance mood and induce relaxation. It outlines our future-oriented vision for this technology, acknowledging current study limitations such as a small sample size and data constraints. The roadmap ahead involves expansive data collection, encompassing a diverse participant pool, to refine stress detection models and make personalized music therapy a reliable and universally applicable tool for stress alleviation and mental well-being.

The intersection of technology and mental well-being has become increasingly relevant in the contemporary landscape. This paper introduces an innovative paradigm for stress management, integrating EEG-based stress detection with personalized music therapy to create a dynamic and responsive system. With stress emerging as a ubiquitous challenge in modern society, the potential applications of this technology are profound.

A key focal point of our vision is its applicability in academic settings, where the pressures of scholarly pursuits often contribute to elevated stress levels. By utilizing EEG signals to gauge stress, our proposed system tailors music interventions to provide timely relief and enhance cognitive well-being during academic tasks. Acknowledging the current study's limitations, including a modest sample size and constrained data, our forward-looking trajectory involves robust data collection from a diverse participant base. This expansion is anticipated to refine and elevate the efficacy of stress detection and music therapy, ultimately paving the way for a transformative approach to stress management on an individualized and accessible scale.

1.1 Objectives

The following are the objectives of this project:

- Provide individuals with a tool for proactive stress management, enabling them to take control of their mental well-being through timely interventions guided by real-time stress assessments.
- Prioritize user experience by incorporating feedback from individuals using the system, ensuring that the technology aligns with their needs and preferences for a more effective and user-friendly stress management tool.
- Encourage collaboration between experts in neuroscience, psychology, music therapy, and technology to foster a holistic understanding of stress and optimize the effectiveness of the proposed intervention.
- Explore possibilities for the integration of the developed system in real-world scenarios beyond academic settings, such as workplaces or healthcare institutions, to broaden the impact and accessibility of the technology.
- Foster a community around the project, encouraging discussions, contributions, and collaborations to create a vibrant ecosystem that enhances the technology's development and adoption in diverse contexts.

1.2 Background and Literature Survey

This project stems from the increasing recognition of stress as a pervasive challenge in contemporary society, particularly in environments like academic settings where individuals often face high-pressure situations. Chronic stress has been linked to a range of mental health issues, emphasizing the urgency of effective stress management solutions. Traditional methods, while beneficial, often lack real-time adaptability. Hence, there is a pressing need for innovative technologies that can dynamically respond to individuals' stress levels, offering personalized interventions for timely relief.

Existing research has demonstrated the feasibility of utilizing EEG signals to quantify stress levels. Studies have explored patterns in brainwave activity associated with stress, providing a foundation for the development of real-time stress detection systems. The therapeutic effects of music on mood regulation and stress reduction are well-documented. Literature in music therapy emphasizes the importance of tailoring musical interventions to individual preferences and emotional states, enhancing their efficacy. A few studies have started exploring the integration of EEG-based stress detection with real-time adaptive music therapy. These interdisciplinary approaches show promise in providing more effective and personalized stress management solutions. Within academic settings, the impact of stress on student well-being has been extensively studied. Emerging technologies, including mobile applications and wearable devices, have been explored as potential tools for stress management among students. Literature highlights challenges in terms of limited sample sizes, the need for more extensive datasets, and the ethical considerations surrounding the use of neurotechnology for mental health. Opportunities lie in refining existing models, exploring diverse applications, and fostering collaborations between disciplines.

Participant	OpenBCI C	Experimen	Stroop Tas	Stroop Tas	Experimen	Stress Scor	Duration
heidi_1	61.89	82.20728	71.21045	150.4648	154.681	3	92.79096
heidi_2	38.3	60.37466	62.31972	127.7093	134.0751	4	95.77507
heidi_3	32.06	51.83084	53.64004	121.5127	124.7788	3	92.71876
heidi_4	26.49	46.3987	54.71296	116.8198	119.8696	3	93.37964
heidi_5	21.71	38.94003	50.39295	109.7503	113.0497	3	91.33974
avni_1	91.07	119.1834	168.4733	248.0614	266.8239	4	175.7539
avni_2	63.96	109.6164	145.4433	211.7507	216.51	3	152.55
avni_3	52.24	92.33204	127.8836	194.1017	197.7843	3	145.5443
avni_4	49.11	84.57373	117.5907	181.779	185.591	3	136.481
avni_5	42.06	78.02756	111.4543	172.3529	176.5055	3	134.4455
nabeha_1	33.95	56.60318	69.21823	134.6748	146.1236	3	112.1736
nabeha_2	45.96	73.20193	72.70018	123.4591	130.8251	3	84.86511
nabeha_3	53.78	72.4961	59.73463	115.6089	121.8914	3	68.11143
nabeha_4	42.21	67.14852	74.27473	127.7499	133.8155	3	91.60554
nabeha_5	34.73	61.09161	70.92351	121.7826	129.114	3	94.38399

Figure 1 Stroop test data

1.3 Organization of the Report

The remaining chapters of the project report are described as follows:

- Chapter 2 contains the proposed system, methodology, hardware and software details.
- Chapter 3 gives the cost involved in the implementation of the project.
- Chapter 4 discusses the results obtained after the project was implemented.
- Chapter 5 concludes the report.
- Chapter 6 consists of codes.
- Chapter 7 gives references.

