NEURO-PHYSIOLOGICAL EMOTIONAL PROFILING MODEL FOR MENTAL FATIGUE

BY

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ABSTRACT

Mental fatigue is one of the critical issues in this world that affects the overall well-being of people in terms of cognitive performance, emotions, and decision-making. Mental fatigue is one of the typical human infirmities. Studies report that sleep deprivation and long work hours increase the likelihood of fatigue and fatigue-related accidents, and contribute to reduced productivity, errors, and accidents. Fatigue is one of the biggest causes of crashes involving cars, lorries, and buses. Traditionally, mental fatigue has been assessed through subjective methods such as interviews and psychometric questionnaires, which are prone to bias, inconsistency, and imprecision. Failure to address mental fatigue effectively may lead to impaired decision-making, reduced safety in transportation and healthcare, and overall decline in quality of life. This research aims to address these gaps by proposing the Neuro-Physiological Emotional Profiling Model for Mental Fatigue (NPEMMF), which integrates electroencephalography (EEG) data with human emotional stimuli to provide a more objective and reliable assessment of mental fatigue. Specifically, the objectives are: (i) to identify the relationship between mental fatigue and its consequences on human emotion, (ii) to develop a neurophysiological emotional profiling model for mental fatigue based on ERP features, and (iii) to evaluate the performance of the neurophysiological profiling model based on the affective space model for detecting the underlying emotions in mental fatigue. Event-Related Potential (ERP) was chosen due to its sensitivity in capturing time-locked brain responses to emotional stimuli, while the Wide Neural Network (WNN) was used as the classifier to analyze the gathered data to find trends and create a model for mental fatigue due to its robustness in handling nonlinear and high-dimensional EEG data. The International Affective Picture System (IAPS) was used as a stimulus instrument for emotions such as happy, calm, fear, and sad. Experimental results indicated that the peak-to-peak data produced more reliable and consistent results compared to peak-to-peak and latency data. EEG channel analysis according to the affective space model revealed that for positive arousal, the frontal EEG channels of F3 and F4 are most appropriate for studying emotions happy and fear. On the other hand, the EEG channel Cz was suitable for studying emotions with negative arousal. The ERP components that are most suitable for positive valence are N1, P1, N2, P2, N3, and P3. For negative valence, the most suitable ERP components are the Late Positive Potentials (LPP). The evaluation confirmed that the NPEMMF framework reduces bias and inconsistency compared to traditional subjective approaches, providing a more objective and accurate profiling of mental fatigue. Overall, this research contributes to advancing knowledge in mental fatigue assessment and emotional profiling. The proposed framework has potential applications in high-risk domains, such as the transportation sector, where reliable detection and regulation of mental fatigue can enhance safety and decision-making.

ملخص البحث

الإرهاق الذهني يعد من القضايا المهمة في هذا العالم، حيث يؤثر على الصحة العامة للإنسان من ناحية الأداء المعرفي والمشاعر وكذلك اتخاذ القرارات. يعتبر الإرهاق الذهني من أبرز العلل البشرية الشائعة. وتشير الدراسات إلى أنقلة النوم وساعات العمل الطويلة تزيد من احتمالية الإرهاق والحوادث المرتبطة به، كما تسهم في انخفاض الإنتاجية وارتفاع معدلات الأخطاء وكذلك الحوادث. فالإرهاق يعد من أحد الأسباب الكبير للإصطدام التي تشمل السيارات والشاحنات والحافلات.كان يتم تقييم الإرهاق الذهني من خلال أساليب ذاتية مثل المقابلات والاستبيانات النفسية، وهي طرق معرضة للتحيّز وعدم الاتساق وعدم الدقة. إن الفشل في معالجة الإرهاق الذهني بفعالية قد يؤدي إلى ضعف في اتخاذ القرارات، وانخفاض مستوى السلامة في مجالي النقل والرعاية الصحية، وتراجع عام في جودة الحياة. يهدف هذا البحث إلى سد هذه الفجوات من خلال اقتراح نموذج التوصيف العاطفي العصبي الفسيولوجي للإرهاق الذهني (NPEMMF)، والذي يدمج بيانات التخطيط الكهربائي للدماغ (EEG) مع المحفزات العاطفية البشرية لتوفير تقييم أكثر موضوعية وموثوقية للإرهاق الذهني. وتتمثل الأهداف تحديدا في ١) تحديد العلاقة بين الإرهاق الذهني وتبعاته على المشاعر الإنسانية. ٢)تطوير نموذج للتوصيف العصبي العاطفي للإرهاق الذهني استنادا إلى خصائص اختيار الجهود المرتبطة بالحدث (ERP). ٣) تقييم أداء النموذج العصبي العاطفي بناء على نموذج الفضاء العاطفي للكشف عن المشاعر الكامنة المرتبطة بالإرهاق الذهني. تم اختيار الجهود المرتبطة بالحدث (ERP) نظرا لحساسيتها في التقاط الاستجابات الدماغية المقترنة زمنيا بالمحفزات العاطفية، في حين استخدم الشبكة العصبية الواسعة (WNN) كمصنّف لتحليل البيانات المجمّعة بهدف اكتشاف الأنماط وكذلك إنشاء نموذج للإرهاق الذهني، وذلك بفضل قدرتها العالية على التعامل مع بيانات EEG غير الخطية وذات الأبعاد المتعددة. تم استخدام النظام الدولي للصور الانفعالية (IAPS) كأداة تحفيزية للمشاعر مثل السعادة، والهدوء، والخوف، والحزن. وأشارت النتائج التجريبية إلى أن بيانات القمة إلى القمة (Peak-to-Peak) أعطت نتائج أكثر موثوقية واتساقا مقارنة ببيانات القمة إلى القمة والتأخير (Latency). كشف تحليل قنوات EEG وفقا لنموذج الفضاء العاطفي أن قناتي الدماغ الأماميتين F3 و F4 هما الأنسب لدراسة المشاعر ذات الإثارة الإيجابية مثل السعادة والخوف، بينما كانت القناة Cz مناسبة لدراسة المشاعر ذات الإثارة السلبية. إن مكونات ERP الأكثر ملاءمة للمشاعر ذات التوجه الإيجابي هي : N1,P1,N2,P2 وN3. أما بالنسبة للمشاعر ذات التوجه السلبي، فإن المكونات الأكثر ملاءمة هي الجهود الإيجابية المتأخرة (LPP). وقد أكّد التقييم أن إطار NPEMMF يحدّ من التحيّز وعدم الاتساق مقارنة بالأساليب الذاتية التقليدية، مما يوفّر توصيفًا أكثر موضوعية ودقة للإرهاق الذهني. بشكل عام،هذا الحث يسهم في تطوير المعرفة في مجال تقييم الإرهاق الذهني والتوصيف العاطفي. كما أن الإطار المقترح يمتلك تطبيقات محتملة في المجالات عالية الخطورة مثل قطاع النقل، حيث يمكن للكشف الموثوق والتنظيم الدقيق للإرهاق أن يعزز السلامة واتخاذ القرارات.

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DECLARATION

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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Signature…………………………… Date 21th August 2025……………………..

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This thesis is dedicated to my beautiful mother for her dedication to raising his children to be the best among the Ummah without giving up. It is also dedicated to my father and other family members who never stopped encouraging me to fulfil my dream. This is also dedicated to my beloved supervisor, co-supervisor, teachers, and friends, who always give me direction when I'm lost in my studies. May Allah bless their soul.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

EEG	Electroencephalogram: Graphical representation of the brain's electrical activity
ERP	Event-Related Potential
BLR	Binary Logistic Regression
Linear SVM	Linear Support Vector Machine
NNN	Narrow Neural Network
MNN	Medium Neural Network
WNN	Wide Neural Network
N1	N100
N2	N200
N3	N300
P1	P100
P2	P200
P3	P300
LPP	Late Positive Potential
SD	Sleep Deprived
NSD	Non-Sleep Deprived
IAPS	International Affective Picture System
NPEMMF	Neuro-Physiological Emotional Profiling for Mental Fatigue
qEEG	Quantitative Electroencephalogram

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF STUDY

Mental fatigue, also known as cognitive fatigue or brain weariness, is a psychophysiological symptom defined by a decrease in mental efficiency and performance following lengthy periods of cognitive work (Pageaux & Lepers, 2018). It often shows as a decrease in attention span, slower cognitive processing, emotional instability, and a general loss of mental focus. Mental fatigue is a common problem in modern culture, impacting people in various settings, including school, healthcare, transportation, and the workplace. Chronic exposure to highly intellectual settings can dramatically affect one's emotional control, decision-making, and long-term cognitive health (Kunasegaran et al., 2023).

Several variables contribute to the development of mental fatigue, with sleep deprivation being one of the reasons. Insufficient sleep has been proven to impair neuronal functioning, lower cognitive ability, and increase emotional reactivity (Khan & Al-Jahdali, 2023). According to a survey, 53% of Malaysian employees report sleeping fewer than seven hours in 24 hours due to overwork and sleep deprivation (Ram, 2019). The findings from the AIA Vitality 2019 survey, Malaysia's Healthiest Workplace, also showed that mental health issues are still becoming more prevalent, with over 50% of survey participants reporting getting less than seven hours of sleep per day, and 14% said they slept poorly or very poorly (Vitality, 2020). Long working hours, greater after-hours work connectivity, and job-related stress are all associated with sleep issues; these characteristics could raise the likelihood that employees will experience severe mental health illnesses.

People in today's society, such as students and working adults, experience mental strain constantly from their daily tasks. Using working adults as an example, the mental load starts when people check their phones for fresh emails or messages, wake up and start reading about the workload and tasks given. Over the day, they deal with challenging assignments like managing, organising, and planning, in addition to unforeseen pauses like tending to a colleague. The mental strain increases when one comes home from work to handle personal and domestic duties like grocery shopping, child care, and cleaning. An individual who is under constant experience of mental load automatically creates anxiety and mental fatigue to the person due to the long list of things they have yet to complete for the day. This persistent psychological pressure leads to chronic fatigue and emotional exhaustion (Rose et al., 2017). A decline in cognitive function and efficiency brought on by extended cognitive effort or sustained attention is known as mental fatigue, also known as cognitive fatigue or brain weariness. It is a complicated issue. It is a typical occurrence in our day-to-day lives, varying from experiencing diminished focus during extended tasks to feeling mentally exhausted after a demanding work or school day.