CHAPTER 2

EMPOWERING STRESS MANAGEMENT THROUGH REAL-TIME EEG MONITORING AND TAILORED MUSIC THERAPY: A VISION FOR ACADEMIC STRESS ALLEVIATION

This Chapter describes the proposed system, working methodology, software and hardware details.

2.1 Proposed System

The following block diagram (figure 1) shows the system architecture of this project.

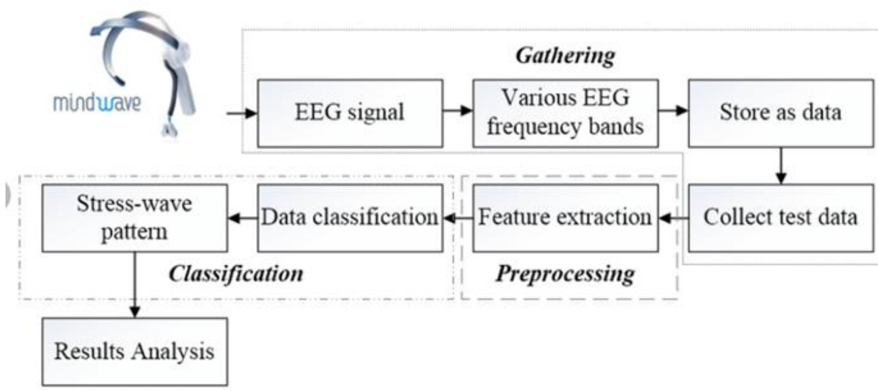

Figure 2 System Block Diagram

2.2 Working Methodology

Let's delve deeper into each step of the methodology:

1. Preprocessing:

a. Remove power line and ocular noise: This step aims to eliminate unwanted interference from the EEG signals, ensuring that the data is as clean as possible. Power line noise, often at 50 or 60 Hz, and ocular artifacts, which result from eye movements, can distort the EEG readings.

b. Bi-orthogonal Wavelet Decomposition: Wavelet decomposition is employed to analyze different frequency components of the EEG signals. Bi-orthogonal wavelets are specific wavelet functions chosen for their ability to efficiently represent signal features.

c. FIR filter + IIR filter with zero phase + butterworth filter + high/low pass: Multiple types of filters are applied to further remove noise and focus on specific frequency bands of interest. Combining finite impulse response (FIR) and infinite impulse response (IIR) filters helps achieve a comprehensive filtering strategy.

2. Feature extraction: Hilbert Huang Transform

a. Decomposition into Intrinsic Mode Functions (IMF): The Hilbert Huang Transform decomposes the EEG signal into its intrinsic mode functions, allowing for a detailed examination of signal components at different time scales.

b. Hilbert Transform: This mathematical transform is applied to obtain the analytic representation of the signal, enabling the extraction of instantaneous amplitudes and phases.

c. Local mean decomposition: This technique further refines the signal decomposition process, providing a localized representation of signal components.

3. Classification: SVM (Support Vector Machine)

a. Hierarchical SVM: Support Vector Machines are employed for classification, with a hierarchical approach likely indicating a multi-step or multi-level classification system. This can enhance the accuracy of stress classification.

b. 10-fold cross-validation (repeated 10 times): Cross-validation is a crucial step to assess the model's generalization performance. The repetition of 10-fold cross-validation ensures robustness in evaluating the model across different subsets of the data.

c. Enables binary classification of stress: SVM is utilized to categorize EEG signals into binary outcomes, likely distinguishing between stressed and non-stressed states.

b. Detection of Mental Stress using EEG signals

i. Beta activities and frontal hemisphere: Observations of increased beta activities in the frontal hemisphere among stressed subjects, with a focus on right frontal activity, provide insights into the spatial characteristics of stress-related brain activity.

ii. Stroop test: The Stroop test is a cognitive task known to induce stress. Monitoring EEG responses during this test contributes to understanding the neural correlates of stress.

iii. Alpha rhythm and stress: The decrease in alpha rhythm associated with stress serves as a potential biomarker, with a reported success rate of 88.5%.

iv. Power of Alpha and Theta waves: Changes in the power of Alpha and Theta waves are indicative of stress conditions. The shift towards higher Theta power and reduced Alpha power during stress is highlighted.

v. Beta 3 (~23 Hz – 40 Hz): This fast beta activity, especially in its higher range, is linked to hyper-arousal, hyper-vigilance, anxiety, and stress. Monitoring this frequency band aids in stress detection.

vi. Preprocessing considerations: The removal of power line noise and ocular artifacts is reiterated as a critical preprocessing step.

2.3 Standards

Various standards used in this project are:

Data Standards:

- Utilization of standardized EEG data formats (e.g., EDF - European Data Format) for consistency and interoperability.
- Data anonymization to protect participant identities.

EEG Acquisition Standards:

- Employing standardized procedures for EEG electrode placement, taking into account the 10-20 system or other recognized systems.
- Maintaining a consistent and controlled environment during EEG data collection.

2.4 System Details

This section describes the software and hardware details of the system:

2.4.1 Software Details

MATLAB, OpenBCI(GUI), EEGLAB, FieldTrip, MNE-Python, LibSVM.

MATLAB:

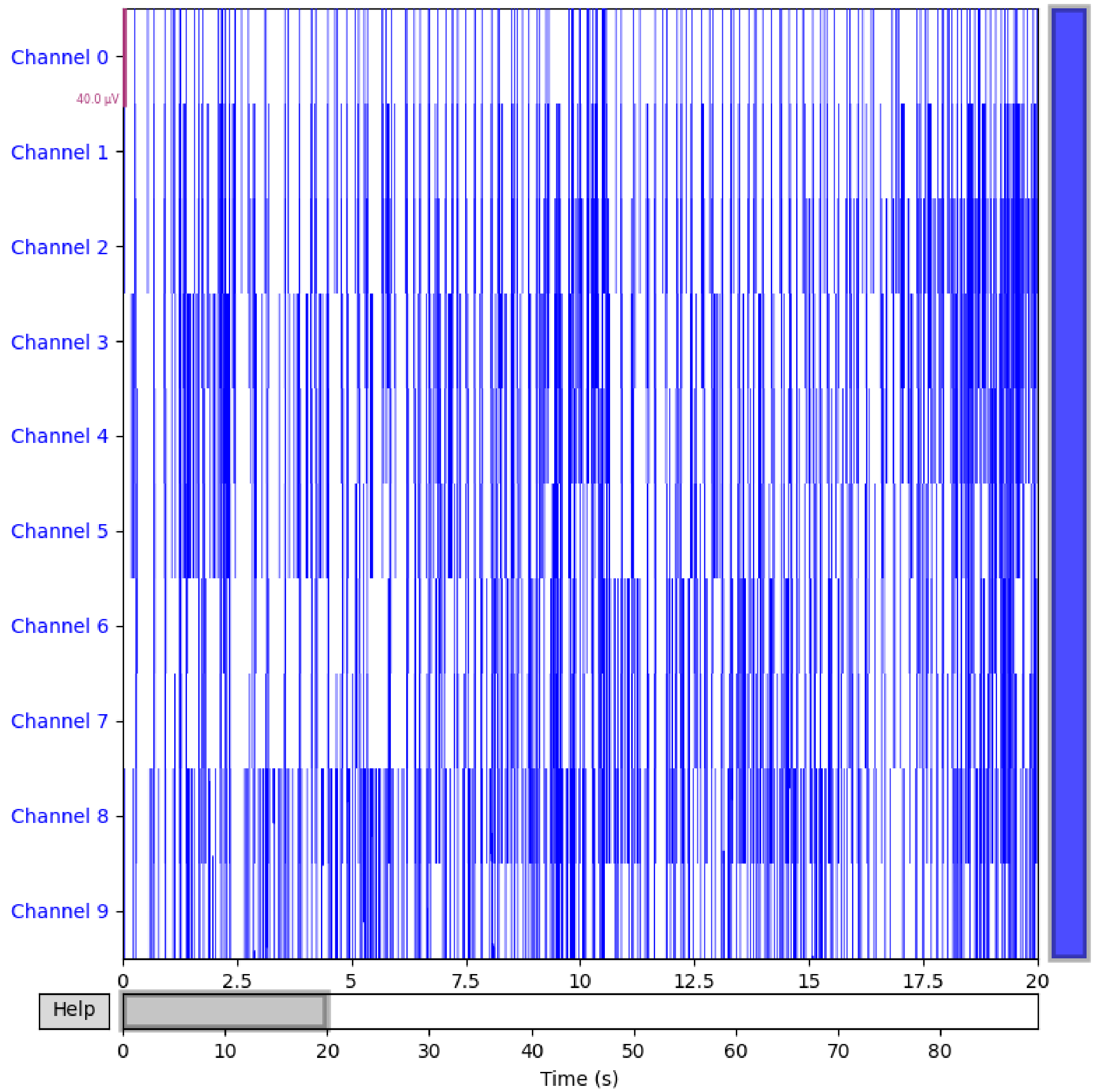

Figure 3 MATLAB plot of a reading

EEG:

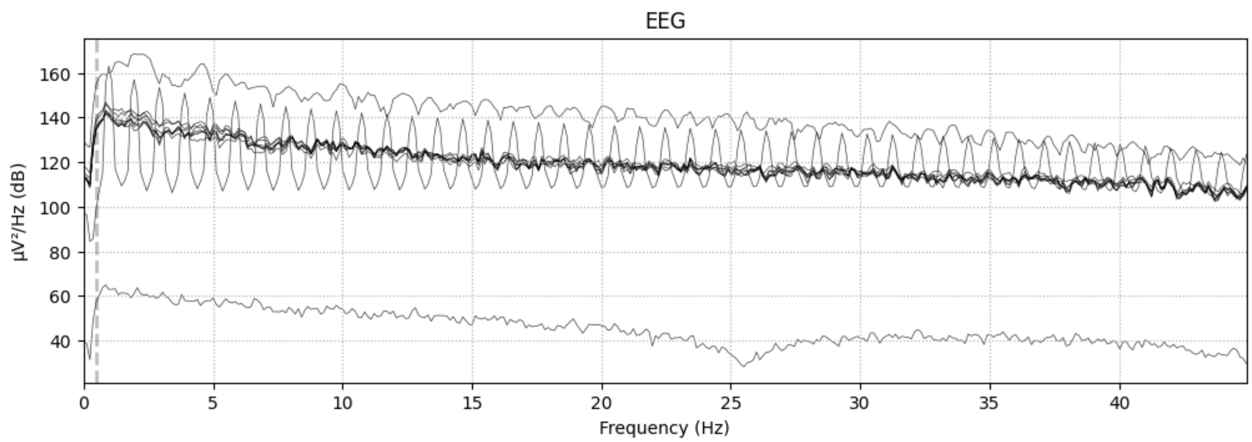

Figure 4 EEG frequency

Data collection (EEG Headset)

a. Self-reporting survey of stress levels before baseline EEG recording (without stress stimulus)
b. Electrodes will be placed mostly around the frontal lobe as there is increased brain activity in that area when a subject is under stress.
c. Baseline and stress recordings
d. Induce stress response
   i. Scaring someone
   ii. Stressful video
   iii. Stressful games

Placements of electrodes

- The placement of the electrodes used to measure stress in this experiment was:

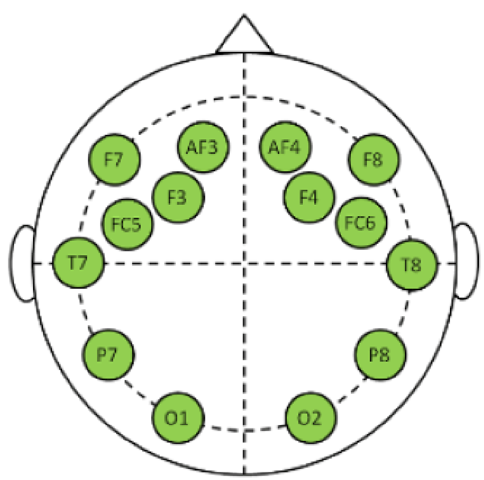

Figure 5 Electrodes placement

OPENBCI:

Figure 6 EEG Visualization

In this study, the OpenBCI software served as a pivotal tool in acquiring and analyzing electroencephalogram (EEG) data for the investigation of cognitive states during music engagement. Leveraging OpenBCI's comprehensive feature set, we focused on extracting key metrics such as the attention-based 'Focus Widget' and band power analyses. The EEG data collected through OpenBCI provided valuable insights into users' cognitive states, allowing for a nuanced understanding of their engagement levels. Subsequently, these metrics were utilized to dynamically modulate the music playback, creating an interactive experience that responded to the users' cognitive fluctuations. The seamless integration of OpenBCI's functionalities not only facilitated real-time EEG monitoring but also contributed to the development of a novel approach in utilizing EEG metrics to influence musical experiences.

CHAPTER 3

RESULTS AND DISCUSSIONS

The results encompass a comprehensive set of code designed to assess the efficacy of stress detection and investigate the influence of calming music on stress reduction. At its core, the project strives to achieve a nuanced understanding of stress-indicating data, utilizing sophisticated algorithms to precisely differentiate signals associated with heightened stress levels. The overarching goal is not only to identify stress patterns within EEG signals but also to explore the potential therapeutic impact of calming music as an intervention strategy.