Though it is essential, little has been discovered about how emotion and mental fatigue relate. Fatigue, particularly brought on by sleep deprivation, seriously impairs emotional performance. The emotional state of the person will also be affected by sleep deprivation. Emotional functioning is one of the impacts of sleep deprivation that is most commonly noticed, and from past research, there has been very little attention paid to emotion due to mental fatigue, more specialised components of emotional processing during sleep loss, such as emotional perception, control, comprehension, and expression, despite a large body of research indicating that mood regularly decreases during sleep deprivation (Walker & Van der Helm, 2009). Chronic mental fatigue may eventually lead to the emergence of mood disorders, cognitive loss, and other mental health issues. According to previous research, sleep deprivation is linked to deteriorating on measures of mental wellness and a decrease in certain facets of emotional intelligence (Killgore, 2013). Sleep quality has a big influence on how emotions are controlled. Lack of sleep has been clearly linked to mental health problems as a risk factor and a sustaining factor, with emotion regulation acting as an essential intermediary (Palmer & Alfano, 2017). According to W. Wang et al. (2024), the research shows that the one who have poor sleep quality experience more dysfunction, which will impacts their emotional regulation. Despite this, the majority of studies continue to focus on cognitive symptoms rather than affective aspects, which leaves a significant knowledge gap about the emotional effects of mental fatigue.

Mental fatigue has widespread and sometimes severe consequences. In high-risk domains like transportation, fatigue is a leading contributor to accidents. Statistics from the World Health Organization (WHO) have revealed that 1.2 million people died because of traffic injuries due to fatigue (World Health Organization, 2015), signifying a global public health issue. A survey of 9,200 accident-involved drivers in Norway found that 3.9% were sleep-related, with almost 20% of night-time accidents involving drivers in sleep-deprived conditions (Sagberg, 1999). Hasan et al. (2021) state that sleep deprivation elements and long work hours increase the likelihood of fatigue and fatigue-related accidents, and it was reported that fatigue is one of the biggest causes of crashes involving cars, lorries, and buses in Malaysia. In a recent study, a physiological and psychological disorder related to fatigue was one of the factors that can lead to serious accidents, as fatigue can affect on driver's vision, hearing, decision making and attention (F. Wang et al., 2015).

Mental fatigue is a complicated problem influenced by several factors, including sleep deprivation and mental workload. To improve cognitive well-being and mitigate the effects of mental fatigue, it is necessary to comprehend its fundamental mechanisms, causes, symptoms, and effects to develop solutions. Further research is needed to better understand the complex interplay between the factors that cause mental fatigue and identify workable strategies for treating and avoiding it.

1.2 PROBLEM STATEMENT

Mental fatigue is a common problem that impairs emotional regulation, cognitive function, and overall well-being in both professional and civilian populations. Traditionally, mental fatigue is assessed using interviews and psychometric questionnaires (Lai et al., 2011; Michielsen et al., 2004).

One statistical issue related to mental fatigue is the measurement and quantification of mental fatigue itself. Mental fatigue is a subjective experience, and no universally accepted objective measure for assessing it exists. This subjectivity can introduce challenges in research studies aiming to quantify mental fatigue's prevalence, severity, and impact. Some common statistical issues related to the measurement of mental fatigue include:

1. Dependency on Self-Report Measures:
   Much research on mental fatigue relies on self-report measures like rating scales or questionnaires to gauge participants' subjective feelings of fatigue. While these metrics offer insightful information on how people perceive their levels of fatigue, biased responses and social desirability bias may affect the results and compromise their accuracy.
2. Lack of Standardised Measurement Tools:
   Researchers' definitions and operationalisations of fatigue vary throughout studies because no standardised tools are available for evaluating mental fatigue. This lack of uniformity limits the generalizability of research findings and makes it difficult to compare findings across investigations.

These self-report measures are prone to biased responses, socially desirable effects, and inconsistent interpretations, compromising the accuracy and reliability of mental fatigue assessments. A key statistical issue in this domain is the absence of standardised, objective measurement instruments. The subjective character of mental fatigue, together with various definitions and implementations by researchers, constrains the comparability and generalisability of findings across multiple studies. These inconsistencies limit the advancement of resilient, data-informed models for evaluating and managing mental fatigue.

In recent years, the measurement of mental fatigue has progressed towards specific psycho-physiological dimensions, such as using the EEG. Such an approach allows for a personalized assessment of mental fatigue states by studying emotions. Electroencephalograms (EEG) detect the electrical potential of firing brain neurons from the scalp. Research has demonstrated that specific frequencies of this electrical potential correspond to particular mental states (Lal & Craig, 2001). Brain-computer interfaces may also be made by pairing EEG equipment with contemporary computing systems. With the use of such an interface, developers may work programmatically with brain wave data, opening the possibility of developing a real-time mental fatigue detection system by studying emotional stimuli.

Despite recent developments in utilising electroencephalography (EEG) as a psycho-physiological instrument for evaluating mental fatigue, most research has concentrated on cognitive or physical dimensions. The emotional aspect of mental fatigue, especially its manifestation in cerebral activity, remains insufficiently explored. This gap is substantial, as emotional disturbances can intensify fatigue and decrease performance, yet are frequently neglected in EEG-based research.

Furthermore, there is a lack of research integrating Event-Related Potentials (ERP) with emotional inputs to identify patterns linked to mental fatigue. In the absence of an emotional profile model, interpreting the various emotional reactions elicited during episodes of mental fatigue becomes challenging (Lewczuk et al., 2022). The lack of a reliable neuro-physiological emotional profiling method restricts a comprehensive knowledge of emotional changes in both sleep-deprived and non-sleep-deprived individuals facing mental fatigue.

This study fills these gaps by creating a neuro-physiological emotional profile model utilising ERP features derived from EEG signals. This model seeks to objectively identify emotional fluctuations associated with mental fatigue, providing an alternative to subjective evaluations and enhancing the precision of real-time mental fatigue detection and monitoring.

Brain region localization is the process of pinpointing the exact location of a particular function or activity within the brain. Understanding how the brain works and diagnosing and treating physiological disorders like mental fatigue depend on this process (Yaacob et al., 2023). However, the capacity to identify or display brain regions or channel analysis is lacking in the current literature (Khare & Acharya, 2023). This allows the researchers to build methods for figuring out which parts of the brain region are experiencing mental fatigue.

In conclusion, the existing literature does not yet have a method for measuring mental fatigue that is impartial, standardized, and inclusive of all emotions. The lack of standardized measuring frameworks, the excessive dependence on subjective self-report instruments, and the underrepresentation of emotional components are significant issues. In order to address these problems, a neuro-physiological method—

specifically, ERP-based emotional profile and EEG may offer a more thorough knowledge of mental fatigue and aid in the creation of more efficient and customized tiredness detection systems.

1.3 RESEARCH OBJECTIVES

The objectives of this study are:

1. To identify the relationship between mental fatigue and its consequences on human emotion.
2. To develop a neurophysiological emotional profiling model for mental fatigue based on ERP features.
3. To evaluate the performance of the neurophysiological profiling model based on the affective space model for detecting the underlying emotions in mental fatigue.

1.4 RESEARCH QUESTIONS

The research questions are:

1. How can we quantify emotion?
2. What are the emotional variations that occur in the human brain during mental fatigue?
3. How can emotion be effectively measured in the context of mental fatigue?
4. How is the performance of the neurophysiological emotional profiling model in identifying mental fatigue?

1.5 RESEARCH HYPOTHESES

There are a few hypotheses in this research as follows:

Hypothesis 1. Emotion can be quantified based on valence and arousal in the affective space model.

Hypothesis 2. The emotional variations in the human brain during mental fatigue can be perceived by means of early and late ERP components as the extracted features.

Hypothesis 3. The emotional variations can be classified using a multi-layer perceptron.

Hypothesis 4. The accuracy of the proposed model is subject to the emotional valence and arousal, and the effective EEG channels.

1.6 RESEARCH FRAMEWORK DIAGRAM

The whole research process is condensed within the research framework. It also outlines the methodology that will be used to conduct the research, which will be based on *Research Objectives (RO), Research Questions (RQ),* and *Method*. Subsequently, the study's contribution may be divided into Theoretical and Practical categories. Finally, the *Expected Outcome* of the studies, after performing all those previous processes as shown in Table 1.1 below:

Table 1.1 Research Framework Diagram

Research Objectives	Research Questions	Methodology	Contribution	Expected Outcome
RO1 To identify the relationship between mental fatigue and its consequences on human emotion.	1. How can we quantify emotion? 2. What are the emotional variations that occur in the human brain during mental fatigue?	Literature Review		Understand the features and technique for emotion and mental fatigue and mental fatigue recognition through EEG Understand and identify the method for measuring mental fatigue levels using human emotion.
RO2 To develop a neurophysiological emotional profiling model for mental fatigue based on ERP features.	1. What are the emotional variations that occur in the human brain during mental fatigue? 2. How can emotion be effectively measured in the context of mental fatigue?	Experiment	Design of Neuro-Physiological Emotional Profiling Model for Mental Fatigue	Experimental Procedure Neuro-Physiological Emotional Profiling model

RO3 To evaluate the performance of the neurophysiological profiling model based on the affective space model for detecting the underlying emotions in mental fatigue.	3. How is the performance of the neurophysiological emotional profiling model in identifying mental fatigue?	Experiment	Validation of the model and application of the procedure/Process	Data analysis on NPEMMF

1.7 EXPECTED RESEARCH OUTCOME

This research is expected to create a neuro-physiological emotional profile model for mental fatigue, employing Event-Related Potential (ERP) characteristics derived from EEG signals. The study seeks to find distinct EEG-based indicators of mental fatigue in both sleep-deprived and non-sleep-deprived people by applying emotional stimuli and evaluating the related ERP patterns.

ERP is a time-locked electrical response of the brain to specific sensory, cognitive, or emotional events. It provides elevated temporal resolution, allowing researchers to instantaneously monitor the brain's reaction to emotional stimuli. The selection of ERP for this investigation was based on its sensitivity to identify subtle emotional and cognitive changes linked to mental fatigue. Examining ERP components facilitates the recognition of emotional fluctuations and their modulation during episodes of mental fatigue.

The anticipated result is a collection of measurable ERP characteristics that can distinguish emotional reactions in tired states, creating an objective emotional profile. The findings may serve as a basis for subsequent research investigating emotion-based detection of cognitive states in several fields, including healthcare, education, and human-computer interaction.

1.8 SIGNIFICANCE OF RESEARCH

This research is significant for its potential theoretical and practical contributions to measuring mental fatigue. This work presents a novel integration of ERP components with affective space emotion models to create a profile system for mental fatigue. This method enables the investigation of emotional aspects in fatigue identification.