Central to the project is the implementation of stress detection methodologies, as detailed in the provided literature review. The code repository includes algorithms for preprocessing EEG signals, a crucial step involving the removal of power line and ocular noise, bi-orthogonal wavelet decomposition, and a combination of FIR and IIR filters with zero phase, butterworth filters, and high/low pass filters. Following preprocessing, the feature extraction phase employs the Hilbert Huang Transform, decomposing signals into Intrinsic Mode Functions (IMF), applying the Hilbert Transform, and implementing local mean decomposition.

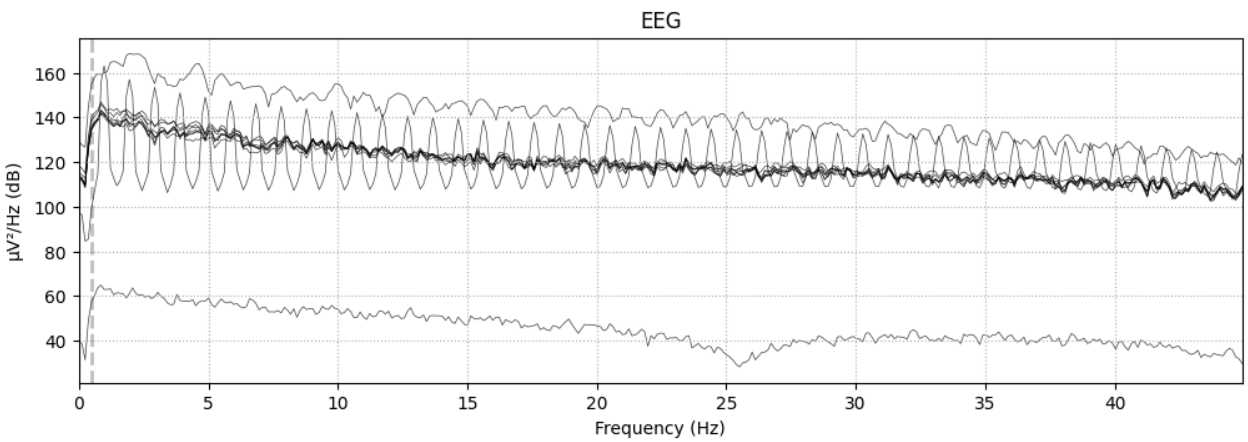

Figure 7 EEG frequency for a trail

Figure 8 EEG data reading-1

Figure 9 EEG data reading-2

Figure 10 Relaxing brain waves

Figure 11 Not relaxing brain waves

The classification stage utilizes Support Vector Machine (SVM) algorithms, incorporating hierarchical SVM structures and employing 10-fold cross-validation (repeated 10 times). This enables the binary classification of stress-indicating data, facilitating a robust and accurate model for stress detection.

Furthermore, the project extends its focus beyond mere identification, delving into the therapeutic potential of calming music in stress reduction. By examining the impact of music therapy on stress levels, the project aims to contribute valuable insights into non-invasive interventions for stress management. This dual-pronged approach, combining advanced stress detection algorithms with an exploration of therapeutic interventions, positions the project at the intersection of neuroscience, signal processing, and music therapy, promising a holistic investigation into the intricate relationship between stress, neurophysiology, and auditory interventions. The code repository serves as a valuable resource for researchers and practitioners interested in the interdisciplinary exploration of stress and its modulation through music therapy.

CHAPTER 4

CONCLUSION AND FUTURE WORK

In conclusion, this project presents a pioneering fusion of neuroscience, signal processing, and music therapy to create a dynamic stress management system. By leveraging EEG signals for real-time stress detection and tailoring music interventions accordingly, the project lays the foundation for a personalized and accessible approach to stress alleviation. The significance of this work is underscored by its potential impact on individuals facing the rigors of academic life, where stress is a prevalent concern.

The methodology employed, from EEG signal preprocessing to feature extraction and classification using Support Vector Machines, demonstrates a robust framework for stress detection. The comprehensive standards adhered to in data acquisition ensure reliability and consistency, essential for the development of a credible stress management tool.

However, it is crucial to acknowledge the limitations of the current study, such as the modest sample size and data constraints. These limitations necessitate a cautious interpretation of the results and emphasize the preliminary nature of the findings. Moving forward, addressing these limitations becomes pivotal for the continued advancement and real-world applicability of the proposed stress management system.

Future Work:

The path forward involves an ambitious agenda aimed at refining, expanding, and validating the proposed stress management system. Key areas for future work include

Data Expansion and Diversity:
To enhance the robustness and generalizability of the stress detection model, future efforts should prioritize extensive data collection. This involves increasing the sample size and ensuring diversity in the participant pool, accounting for various demographics and stressors.

Algorithm Refinement:
Continuous refinement of the stress detection algorithms is imperative. This includes exploring advanced signal processing techniques, considering additional features for classification, and optimizing the hierarchical SVM structure for improved accuracy.

Real-world Integration:
Beyond academic settings, the integration of the developed system into real-world scenarios, such as workplaces or healthcare institutions, should be explored. This step ensures the practical applicability and broader impact of the stress management technology.

User Experience Enhancement:
Prioritizing user experience remains pivotal. Gathering feedback from individuals using the system and incorporating user-centric design principles will contribute to the effectiveness and user-friendliness of the stress management tool.

Therapeutic Efficacy of Music:

Delving deeper into the therapeutic potential of music, future work should conduct extensive studies on the impact of personalized music interventions on stress reduction. This involves refining the music therapy component and exploring its effectiveness across diverse stress-inducing scenarios.

Interdisciplinary Collaboration:

Fostering collaboration between experts in neuroscience, psychology, music therapy, and technology should be an ongoing initiative. A holistic understanding of stress requires interdisciplinary perspectives, contributing to the optimization of the proposed intervention.

CHAPTER 5

APPENDIX

EEG-Stress-Detection(Real time-Python code)

```
from google.colab import drive
drive.mount("/content/drive/")
```

In [ ]:

```
import pandas as pd
import numpy as np
!pip install mne
import mne
```

In [ ]:

```
#### Load data ####
raw_data = {"nabeha":[], "heidi":[], "avni":[]}

# Iterate thru all trials for each subject
for subj in raw_data.keys():
  for i in range(1,6):
    # Load data from CSV into an array
    trial_data =
np.genfromtxt('/content/drive/Shareddrives/Neuromancers_Data/'+subj+'_data/
OpenBCISession_'+subj+'_'+str(i)+'/BrainFlow-
RAW_'+subj+'_'+str(i)+'_0.csv', delimiter='\t', dtype=str)
    trial_data = np.char.replace(trial_data, '\t', ' ')
    trial_data = trial_data.astype(float)

    # Declares channel names and types of each set of data
    ch_names = ['Channel {}'.format(i) for i in range(trial_data.shape[1])]
    ch_types = ['eeg' for i in range(trial_data.shape[1])]

    # Create info structures and RawArray objects for each set of data
    sfreq = 250  # sample rate in Hz
    info = mne.create_info(ch_names=ch_names, sfreq=sfreq,
ch_types=ch_types)
    raw_array = mne.io.RawArray(trial_data.T, info)

    # Removing irrelevant channels
    ch_names = [raw_array.ch_names]
    ch_names_to_keep = [ch_names[0][0:10]]
    raw_array = raw_array.pick_channels(ch_names_to_keep[0])

    # Add RawArray
    raw_data[subj].append(raw_array)
```

In [ ]:

```
#### Truncate and filter data ####
data_segments =
pd.read_csv('/content/drive/Shareddrives/Neuromancers_Data/EEG_Data_Segment
ation.csv')

filtered_data = {"nabeha":[], "heidi":[]}

# Iterate thru all trials for each subject
for subj in filtered_data.keys():
  for i in range(5):
    # Filter current trial data
    curr_trial = raw_data[subj][i]
    print(curr_trial)
    filtered_trial = curr_trial.copy().filter(l_freq=0.5, h_freq=45,
picks=None,
                                    method='fir', fir_design='firwin',
                                    l_trans_bandwidth='auto',
h_trans_bandwidth='auto',
                                    filter_length='auto', phase='zero')
    filtered_trial = filtered_trial.filter(l_freq=0.5, h_freq=45,
picks=None,
                                    method='iir', l_trans_bandwidth='auto',
                                    h_trans_bandwidth='auto',
filter_length='auto', phase='zero')

    # Crop filtered_trial to within experiment duration
    curr_row = data_segments[data_segments["Participant"] ==
subj+'_'+str(i+1)].index
    start = data_segments.at[curr_row[0], "Experiment Start"]
    end = data_segments.at[curr_row[0], "Experiment End"]
    print(f"{subj}_{str(i+1)}: {start} {end}")
    filtered_trial = filtered_trial.crop(tmin=start,tmax=end)

    # Add filtered_trial to filtered_data dictionary
    filtered_data[subj].append(filtered_trial)
```

In [ ]:

```
#### Check for bad channels ####
for i in range(5):
  print(f"-------- Trial {i+1} --------")
  trial = filtered_data["nabeha"][i]
  trial.plot(duration=20)
  trial.plot_psd(fmax=45)
```

EEG_Preprocessing

```
! pip install numpy
! pip install mne
! pip install scikit-learn
! pip install brainflow
! pip install pyqtgraph
! pip install pyQt5
! pip install playsound
```