The results of this research possess potential significance for multiple stakeholders. This initiative in the transport sector corresponds with Malaysia's National Transport Policy 2019–2030, specifically Strategy 3.2, which focuses on mitigating driver weariness to improve road safety and decrease accidents (Ministry of

Transport Malaysia, 2019). This work provides an objective, emotion-based fatigue detection model that could assist policymakers and transportation firms in establishing fatigue monitoring systems for drivers.

The concept could be applied to other high-stress professions requiring effective fatigue management, including aviation, healthcare, and industrial operations. Researchers and developers engaged in brain-computer interfaces (BCIs) may find the proposed technique advantageous, as it illustrates the viability of employing EEG and ERP to construct real-time fatigue monitoring systems.

This project will contribute to advancing affective computing and neuroinformatics by establishing a novel approach for emotion-based characterisation of mental fatigue. It fills a significant void in the literature and provides a scalable framework for future applications in safety, performance improvement, and mental health assessment.

1.9 SCOPE OF RESEARCH

This research is confined to the development of a neuro-physiological emotional profiling model for mental fatigue using electroencephalogram (EEG) signals. The study utilises EEG data collected through the 19 channels EEG Dabo Machine under both sleep-deprived and non-sleep-deprived conditions, focusing on identifying distinct emotional patterns associated with mental fatigue. Specifically, four basic emotions are considered in this study: happy, calm, fear, and sad. These emotions are selected to represent both positive and negative affective states, enabling a balanced assessment of emotional fluctuations under fatigue.

EEG recordings are obtained using the standard 10–20 electrode placement system, with particular focus on the frontal and central regions of the brain. The frontal channels include FP1, FP2, F3, F4, F7, and F8, while the central channel is CZ. These regions are chosen due to their strong association with emotional regulation, executive functioning, and fatigue-related brain activity. The frequency bands analysed in this study include delta (0.5–4 Hz), theta (4–8 Hz), and alpha (8–13 Hz), which are known to reflect cognitive fatigue, drowsiness, and attentional processes.

For feature extraction, this research focuses on Event-Related Potentials (ERP) to capture time-locked neural responses to emotional stimuli. ERPs are particularly suited for tracking changes in brain activity in response to internal emotional events, making them ideal for emotional profiling in fatigue conditions. A Multi-Layer Perceptron (MLP) classifier with a wide neural network architecture is employed to categorise emotional states and mental fatigue levels. This classifier is selected for its ability to model complex, non-linear relationships within high-dimensional EEG data.

In conclusion, the scope of this research is defined by the use of EEG signals to build an emotional profiling model for mental fatigue. It involves the selection of specific emotions, targeted EEG channels, relevant frequency bands, ERP-based feature extraction, and neural network-based classification. The study is experimentally limited to adult participants, with controlled testing environments under both sleep-deprived and non-sleep-deprived conditions to examine the impact of fatigue on emotional processing. This research is limited to creating a Neuro-physiological emotional profiling model for mental fatigue based on EEG signals.

1.10 THESIS ORGANIZATION

This thesis is divided into six chapters, each incorporating the different stages of the scientific method of research.

Chapter one introduces the background of the study and problem statements, research questions, research objectives, research hypothesis and assumptions, research framework diagram, significance of research, expected research outcome, and scope of research. It is an introductory part of a whole thesis.

The literature review for the thesis is presented in Chapter 2. It focuses on the differences between physical and mental fatigue and explores the causes of mental fatigue, with sleep deprivation being one of its main causes. The chapter also goes over the traditional methods for measuring mental exhaustion and how EEG sensors can be used to analyse mental fatigue. This section explains how to handle EEG signals, covering the preprocessing, feature extraction, and classification stages.

The research method for the thesis is presented in Chapter 3. It outlines the tools utilised in the tests and the general experimental procedure to collect data. A new framework was developed, adapted from previous research, to guide this study. The experimental setup is also covered in length in this chapter, along with the methods used to acquire EEG data and the data processing techniques. Additionally, this chapter presents the International Affective Picture System (IAPS) and explains why it is appropriate for use in the experiment as emotional stimuli.

The experimental apparatus and data acquisition process employed in this thesis are explained in Chapter Four. The study's participants are defined, and the procedures used to establish both sleep-deprived and non-sleep-deprived conditions are explained. The experimental configuration for data collection is described in the chapter, which is followed by the preprocessing steps. These steps include the selection of EEG channels and frequency bands that are appropriate for analysis. Additionally, it provides an explanation of the approach used to extract event-related potentials (ERP) and the application of classification techniques during the data analysis.

Chapter five presents the data analysis results from the experiments based on emotion recognition stimuli using event-related potential. The selection of classifications will also will be discussed in this chapter. Findings are illustrated in tables, and figures.

Chapter six concludes this whole research, illustrated with tables, graphs, and figures. It also provides recommendations for further research in the affective space model of emotion and mental fatigue, answers research objectives, and provides an overview of the research findings.

1.12 SUMMARY

This chapter concludes with research objectives, research questions, objectives, hypotheses, and the significance of this research.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter will focus on past literature that specializes in this area. It covers issues related to mental fatigue, the human brain, emotion, and Electroencephalogram (EEG). The purpose of the literature review is to gain context and background information on the research issue before it is carried out, which will aid in understanding the study's importance concerning a larger body of knowledge. It is also one way to gain some answers to the study questions and to obtain insights and information that can help the research.

For this research, two significant prerequisites must be met. The first is a list of terminology definitions and background information to highlight the importance of particular study components. Finding related technologies and other advancements to incorporate into this research's design is the other. The first is conducted by looking into recently completed and earlier works. The next step is to investigate the works that could support the research design.

It is essential that the literature evaluation be conducted methodically and stay relevant to this area of study. The most crucial thing to remember is that some of the goals and research questions outlined in Chapter 1 must be addressed by evaluating earlier studies. In the end, the literature review ought to offer the following:

1. Precise definitions and explanations of keywords utilised in this study.
2. Details about how mental fatigue affects human emotions.
3. Understanding the sleep deprivation in mental fatigue and its relation to emotion.
4. Knowledge of the models, techniques, and technologies currently in use that are required to conduct this EEG and machine learning study.

2.2 FATIGUE

Numerous definitions for the term "fatigue" have been proposed in the last decades; however, a sufficiently accurate definition accepted by the scientific community is still not available, mainly because fatigue is a very complex phenomenon involving various physical, psychological, behavioural and psychosocial processes. Some scientists attempt to define fatigue in terms of its source, while others view it based on a behavioural perspective, treating it as an impairment in performance. According to Grandjean (1979), fatigue is defined as "a state declined in the level of psychomotor efficiency, work performance and activation (arousal) of the central nervous system".

Lal & Craig (2001) proposed that weariness is "a transitory period between awake and sleep and if uninterrupted, can lead to sleep," even though there is no universally agreed definition of the term. It has been demonstrated that fatigue impairs judgement, impairs focus, and affects one's ability to make decisions (Jia et al., 2022).

Most recently, Billones et al. (2021) shared their opinion about the definition of fatigue, which is a common and possibly impairing symptom affecting quality of life. It was supported by J. Shen et al. (2006) as fatigue is defined in the paper: "Fatigue is an overwhelming sense of tiredness, lack of energy and a feeling of exhaustion, associated with impaired physical and/or cognitive functioning, which needs to be distinguished from symptoms of depression, which include a lack of self-esteem, sadness and despair or hopelessness."

The intermediate state between alert and sleep is considered as fatigue which leads towards the reduction of mental or physical performances, behaviours and decision making often comply with drowsiness (Gharagozlou et al., 2015) and frequently used interchangeably in the fatigue detection literature. Fatigue is also considered a functional state somewhere between the extremes of alertness and sleep (Grandjean, 1979; Hancock & Desmond, 2001). Bakker et al. (2004) considers fatigue to be a response of both mind and body to a reduction in resources due to execution of a mental task, it leads to an increasing risk of performance failing as the task continue. Zhang et al. (2009) defines cognitive fatigue as the unwillingness to continue performance of mental work in alert, motivated subjects, characterised by a reduction in performance after continuous workload, and accompanied by subjective feelings of exhaustion. Fatigue is a problematic condition because, due to its personal nature, it is difficult to identify explicitly and therefore difficult to measure and regulate (Hancock & Desmond, 2001). Nilsson et al. (1997) state that any activity, if pursued long enough, will result in the inability to maintain skilled performance. Furthermore, Schmidt et al. (2009) note that a task such as monotonous driving integrates both active and passive fatigue. This further compounds the problem of identifying a state of fatigue, as it is hypothesized that active and passive fatigue states may elicit different patterns of both physiological and subjective state response (Saxby et al., 2007). Matthews & Desmond (2002), for example, found in their "fatigue induction" condition that performance deteriorated significantly on the straight road (monotonous) sections, while no significant change in performance occurred during sections where a curved road was used.

Past researchers have documented numerous traffic casualties caused by fatigue. "Tiredness" has been the main factor in 7.3% of the accidents in the United Kingdom, and the drivers reported that fatigue was a factor in 7% of incidents involving cars or 9–10% of all accidents (Maycock, 1995). In a recent study, a physiological and psychological disorder related to fatigue was one of the factors that can lead to serious accidents as fatigue can affect on driver's vision, hearing, decision making and attention (F. Wang et al., 2015).

There are two types of fatigue: mental fatigue and muscle fatigue. The description of muscle and mental fatigue will be discussed in the next section.

2.2.1 Muscle Fatigue

Meanwhile, too much strain on the muscles can result in physical fatigue mainly caused by muscular fatigue (Grandjean, 1979). Muscle fatigue will develop due to the large amount of energy that was used repeatedly on the muscle when exercising, and it will also reduce the effectiveness of the muscles as it results in stiffness and tension in the muscle (W. Hu et al., 2017; Ito et al., 2015). If one is physically exhausted due to high-intensity physical activity, they may struggle to run, lift, or play, but their alertness and concentration will remain intact. Most research concludes that physical activity has either a positive effect or, more often, little or no impact on mental performance. Meanwhile, it said that mental fatigue can affect your physical performance.

2.2.2 Mental Fatigue

The usage of cognitive activity for a long time will reduce the efficiency in cognitive performance, and this psychobiological state is defined as mental fatigue (Tanaka et al., 2014). Mental fatigue will also effect and worsening the process of information in our brain such as concentration on doing something, mental control, and even lead to decision/action errors (Yang et al., 2015). In this modern life, it was a common phenomenon and a major cause of accidents in the modern world (Tanaka et al., 2014). According to a landmark study, mental fatigue is a condition that emerged due to gradual and accumulative mental effort which can cause sleepiness, distraction and poor concentration (Grandjean, 1979). Mental fatigue can affect driving performance as it decreases the capacity to concentrate and lead to a slow reaction to decision-making (Guo et al., 2016). When drivers drive for extended periods, they experience exhaustion, which is akin to mental fatigue. This phenomenon is known as driver fatigue. Long distances travelled, uneventful work schedules, and boring driving sessions are all factors that might lead to driver tiredness (Lal & Craig, 2000). While it can happen to any individual, the transportation sector is particularly affected by driver fatigue.

Thus, mental and muscle fatigue are governed by very different underlying processes. As it is known that cognitive load in the brain can reduce the effectiveness of utilizing the full capabilities and attention of the brain, this is why mental fatigue is more considerable to be studied for brain and cognitive activity (Chakraborty & Nakano, 2016).

2.3 Mental Fatigue

Mental fatigue is often associated with brain or cognitive fatigue, which is considered mental exhaustion that reduces brain performance and human emotional well-being. Understanding the symptoms, causes, and implications of mental fatigue will greatly benefit this study.

Mental fatigue can take many different forms and affect mental, emotional, and physical functioning. Typical signs and symptoms include:

1. Brain and cognitive symptoms

   An increased risk of performance decrements, or issues maintaining adequate levels of behavioural and mental functioning, is a result of mental fatigue, thus increasing the likelihood of mistakes, poor decision-making, brain performance, and poor problem-solving as it will make our brain thought to be slower due to mental fatigue (Lorist, 2008). It is hard for certain individuals to concentrate and focus on the task in mental fatigue conditions because mental fatigue impairs a person's capacity to suppress reactions, process information, and focus. It has been demonstrated to be one of the primary causes of lower productivity and general cognitive function (Kunasegaran et al., 2023).
2. Emotional symptoms

   In terms of emotional symptoms, there are past studies related to nurses during the COVID-19 pandemic where nurses worked more intense hours compared to the past and had a severe lack of sleep quality, resulting in high levels of mental fatigue leading towards a high level of negative emotions (D. Wang et al., 2022). The past findings significantly contribute to the idenntification of a factor, mental fatigue, that is essential to emotion control, with mental fatigue weakening emotion regulation (Grillon et al., 2015), leading to a decrease in motivation and interest in doing any activities (Muraven & Slessareva, 2003).

2.3.1 Factors that cause Mental Fatigue

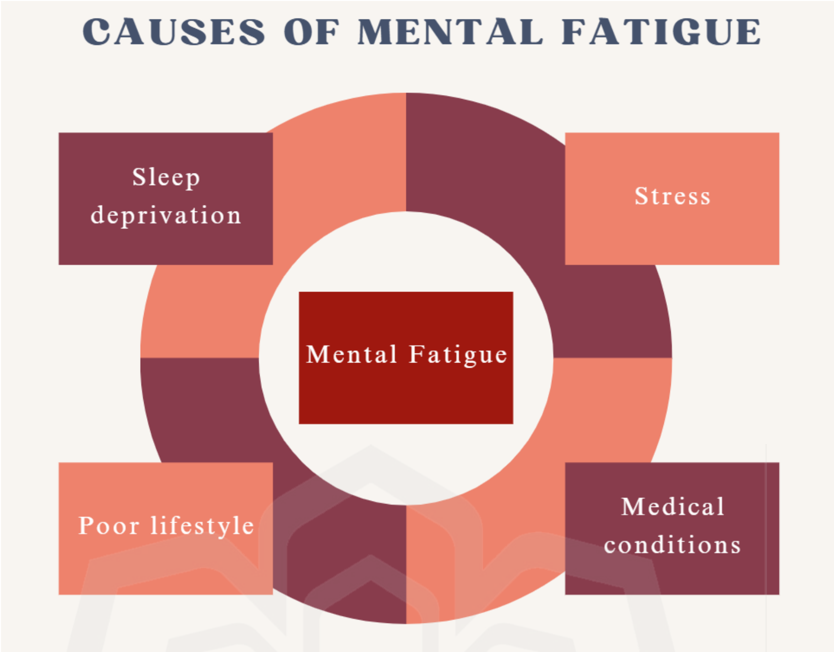

Figure 2.1 Causes of mental fatigue

Mental fatigue can result from a variety of interconnected causes that affect cognitive performance and overall health. Here is a more detailed explanation of the primary causes based on Figure 2.1:

1. Sleep Deprivation and Poor Sleep Quality

   The brain's capacity to recover and solidify memories is hampered by inadequate sleep, both in terms of quantity and quality. Lack of sleep is a significant cause of mental fatigue since it affects focus, problem-solving abilities, and emotional control sleep (Kunasegaran et al., 2023), Cognitive fatigue can result from poor sleep quality, which can be caused by disruptions, insomnia, or sleep disorders, even when people get enough sleep.

2. Stress

   Acute and constant stress both severely deplete mental capabilities. Cortisol and other stress hormones are released in response to psychological stress, and these hormones eventually impair cognitive functions like emotional regulation, focus, and decision-making. Chronic stress can increase feelings of fatigue and cognitive overload by causing burnout and a reduction in mental resilience (Souza-Talarico et al., 2011).

3. Unhealthy Lifestyle Factors

   Brain function is adversely affected by poor diet, inactivity, dehydration, and excessive coffee or alcohol use. Low amounts of vital nutrients, including vitamins, minerals, and omega-3 fatty acids, can impact energy and mental function (Hepsomali et al., 2025). Such lifestyle decisions eventually cause a decline in mental sharpness and a rise in feelings of fatigue.

4. **Medical Conditions**

   Persistent mental fatigue can result from a number of medical illnesses, such as neurological disorders, depression, anxiety disorders, and chronic fatigue syndrome. Additionally, by influencing metabolism and energy levels, diseases including diabetes, thyroid issues, and anemia may potentially increase cognitive fatigue (Kalra & Sahay, 2018).

If not appropriately controlled, these variables frequently combine to cause mental fatigue over time. The illness known as mental fatigue is intricate and multidimensional, with the potential to greatly affect a person's life. Identifying mental fatigue, comprehending its root causes, and addressing its consequences are essential in effectively managing it. Regular breaks, stress reduction methods, enough sleep, a healthy diet, and seeking professional assistance when needed are all helpful in reducing the negative consequences of mental fatigue and enhancing mental health in general.

2.3.2 Sleep deprivation as a subcomponent of Mental fatigue

Lack of sleep has a direct effect on cognitive and emotional functioning, which makes it a major contributor to mental fatigue. Sleep deprivation causes mental fatigue, which is characterized by decreased motivation, emotional control, and cognitive performance. According to research, getting too little sleep affects mental energy and focus by affecting attention, memory, problem-solving, and decision-making capabilities (National Heart Lung and Blood Institute, 2022). For instance, people who don't get enough sleep frequently complain of feeling "foggy," less attentive, and more likely to make mistakes when performing tasks that call for prolonged focus.

Furthermore, emotional instability brought on by sleep loss includes mood swings, anxiety, and irritability, all of which are signs of mental exhaustion. Research has shown that inadequate or poor sleep causes people to perceive tasks as more difficult and to rely more on mental shortcuts, or heuristics, which further impairs cognitive function. Over time, chronic sleep deprivation builds as "sleep debt," magnifying sensations of fatigue and contributing to the larger experience of mental fatigue

For this thesis, we define sleep deprivation as one of the subcomponents of mental fatigue. Mental fatigue is thought to be caused by sleep deprivation, which is a major contributing factor. This recent study on sleep deprivation shows that the mental fatigue index continued to increase during sleep deprivation (Cheng et al., 2021). Lack of sleep can result in various mental fatigue symptoms since sleep is essential for preserving emotional stability and cognitive abilities. Here is how mental fatigue and sleep deprivation are connected.

2.3.3 Relationship Between Sleep Deprivation and Mental Fatigue

1. Cognitive impact

   There seem to be both general and specialised effects on cognitive performance because various functionally interconnected brain systems are more or less vulnerable to sleep deprivation (Killgore, 2010). Additionally, research indicates that sleep deprivation alters brain activity in specific regions. You may struggle to control your emotions and behavior, solve problems, make decisions, and adjust to change if you don't get enough sleep (National Heart Lung and Blood Institute, 2022). Whether the outcome of a clinical condition or lifestyle decisions, acute or chronic sleep deprivation offers serious cognitive issues when performing several daily tasks. It is widely acknowledged that sleep deprivation impairs a number of activities, including immune-related regulation, metabolic management, and neurocognitive abilities like memory and learning (Walker & Stickgold, 2006). Attention is a particularly vulnerable cognitive function to sleep deprivation (Goel et al., 2009). Since cognitive processes depend on sustained attention and basic attention, sleep deprivation appears to have a global degrading effect, and the most consistent effects of sleep deprivation are reduced attention and psychomotor vigilance as well as increased variability in behavioural responses (Killgore, 2010). These effects are linked to sleep deprivation in the cognitive systems.

2. Emotional impact

   Lack of sleep also affects how normal emotions are processed, possibly by weakening prefrontal inhibitory processes, which let emotional systems function more freely without proper integration or moderation. In the end, this affective dysregulation results in a negative emotional bias in mood, perception, and memory, a decreased ability to tolerate frustration, and trouble utilising emotion to guide decision-making adaptively (Killgore, 2010). Thus, people who are sleep-deprived frequently have mood swings and struggle to control their emotions, which leads to mental fatigue.

   Lack of sleep plays a major role in the emergence and expression of mental fatigue. Maintaining emotional stability, bodily health, and cognitive abilities depends on getting enough sleep. An imbalance in the activity of the brain system and an exaggeration of one's negative moods were associated with a rise in mental fatigue due to sleep deprivation (Cheng et al., 2021). Managing stress, practising better sleep hygiene, and seeking medical attention when needed can help greatly lessen mental fatigue symptoms and enhance general well-being. Without sleep, our cognitive and emotional abilities become markedly disrupted. Thus, our emotional and cognitive functioning significantly deteriorate when we are in sleep deprivation condition (Krause et al., 2017).

2.3.4 Measurement of Mental Fatigue

As mental fatigue is an unclear symptom that makes it challenging to pinpoint the cause of the illness, a single assessment measure would not be adequate. Multiple detection techniques must be applied to validate a single parameter. There are differences between the measurements made by the psychological and neurophysiological experts.