In [ ]:

```
import argparse
import logging
import sys

import pyqtgraph as pg
from brainflow.board_shim import BoardShim, BrainFlowInputParams, BoardIds
from brainflow.data_filter import DataFilter, FilterTypes,
WindowOperations, DetrendOperations
from pyqtgraph.Qt import QtWidgets, QtGui, QtCore


class Graph:
    def __init__(self, board_shim):
        pg.setConfigOption('background', 'w')
        pg.setConfigOption('foreground', 'k')
        self.fhandle = open("silly.txt", "w")

        self.board_id = board_shim.get_board_id()
        self.board_shim = board_shim
        self.exg_channels = BoardShim.get_exg_channels(self.board_id)
        self.sampling_rate = BoardShim.get_sampling_rate(self.board_id)
        self.update_speed_ms = 50
        self.window_size = 4
        self.num_points = self.window_size * self.sampling_rate

        self.app = QtWidgets.QApplication(sys.argv)
        self.win = pg.GraphicsLayoutWidget(title='BrainFlow Plot',
size=(800, 600))

        self._init_pens()
        self._init_timeseries()
        self._init_psd()
        self._init_band_plot()

        # yes
        self.musicTriggered = 0

        timer = QtCore.QTimer()
        timer.timeout.connect(self.update)
        timer.start(self.update_speed_ms)
        QtWidgets.QApplication.instance().exec_()

    def _init_pens(self):
```

```
        self.pens = list()
        self.brushes = list()
        colors = ['#A54E4E', '#A473B6', '#5B45A4', '#2079D2', '#32B798',
'#2FA537', '#9DA52F', '#A57E2F', '#A53B2F']
        for i in range(len(colors)):
            pen = pg.mkPen({'color': colors[i], 'width': 2})
            self.pens.append(pen)
            brush = pg.mkBrush(colors[i])
            self.brushes.append(brush)

    def _init_timeseries(self):
        self.plots = list()
        self.curves = list()
        for i in range(len(self.exg_channels)):
            p = self.win.addPlot(row=i, col=0)
            p.showAxis('left', False)
            p.setMenuEnabled('left', False)
            p.showAxis('bottom', False)
            p.setMenuEnabled('bottom', False)
            if i == 0:
                p.setTitle('TimeSeries Plot')
            self.plots.append(p)
            curve = p.plot(pen=self.pens[i % len(self.pens)])
            # curve.setDownsampling(auto=True, method='mean', ds=3)
            self.curves.append(curve)

    def _init_psd(self):
        self.psd_plot = self.win.addPlot(row=0, col=1,
rowspan=len(self.exg_channels) // 2)
        self.psd_plot.showAxis('left', False)
        self.psd_plot.setMenuEnabled('left', False)
        self.psd_plot.setTitle('PSD Plot')
        self.psd_plot.setLogMode(False, True)
        self.psd_curves = list()
        self.psd_size =
DataFilter.get_nearest_power_of_two(self.sampling_rate)
        for i in range(len(self.exg_channels)):
            psd_curve = self.psd_plot.plot(pen=self.pens[i %
len(self.pens)])
            psd_curve.setDownsampling(auto=True, method='mean', ds=3)
            self.psd_curves.append(psd_curve)

    def _init_band_plot(self):
        self.band_plot = self.win.addPlot(row=len(self.exg_channels) // 2,
col=1, rowspan=len(self.exg_channels) // 2)
        self.band_plot.showAxis('left', False)
        self.band_plot.setMenuEnabled('left', False)
        self.band_plot.showAxis('bottom', False)
        self.band_plot.setMenuEnabled('bottom', False)
        self.band_plot.setTitle('BandPower Plot')
        y = [0, 0, 0, 0, 0]
        x = [1, 2, 3, 4, 5]
        self.band_bar = pg.BarGraphItem(x=x, height=y, width=0.8,
pen=self.pens[0], brush=self.brushes[0])
        self.band_plot.addItem(self.band_bar)

    def update(self):
```

```
        data = self.board_shim.get_current_board_data(self.num_points)
        avg_bands = [0, 0, 0, 0, 0]
        for count, channel in enumerate(self.exg_channels):
            # plot timeseries
            DataFilter.detrend(data[channel],
DetrendOperations.CONSTANT.value)
            DataFilter.perform_bandpass(data[channel], self.sampling_rate,
3.0, 45.0, 2,
                                        FilterTypes.BUTTERWORTH.value, 0)
            DataFilter.perform_bandstop(data[channel], self.sampling_rate,
48.0, 52.0, 2,
                                        FilterTypes.BUTTERWORTH.value, 0)
            DataFilter.perform_bandstop(data[channel], self.sampling_rate,
58.0, 62.0, 2,
                                        FilterTypes.BUTTERWORTH.value, 0)
            self.curves[count].setData(data[channel].tolist())
            if data.shape[1] > self.psd_size:
                # plot psd
                psd_data = DataFilter.get_psd_welch(data[channel],
self.psd_size, self.psd_size // 2,
                                                    self.sampling_rate,