1. Interview and questionnaires

   Traditionally, mental fatigue is assessed using interviews and psychometric questionnaires (Michielsen et al., 2004; Lai et al., 2011). Subjective measures, like self-reporting questionnaires, have generally been criticised for being biased because it is easy to compromise participants' honesty (i.e., being truthful instead of answering based on socially acceptable behaviours) and introspective abilities (i.e., accurately assessing a person). As stated by (Schmidt et al., 2009),humans cannot assess their cognitive states appropriately. This highlights a drawback where questionnaires do not offer a quick and easy way to identify momentary mental fatigue.
2. EEG

   In recent years, the measurement of mental fatigue has progressed towards specific psycho-physiological dimensions such as using the EEG. An alternative for studying these mental activities is using human EEG, a practical approach for understanding human brain activities compared to other brain imaging techniques due to its mobility and high temporal resolution.

2.4 EMOTION

Emotion is a complex psychological state that allows an organism to react adaptively to internal or external stimuli. It includes subjective experience, physiological response, and behavioural expression (Adolphs & Anderson, 2018). It is generally accepted that an individual's emotions are temporary phenomena, but their actions and attitudes are more permanent personality characteristics. In other words, an individual's impression of mental fatigue is often influenced by specific physiological conditions that are correlated with their emotional moods. Positive stimuli may trigger specific brain impulses connected to happiness and calm. Relative inputs may result in brain signals associated with fear or sadness in a different person. Emotions are typically warning signals for circumstances that need to be attended to and occasionally even resolved.

Psychological theories of emotion have used two characteristics to characterise emotional experience: valence as pleasantness and arousal as intensity. These characteristics, which are known as the "core affect," are crucial in differentiating emotions from other mental states (Russell, 2003).

There is no study explicitly examining how mental fatigue, especially from sleep deprivation, affects emotional processing, despite the fact that previous psychological studies have looked at mental fatigue and emotional responses separately. This study intends to advance this comparatively unexplored field by examining the relationships among emotions, mental exhaustion, and cognitive processes in the human brain. The study uses EEG-based event-related potential (ERP) measurements to improve understanding of the emotional changes that take place under various fatigue conditions by combining viewpoints from psychology and neuroscience.

2.4.1 Types of Emotions Model

The two theories of emotion that have dominated psychology in recent years are the dimensional and categorical theories. These theories use two methods—dimensional models and categorical models—to represent and analyse emotions in different situations.

1. Categorical Emotional Model

   The classification of emotions into discrete, separate categories is a feature of a categorical emotional model (Akçay & Oğuz, 2020). These classifications frequently stem from the discrete emotion theory, which postulates that an individual is only capable of experiencing a certain range of emotions. Selecting a positive or negative mood is the simplest categorical classification. Certain models employ more specialised categories, such as "happy" and "sad" or "anger" and "fear." These models are widely applied in natural language processing and affective computing for sentiment analysis and emotion recognition tasks. The six basic emotion categories—sadness, happiness, fear, anger, disgust, and surprise—that were outlined by Ekman & Oster (1979) Ekman and Oster (1979) and Ekman et al. (2013) serve as the foundation for discrete emotion theory.

2. Dimensional Emotional Model
   The dimensional model of emotion is a framework for characterising and grouping emotions according to two or three dimensions. In contrast to categorical models, which divide emotions into discrete groups (such as pleasure, sorrow, and rage), dimensional models suggest that emotions may be comprehended as fluctuating along certain dimensions. Arousal and valence are two of the most often used dimensions. According to Posner et al. (2005), the dimensional model of emotions suggests that a single, central, networked neurophysiological system causes all affective states. As a result, emotions and their corresponding reaction patterns can be categorised using an EEG analysis of all brain areas. Table 2.1 is an example of the Dimensional emotional model.

Table 2.1 Dimensional Emotional Model

MODEL	**DIMENSIONS**	**REFERENCES**
2-Dimensional Model	Valence-Arousal	Akçay & Oğuz (2020)
Circumplex Model of Affect	Valence-Arousal	Russel(1980)
Affective Space Model	Valence-Arousal	Kamaruddin & Wahab (2012)
Affective Space Model of Emotion	Valence-Arousal	Yaacob (2019)

One of the most popular dimensional models is a two-dimensional model that uses arousal, activation, or excitation on one dimension and valence, appraisal, or assessment on the other (Akçay & Oğuz, 2020). The valence dimension, which spans from unpleasant to pleasant, characterises an emotion's state as either positive or negative. The arousal dimension determines the intensity of the sensed emotion. Dimensional models can be utilised when it is necessary to capture the nuances of emotional experiences and offer a more sophisticated understanding of emotions.

The Circumplex model of emotion, which has arousal and valence dimensions and distributes emotions in a two-dimensional circular space, is one example of a two-dimensional space model. Russell (1980) stated the distribution of the emotions is circular, with neutral valence and medium arousal at its centres.

Arousal (y-axis) represents the level of emotion (high or low), and valence (x-axis) represents the positive and negative degree of emotion (pleasure/displeasure). Based on Figure 2.2, the arousal value is on the horizontal axis, and the emotional valence value is on the vertical axis. Valence is defined as either positive or negative affectivity, and arousal is the degree of calmness or excitement associated with the subject matter, as shown in Figure 2.2 below. As indicated in Table 2.2, the combination of valence and arousal yields the four fundamental emotions.

Table 2.2 Valence and Arousal Emotion Interpretation

	Arousal	Valence
Happy	Positive	Positive
Calm	Negative	Positive
Fear	Positive	Negative
Sad	Negative	Negative

Figure 2.2 Affective Space Model of Emotion (Yaacob, 2019)

The Affective Space Model is a more focused variant of the circumplex model that was more suitable for this study (Yaacob, 2019; Kamaruddin & Wahab, 2012). The choice of model is significant. The appropriate model can produce more accuracy and/or resolution than the others when classifying emotions from brain signals resulting from mental fatigue. The goal of this study is not to find the most realistic model of emotions. Instead, the most reliable one will be chosen. Emotions need to be categorised using a dimensional model to be studied concerning mental fatigue, particularly in this thesis study. The most suitable model related to the emotion that will be used is the circumplex model of emotion.

As in Figure 2.2, emotional states with a positive valence are those positioned on the right side of the vertical axis, while those with a negative valence are positioned on the left. Similarly, emotional states positioned above the horizontal axis are regarded as having positive arousal, and those positioned below the horizontal axis are regarded as having negative arousal. Additionally, emotions with positive valence and positive arousal are labelled as happy, those with negative valence and positive arousal as fear, those with negative valence and negative arousal as Sad, and those with positive valence and negative arousal as calm.

2.4.2 Emotion Stimuli

Emotion stimuli play a crucial role in experimental studies involving emotion and brain activity analysis. These stimuli are frequently employed in studies on human-computer interaction, psychology, and neuroscience because they have been designed or chosen to elicit particular emotional reactions. The different forms of emotion stimuli include images, videos, speech, and other media such as text or music. Based on the target population, measuring instruments, and experimental objectives, each modality offers distinct benefits. Each type of emotional stimulus is covered in Table 2.3.

Table 2.3 Comparison of Emotional Stimuli Modalities for EEG and ERP-Based Emotion Research

Stimuli	Advantages	Reference
Image	Widely used in experimental research, Easy to standardize (IAPS), Trigger fast emotional responses	(Botta et al., 2021; Nakakoga et al., 2020)
Video	Richer emotional content, Videos closely resemble real-life scenarios and have a high degree of ecological reality.	(Hariyady et al., 2023)
Speech	Useful in voice-based emotion detection Reflect natural communication	(Burange et al., 2025)

The table compares image, video, and speech emotional stimuli and their advantage and suitability for EEG and ERP studies. While video and speech stimuli provide richer emotional content but present timing and complexity challenges, other stimuli like music or text introduce variability and are less ideal for time-locked neural measurements. The comparison table indicates that image-based emotional stimuli are best suited for EEG and ERP studies because of their simplicity, standardised format, and precise timing control (Botta et al., 2021; Burange et al., 2025; Hariyady et al., 2023; Nakakoga et al., 2020).

International Affective Picture System (IAPS) is a visual system designed to elicit specific feelings in study subjects (volunteers or participants) (Lang, 2005). This tool is frequently utilized to elicit human emotions in psychology research (Lang & Bradley, 2007). IAPS was developed at the University of Florida's National Institute of Mental Health Centre for Emotion and Attention in the United States. This instrument is ideal for the research because it is well-established and extensively used, meaning plenty of references are available.

IAPS is consists of a popular collection of colour photographs intended to elicit particular feelings in participants. Arousal (high-low activation), dominance (control-submission), and valence (pleasure-displeasure) are some of the emotive qualities that are used to categorise the images. Research on emotions is frequently conducted using the IAPS, especially in the domains of affective computing, psychology, and neuroscience. The study by X. Hu et al. (2017) used selected clips of images of positive emotions in the video-watching paradigm and successfully evoked the desired positive feelings, as demonstrated by the behavioural outcomes. IAPS has been around since 1995, and the fact that additional validations have been released in several nations shows how effective and relevant it is for researching emotion (Branco et al., 2023).

A statistical investigation revealed that in the Malaysian population, the total mean differences between all low-arousal IAPS pictures and all high-arousal photographs are highly significant(Rahman & Reza, 2017). The study demonstrated how standardised image and sound databases may be combined to create films that were intended to evoke intense emotional responses (Horvat et al., 2015). Thus, the

IAPS method is considered one of the most suitable methods for emotion stimulation for this study and will be used with the affective space model of emotions.

2.4.3 Emotion Elicitation and Identification

Numerous behavioral and physiological reactions can be used to evoke and quantify emotions. To guarantee data accuracy and relevance in emotion recognition research, the best method for detecting and evaluating these reactions must be chosen. Speech, facial expression, skin conductance, electroencephalography (EEG), and heart rate are a few of the often utilized indicators. Each of these indicators provides distinct information on a person's emotional state, and the appropriateness of each one relies on the goals of the study, the level of accuracy needed, and the limitations of the experiment. These emotion markers are compared in the following table according to their descriptions, benefits, and corroborating research.

Table 2.4 Descriptions of Common Emotion Indicators Used in Emotion Recognition Research

Emotion Indicator	Description	References
Speech	Pitch, tone, volume, speech tempo, and articulation are just a few of the speech qualities that may be dramatically changed by emotional states. For instance, while grief and exhaustion may promote slower speech and lower loudness, emotions like rage and enthusiasm frequently cause higher pitch and louder speaking. Both arousal and valence can be reflected in these spontaneous vocal alterations.	(Burange et al., 2025; Johnstone, 2001; Kamiloğlu et al., 2020)

Facial Expression	Certain facial muscle movements, such as lifting one's eyebrows, frowning, smiling, or expanding one's eyes, are visible manifestations of emotions. These expressions offer unmistakable markers of fundamental emotions like joy, sorrow, rage, and fear and are essentially culturally universal.	(Boggio & Wingenbach, 2023)
EEG	EEG uses electrodes applied to the scalp to assess electrical activity in the brain. Through the capture of electrical impulses over many frequency bands (e.g., alpha, beta, theta), it offers a straightforward and objective evaluation of brain function. EEG patterns that differentiate between positive and negative valence, like frontal alpha asymmetry, are indicative of emotional processing. Additionally, EEG has temporal precision down to the millisecond, which makes it ideal for monitoring abrupt mood shifts.	(Biasiucci et al., 2018)
Skin Conductance	Galvanic skin response (GSR), another name for skin conductance, is a measure of the sympathetic nervous system-regulated activity of sweat glands. Skin conductance levels rise with emotional arousal, particularly in reaction to stress, excitement, or fear. This measure is extremely	(Markiewicz et al., 2022)

	sensitive to the strength of emotional reactions, but it does not differentiate between emotional valence.	
ECG	The autonomic nervous system controls heart rate and heart rate variability (HRV), which fluctuate in reaction to emotional stimuli. For example, whilst calm or contented emotional states may cause a decrease in heart rate, anxiety or dread usually causes an increase. Understanding how people biologically control their emotions over time can be gained through HRV analysis.	(Buzzell et al., 2023; Lee, 2023)

While speech, facial expressions, skin conductance, and heart rate are useful for identifying emotional shifts, the comparative study of emotion indicators reveals that they are frequently restricted to surface-level or autonomic reactions. EEG, on the other hand, uses direct brain activity monitoring to provide a more thorough knowledge of emotion. EEG is the most suitable and dependable technique for emotion recognition in this study because of its capacity to record the nature (valence) and strength (arousal) of emotional reactions, as well as its high temporal resolution and sensitivity to unconscious processes.

2.5 HUMAN BRAIN AND ELECTROENCEPHALOGRAM (EEG)

As a component that supports the central nervous system, the brain is crucial in the assessment of mental fatigue. A healthy body's brain is found towards the top, usually near the sensory organs. The cerebral cortex of the human brain contains between 15 and 33 billion neurons (Pelvig et al., 2008), each of which is synaptically coupled to several thousand other neurons. Long protoplasmic fibres known as axons, which transport trains of signal pulses known as action potentials to distant regions of the brain or body and target particular recipient cells, are how these neurons communicate with one another.

The human brain is a unique organ that can interact and exchange information with several body systems, including the neurological, respiratory, and muscular systems. These systems work together to form the human body's broader structure. In summary, the human brain plays a critical role in assessing, directing, and regulating human behaviour and emotion (Davis et al., 2017).

EEG was defined as "the writing and drawing of electrical signals emitted from the human scalp (Sanei & Chambers, 2023). A research by Gharagozlou et al. (2015) state that electrodes placed on the human scalp can record the electroencephalogram (EEG). By examining the human EEG, it is possible to comprehend the connection between various cognitive states and the subject's corresponding brain dynamics (Davis et al., 2017). Table 2.5 displays the brain regions that are being especially researched for EEG and their electrode placement.

Table 2.5 Region of the Brain and Its Electrode Placement

Brain Region	Electrode Placement	Description
Frontal Region	Fp1, Fp2, F3, F4, F7, F8, Fz	The frontal lobes influence numerous functions, including motor control, voiding, cognition, neuropsychiatric function, memory, emotions, and mood (Chayer & Freedman, 2001). The frontal lobes, which are thought to be our behaviour and emotional control centres, influence the interpretation, expression, and regulation of emotion (Alipour et al., 2011). According to another theory, the brain's frontal lobes are

		the "seat of personality," or the place in the brain where identity is stored (Mesulam, 2002).
Occipital Lobe	O1, O2	The occipital lobe is the smallest of the four lobes of the cerebral hemisphere. It is located behind the temporal and parietal lobes. The occipital lobe is the brain region responsible for visual processing. It is linked to memory formation, colour perception, distance and depth perception, object and face identification, and visuospatial processing (Rehman & Al Khalili, 2023).
Parietal Lobe	P3, P4, Pz	The top part of the brain, known as the parietal lobe, is involved in movement, direction, stimulus recognition, and perception (Brownsett & Wise, 2010).
Temporal Lobe	T3, T4, T5 , T6	The left and right sides of the brain, which are connected to speech, memory, and the detection and identification of auditory stimuli (A. Patel et al., 2023).

Neurons are the building blocks of human mind. Synapses allow neurons to communicate with other neurons and receive information from them (Caire et al., 2023). Consider a synapses as a wire that transfers power from a neuron, which serves as the source of electricity. One well-established method for identifying brain activity is the electroencephalogram (EEG). Tiny electrical activity bursts produced by neurons interacting with one another can be detected using EEG equipment. With electrodes applied to the scalp, EEG detects the electrical activity of sizable groups of neurons firing simultaneously in the brain (Light et al., 2010).

The basis of EEG is the identification of brain electrical activity resulting from neuronal firing during cognitive processes. Electrodes can be applied to the human scalp to record these impulses. It is possible to record a standard EEG using 16, 20, 32, and 64-channel setups. In clinical neurology and cognitive neuroscience, EEG is a vital tool for assessing brain network connectivity, identifying functional brain areas, and comprehending the quick neuronal processes that underpin both pathological and cognitive states (Buzzell et al., 2023; Lee, 2023). By modelling a user's affective state and using electroencephalography (EEG) as a bio-signal sensor, it is now feasible to develop a system to identify mental fatigue based on the participant's emotions.

2.5.1 EEG Channels

In most previous work, EEG signals can be obtained through 3 channels to 62 channels using an EEG device (Yaacob et al., 2023). It appears that EEG montage is quite reliant on the study design, making generalisation difficult. The channel accuracy utilised in the EEG study is displayed in Table 2.6.

Table 2.6 Channel Accuracy (Dimitrakopoulos et al., 2017)

Channels	Accuracy
62	0.727
36	0.770
25	0.757
13	0.741
10	0.730
7	0.660
4	0.493
3	0.570

According to an investigation, the accuracy findings from 10, 13, 25, 36, and 64 are highly comparable in the range of 70 to 77 percent accuracy, with lower accuracy for 7 channels and below (Dimitrakopoulos et al., 2017) as shown in Table 2.6. In most research, the most widely used and standardized technique for positioning

EEG electrodes is still the worldwide 10-20 system (Artinis Medical Systems, 2024). By positioning electrodes at intervals of 10% or 20% of important cranial distances, it guarantees consistent, repeatable scalp coverage while successfully taking into account differences in head size and shape.

The nasion (the nasal bridge), the inion (the bulge on the back of the head), and the preauricular points (the area directly above the ears) are landmarks. Sites of Electrodes: The terms "10" and "20" denote that the actual distances between adjacent electrodes are 10% and 20% of the entire front-back or right-left distance of the skull, respectively (Shafiq Ibrahim et al., 2023). The distance between these landmarks is marked with electrodes spaced 10% or 20% apart. Common locations for electrodes are as follows:

- Frontal pole: Fp1, Fp2, F3, F4, F7, F8
- Parietal lobe (P): P3, P4, Pz
- Occipital (O): O1, O2
- Temporal lobe (T): T3, T4, T5, T6
- Central region (C): C3, C4, Cz

Figure 2.3 illustrates the arrangement of various electrodes on the scalp.

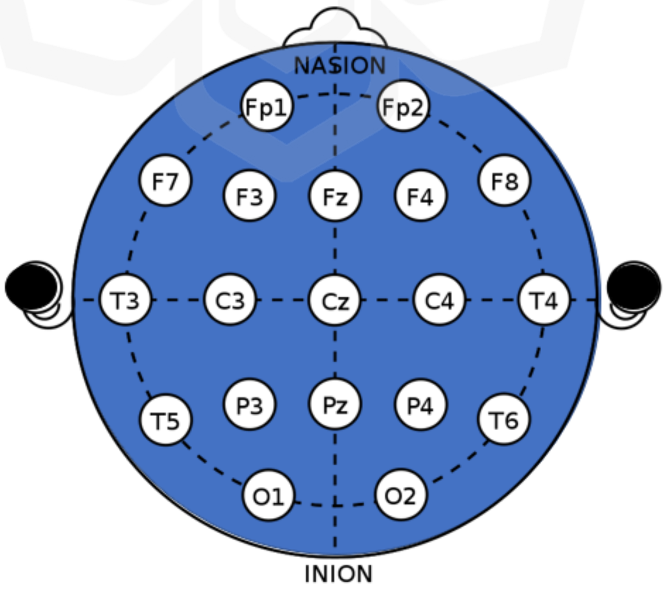

Figure 2.3 EEG Electrode Placement

For most clinical and research EEG applications, the 10-20 channel method provides enough spatial resolution. Results are consistent and comparable between patients and studies because of the 10–20 system's accurate identification of brain areas (Artinis Medical Systems, 2024).

2.5.2 Sampling Rate and Pre-processing

Sampling frequency in the past studies may be as high as 2048Hz (Gharagozlou et al., 2015), with 3 out of seven studies having a higher sampling rate that were downsampled to 256Hz (Gharagozlou et al., 2015; Guo et al., 2016; Sarkar & Parnin, 2017). Powerline interference was commonly removed, with 3 studies utilizing a bandpass of 1-40Hz to yield theta, delta, alpha, beta, and gamma bands. The Independent Component Analysis (ICA) algorithm is one of the most widely used algorithms in EEG preprocessing for noise and artefact reduction. Eye blinks, muscle activity, and line noise are examples of independent sources that ICA successfully isolates from EEG data, enabling their removal prior to additional analysis (Yosrita et al., 2021). For eliminating both physiological and non-physiological artefacts, this method is particularly popular.

2.5.3 EEG Frequency Band

Electrical recordings of brain activity are known as electroencephalography (EEG) signals. They possess a number of traits that are used to assess brain activity and identify neurological disorders. The most essential elements of EEG signals are the EEG frequency bands. These elements bands are wave patterns characterized by a range of frequencies, with diverse EEG activities in a developing brain, in contrast to the adult brain. The various frequency bands that EEG signals fall within are linked to distinct mental states.

The following rhythmic wave patterns can be found in EEG signals: mu, kappa, lambda, delta, theta, beta, gamma, and gamma waves. Now, there are five widely acknowledged frequencies at which the brain functions: delta, theta, alpha, beta, and gamma. The delta waves, which are the slowest, range from 0.5 to 4 Hz, theta waves run from 4 to 8 Hz, alpha waves span from 8 to 13 Hz, beta waves reach from 13 to 30 Hz, and the gamma spectrum includes all frequencies over 30 Hz (H. Hu et al., 2017). Figure 2.4 shows the brain wave samples for each of the frequency bands.