WindowOperations.BLACKMAN_HARRIS.value)
                lim = min(70, len(psd_data[0]))
                self.psd_curves[count].setData(psd_data[1][0:lim].tolist(),
psd_data[0][0:lim].tolist())
                # plot bands
                avg_bands[0] = avg_bands[0] +
DataFilter.get_band_power(psd_data, 2.0, 4.0)
                self.fhandle.write(str(avg_bands[0]) + ", ")
                avg_bands[1] = avg_bands[1] +
DataFilter.get_band_power(psd_data, 4.0, 8.0)
                self.fhandle.write(str(avg_bands[1]) + ", ")
                avg_bands[2] = avg_bands[2] +
DataFilter.get_band_power(psd_data, 8.0,  18.5)
                self.fhandle.write(str(avg_bands[2]) + ", ")
                avg_bands[3] = avg_bands[3] +
DataFilter.get_band_power(psd_data, 18.5, 30.0)
                self.fhandle.write(str(avg_bands[3]) + ", ")
                avg_bands[4] = avg_bands[4] +
DataFilter.get_band_power(psd_data, 30.0, 50.0)
                self.fhandle.write(str(avg_bands[4]) + ", ")
                self.fhandle.write("\t")

        # Gonna need to figure out epoching scheme so that if bro stressin
for certain period of time,
        # the music will be played
        while not self.musicTriggered:
            if (not 1 < avg_bands[3] < 3000) and (avg_bands[2] >= 3000):
                print('not stressin!')
            elif (avg_bands[3] >= 3000) and (not 1 < avg_bands[2] < 3000):
                print('----------> bro stressin :O <-------------')

        avg_bands = [int(x * 100 / len(self.exg_channels)) for x in
avg_bands]
        self.band_bar.setOpts(height=avg_bands)
```

```
        self.app.processEvents()
        self.win.show()

    def playMusic(self):
        from playsound import playsound
        playsound('audio.mp3')
        print("yeah")


def main():
    BoardShim.enable_dev_board_logger()
    logging.basicConfig(level=logging.DEBUG)

    parser = argparse.ArgumentParser()
    # use docs to check which parameters are required for specific board,
e.g. for Cyton - set serial port
    parser.add_argument('--timeout', type=int, help='timeout for device
discovery or connection', required=False,
                        default=0)
    parser.add_argument('--ip-port', type=int, help='ip port',
required=False, default=0)
    parser.add_argument('--ip-protocol', type=int, help='ip protocol, check
IpProtocolType enum', required=False,
                        default=0)
    parser.add_argument('--ip-address', type=str, help='ip address',
required=False, default='')
    parser.add_argument('--serial-port', type=str, help='serial port',
required=False, default='')
    parser.add_argument('--mac-address', type=str, help='mac address',
required=False, default='')
    parser.add_argument('--other-info', type=str, help='other info',
required=False, default='')
    parser.add_argument('--streamer-params', type=str, help='streamer
params', required=False, default='')
    parser.add_argument('--serial-number', type=str, help='serial number',
required=False, default='')
    parser.add_argument('--board-id', type=int, help='board id, check docs
to get a list of supported boards',
                        required=False, default=BoardIds.SYNTHETIC_BOARD)
    parser.add_argument('--file', type=str, help='file', required=False,
default='')
    parser.add_argument('--master-board', type=int, help='master board id
for streaming and playback boards',
                        required=False, default=BoardIds.NO_BOARD)
    args = parser.parse_args()

    params = BrainFlowInputParams()
    params.ip_port = args.ip_port
    params.serial_port = args.serial_port
    params.mac_address = args.mac_address
    params.other_info = args.other_info
    params.serial_number = args.serial_number
    params.ip_address = args.ip_address
    params.ip_protocol = args.ip_protocol
    params.timeout = args.timeout
    params.file = args.file
    params.master_board = args.master_board
```

```
    board_shim = BoardShim(args.board_id, params)
    try:
        board_shim.prepare_session()
        board_shim.start_stream(450000, args.streamer_params)
        Graph(board_shim)
    except BaseException:
        logging.warning('Exception', exc_info=True)
    finally:
        if board_shim.is_prepared():
            logging.info('Releasing session')
            board_shim.release_session()


if __name__ == '__main__':
    main()
```

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NOTE: Its **MANDATORY** for a student to attach all the PPT's, Sample Materials, Specification Sheets, Programming Codes and a 5-10 minutes demo Video of the Project Digitally In CD . Stick the Compact Disk (CD) in the final page of the Thesis after binding it.