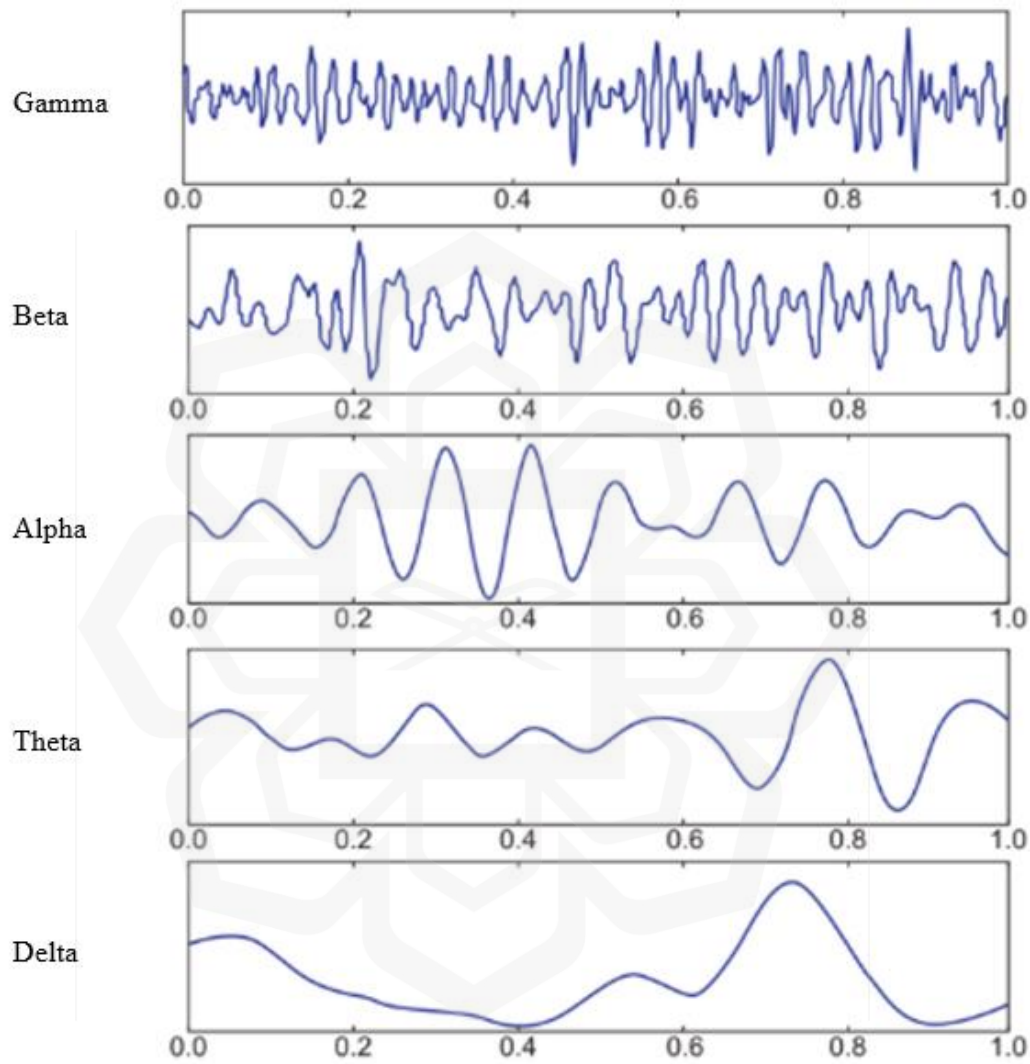

Figure 2.4 EEG frequency bands represented (Gamma, Beta, Alpha, Theta, Delta) over a 1-second time frame (Abhang et al., 2016).

The raw EEG data are often transformed into the five frequencies listed below for analysis purposes:

Comprehending these attributes enables scientists and medical professionals to analyse EEG information for diverse purposes, such as identifying epilepsy, sleep disturbances, and other neurological ailments, and examining cognitive and affective mechanisms.

Table 2.7 EEG Wave Patterns

Frequency band	Frequency	Conditions
Delta (δ) waves	0.5 – 40 Hz	According to Baars & Gage (2013), they can happen during profound sleep or in uncommon medical situations including comas and vegetative states.
Theta (θ) waves	4 – 8 Hz	Theta waves have been seen during short-term memory activities like memory retrieval, and they are normally produced in the brain during profound relaxation like meditation and sleep Baars & Gage (2013).
Alpha (α) waves	8 – 13 Hz	Alpha waves are typically detected while the eyes are closed and are linked to deep levels of relaxation Olaniyan et al. (2023).
Beta (β) waves	13 – 30 Hz	Solving complex tasks is frequently linked to beta-wave activity, which is seen in the brain during attentional and concentrational stages (Lal & Craig, 2001).
Gamma (γ) waves	Higher than 30 Hz	Connected to information processing and higher-order cognitive processes

This table simplifies each function of the frequency band wave, but the most reliable and consistent occurrences of waves are alpha, beta, delta, and theta (Andreassi, 2010). Low signal intensity at high frequency in scalp EEG, contamination by muscle and eye movement artifacts, and technical/equipment constraints are the primary reasons gamma band activity is not frequently or readily used in EEG research (Hipp & Siegel, 2013; Pattisapu & Ray, 2023). Periodic waveforms, particularly alpha, beta, delta, and theta, are frequently used to characterise EEG signals. In terms of frequency, they have proven to be the most reliable (Andreassi, 2010). Numerous researchers have classified emotions by dividing EEG data into distinct frequency bands (Murugappan et al., 2011; Zheng et al., 2019).

Comprehending these attributes enables scientists and medical professionals to analyse EEG information for diverse purposes, such as identifying epilepsy, sleep disturbances, and other neurological ailments, and examining cognitive and affective mechanisms.

2.5.4 Categories of EEG analysis

Electroencephalography (EEG) is an essential instrument in neuroscience that records the brain's electrical activity. There are two primary methods for analysing EEG data: qualitative EEG and quantitative EEG (qEEG). The approaches, applications, and depth of information provided by these technologies vary considerably. EEG characteristics in mental fatigue can be identified either using qualitative or quantitative methods.

1. Qualitative EEG

   Electroencephalography (EEG) data can be analysed using a technique called qualitative EEG (EEG), which emphasises the visual interpretation of the raw EEG signals above the extraction of numerical value (Hatton et al., 2023). This approach is commonly used in clinical settings to make diagnoses, where researchers and clinicians examine the rhythms, patterns, and abnormalities in the EEG data to form inferences about possible problems with brain function.

This method is more subjective and depends on the interpreter's education and previous experience.

2. Quantitative EEG

Electroencephalography (EEG) analysis has evolved into quantitative electroencephalography (qEEG), a modern method that records digital EEG data and uses sophisticated mathematical algorithms for processing, transformation, and analysis (Popa et al., 2020). On the other hand, quantitative EEG (qEEG) uses a collection of computerized tools encompassing multiple mathematical and statistical algorithms to analyze EEG signals. Categories of qEEG analyses in mental fatigue include spectral analysis and functional connectivity analysis. Values and new patterns discovered through qEEG are collectively termed "EEG features".

Functional connectivity analysis examines the link between EEG signals in various brain regions. These connections are measured as various indicators of multiregional synchronization (Gurau et al., 2017). Some measurements use statistical techniques like the clustering coefficient and coherence analysis (Chua et al., 2017).

Spectral analysis is the most popular technique for analysing EEG time series, which involves breaking them down into a frequency domain and obtaining the spectrum of the EEG signals. Usually, the Fourier Transform (FT) must be applied to obtain the related frequency bands. According to Stein & Shakarchi (2011), the fundamental concept of an FT is that a complicated function, like the one seen in the raw EEG signals, can be represented by the sum of generic functions.

Determining the spectral power at each sensor for every sub-band is possible. One power value per frequency band can be obtained by computing the total power value across all sensors. Consequently, it is possible to report the power in the alpha band at each sensor location or the power throughout the scalp in the alpha band (Gurau et al., 2017). Furthermore, the outcomes can also be displayed as relative or absolute power. The band power ratio in a frequency band over all bands is known as relative power. Afterwards, machine learning methods were used in a few research studies to examine the causal connections between the EEG observations and the retrieved features.

Electroencephalography (EEG) data analysis is considered quantitative when using event-related potentials (ERP) that are activated following eliciting events through sensory or cognitive stimulus (Yordanova & Kolev, 2009). Traditionally, the ERP is visually inspected by a trained neurologist. More recent studies have used computers to assist with a finer-grained ERP analysis. ERPs identify relevant waveforms from background EEG activity by averaging the brain's electrical responses time-locked to certain sensory, cognitive, or motor events.

2.6 Feature Extraction

The three primary domains of quantitative EEG analysis (qEEG) techniques are time-domain, frequency-domain, and time-frequency-domain. These various configurations forms the basis for feature extraction techniques for the EEG signals. An outline of these methods is provided below:

1. Time-domain technique

   EEG data are analysed using time-domain methods according to their time and amplitude characteristics. Analysing physical signals, mathematical functions, or time series of environmental or economic data in relation to time is known as time-domain analysis (Ambaye, 2020). These techniques are usually simple and entail monitoring the raw EEG signal directly over a period of time. They provide insight into information included in a signal's time domain and are performed on raw EEG data. The most widely used techniques for time-domain EEG analysis are event-related potentials.

   Event-related potentials (ERP) are brain-generated electrical potentials associated with certain external or internal events, such as stimuli, reactions, or decisions (Luck, 2012). The electroencephalogram (EEG), which measures brain activity, is the source to measure event-related potentials (ERP). Event-related potential is the process by which brain reactions are directly associated with certain sensory, cognitive, or motor events, and it is known as ERP. ERP is extracted by averaging the EEG signal over several trials that are synchronised with the stimulus's onset. This procedure reveals stimulus-specific responses such as the N100, P100, N200, P200, N300, P300 and LPP components and improves the signal-to-noise ratio (Sur & Sinha, 2009).

Time domain analysis provides information on the signal's behaviour throughout time. This enables regression models and predictions for the signal. Time domain analysis is used to comprehend data conveyed in such bit patterns across time (Ambaye, 2020).

2. Frequency domain technique

Frequency-domain techniques can reveal information about oscillatory behaviours linked to various mental states and functions by breaking the EEG signal into individual frequencies. Analysis of signals or mathematical functions with respect to frequency is known as frequency domain analysis (Ambaye, 2020). A frequent domain analysis technique was used, and the most reliable and traditional technique for analysing EEG data was often known as spectral analysis.

Power spectral density (PSD) is one of the common and reliable methods that calculates how power is distributed among various frequencies. Techniques like Welch's approach increase the precision of PSD estimates by averaging many periodograms derived from overlapping EEG signal segments. The most widely used spectral method is power spectral analysis because the power spectrum shows the signal's "frequency content," or how its power is distributed over frequency (Stancin et al., 2021).

One technique used to classify EEG activity into frequency bands (delta: 0.5–4 Hz, theta: 4–8 Hz, alpha: 8–12 Hz, beta: 13–30 Hz, gamma: >30 Hz) is called band power analysis. The power inside these bands, which is associated with various physiological and cognitive states, is quantified using band power analysis. For instance, higher beta power is connected to alertness and active thought, while higher alpha power is linked to rest.

3. Time-Frequency Domain

Time-frequency methods offer a dynamic presentation of the EEG signal's frequency content variations across time. These techniques are crucial for analysing non-stationary signals, such as EEG, which show fluctuations in brain activity. The most common method used is the Wavelet transform (WT) (Herrmann et al., 2014).

Wavelets are functions that can be stretched or compressed to capture both low-frequency components (over large time windows) and high-frequency components (over short time windows). WT uses wavelets to divide the EEG signal into time-frequency space. Commonly used variations include the Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT).

Table 2.8 Various models for mental fatigue using time and frequency domain analysis

Types of analysis	Feature Extraction	Classifier	Accuracy	Reference
Time domain	Fuzzy entropy	SVM, RF	87.07 (SVM) 89.8 (RF)	(Xu et al., 2023)
Time domain	ERP	XGBoost	65–75%	(M. Wang et al., 2023)
Time-frequency domain	Wavelet	SVM, Random Forest	66–97% (SVM), >90% (RF)	(Chen et al., 2025)
Time frequency domain	Wavelet Transform	Boosted Trees Ensemble	70.5%	(Daud & Sudirman, 2025)
Frequency domain	Spectral analysis	CNN	70	(X. Li et al., 2022)
Frequency Domain	PSD	Multi Layer Perceptron (MLP)	80.6%	(Siravenha et al., 2019)
Frequency domain	Spectral analysis	Multi Layer Perceptron Linear Regression	73% (MLP) 68% (LR)	(Hossain, 2024)

		Support Vector Machine	68% (SVM)	
Frequency domain	PSD	Deep Generic Model (DGM) + Support Vector Machine (SVM)	73.29% (DGM+SVM)	(San et al., 2016)
Frequency domain	Spectral analysis	Linear Support Vector Machine	85.4% (Linear SVM)	(K. Q. Shen et al., 2008)

Table 2.8 summarizes the previous research on mental fatigue using EEG with different types of analysis: time domain, time frequency domain, and frequency domain analysis. With classifiers like SVM, RF, and XGBoost, time domain features like fuzzy entropy and ERP (Event-Related Potentials) have been extensively employed, yielding accuracies of 65–90%(M. Wang et al., 2023; Xu et al., 2023). With their comparatively high accuracy (70–97%), time–frequency domain features in particular, Wavelet Transform have also been used with classifiers like SVM, Random Forest, and Boosted Trees. This makes them useful for capturing both temporal and spectral changes(Chen et al., 2025; Daud & Sudirman, 2025). The literature is dominated by frequency domain methods, such as PSD (Power Spectral Density) and spectral analysis. Classifiers with accuracy levels ranging from roughly 68% to 85% have been used, including CNN, MLP, LR, and SVM. The power distribution of EEG signals across frequency bands, which are frequently connected to mental exhaustion states, can be understood using these techniques (Hossain, 2024; X. Li et al., 2022; San et al., 2016; K. Q. Shen et al., 2008; Siravenha et al., 2019).

Overall, the table demonstrates that no single approach is inherently better; rather, the selection is based on the experiment's characteristics, the relative significance of temporal versus spectral information, and the classifier's versatility. ERP was chosen as the primary feature extraction technique because it is very appropriate for evaluating mental fatigue under controlled conditions, as it is time-locked to certain experimental events or stimuli. Due to the time-locked nature of your experimental setup (IAPS and driving stimuli), ERP gives you exact information on how the brain reacts to events at particular times (McWeeny & Norton, 2020). Your study question on emotional changes during mental fatigue, utilising ERP, is directly addressed by ERP, which records temporal variations in cognitive and emotional processing in contrast to PSD or spectral characteristics, which primarily concentrate on frequency power distribution. Due to the inherent noise, subject-dependency, and non-stationarity of EEG signals, an accuracy of 65% and above is already regarded as satisfactory in EEG-based mental fatigue research. Also supported by Dimitrakopoulos et al. (2017), the EEG channel range, from 7 channels to 62-channel EEG, will have an accuracy from 65 % to 80 %.

2.6.1 Event-Related Potential (ERP)

Event-related potentials (ERP) are brain-generated electrical potentials associated with certain external or internal events, such as stimuli, reactions, or decisions (Luck, 2012). The electroencephalogram (EEG), which measures brain activity, is the source to measure event-related potentials (ERP). In ERP, many components are used for the research study, such as P100, N100, P200, N200, P300, N300, and Late Positive Potential (LPP) (Sur & Sinha, 2009). The ERP is produced by taking various temporal segments that characterise the event of interest from the ongoing EEG signal and averaging them (Luck, 2012), as shown in Figure 2.5.

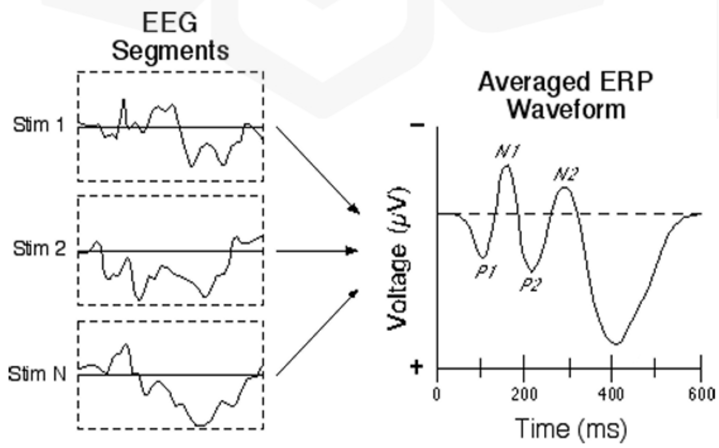

Figure 2.5 Event-Related Potential Technique (Sénecal et al., 2014)

EEG measures event-related potentials at the scalp when stimuli elicit them. Their recording is a reaction to a single, specific event. In order to average the EEG after excluding low-quality trials, this stimulus is frequently displayed several times. The ERP waveforms are made clear in this manner. Figure 2.6 provides a schematic representation of this procedure.

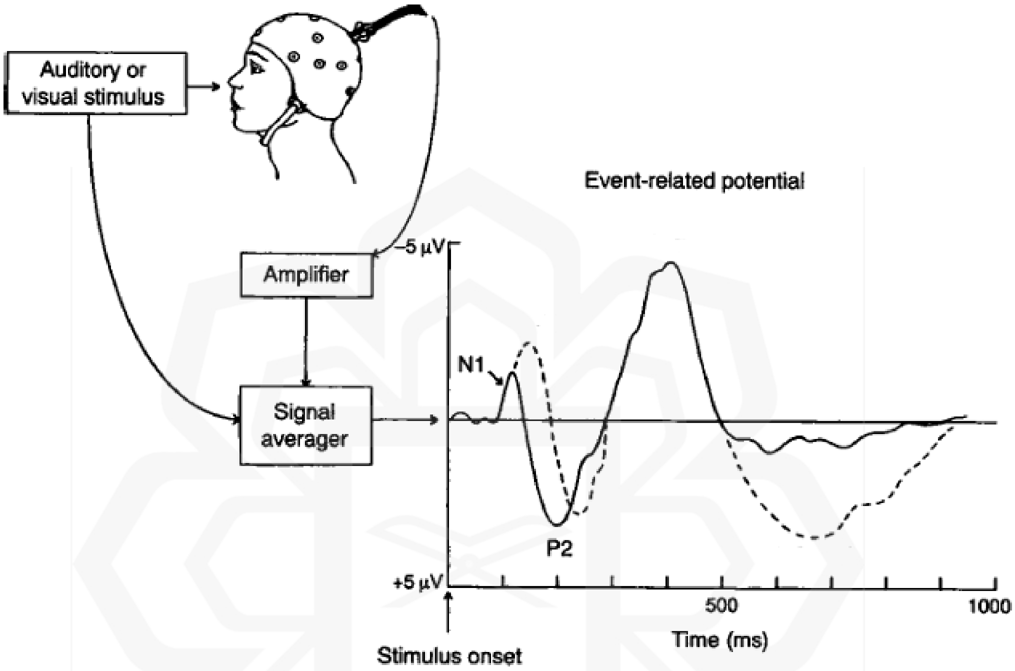

Figure 2.6 An example of the process used to obtain ERP (Kaan, 2007)

For example, electrical activity from the scalp is recorded when a subject is reading or listening to words. The resulting signal is then time-locked to the stimulus of interest, averaged, and amplified to produce the ERP. (Kaan, 2007).

ERP is well known as the feature extraction of emotion and has incredible results. Thus, it is the preferred feature extraction method for this research. Measured brain reactions directly resulting from a particular sensory, cognitive, or motor event are known as event-related potentials or ERP. A specific measurement obtained from EEG data is called an event-related potential (ERP). EEG continuously measures the electrical activity of the brain. In contrast, ERPs are brief EEG data segments averaged over several experiment trials and time-locked to specific events of interest

(McWeeny & Norton, 2020). Normally, we continuously record EEG data during an experiment, and then we divide the data into time-locked short pieces known as epochs, which correspond to the events of interest. The start of stimuli, such as emotional stimulation via IAPS, is typically the event of interest. The theory behind ERP is that by temporally locking brain activity to certain events, we can observe systematic patterns of brain activity occurring in reaction to those events. When examining the temporal fluctuations of brain activity, we can see the signals related to mental fatigue using emotional stimuli. Different components that represent different phases of brain processing, such as P100, N100, P200, N200, P300, N300, and the Late Positive Potential (LPP), are what define ERP.

Key parameters are retrieved for each identified ERP component, such as amplitude (the peak or trough value) and latency (the period at which the peak or trough occurs) (Gibney et al., 2020). An important development in affective neuroscience and its applications is modelling emotion by feature extraction from Event-Related Potentials (ERP). In this process, particular features of the brain responses elicited by emotional stimuli are recognised and used. By doing this, scientists and professionals can create predictive models that offer insights into the emotional states of mental fatigue conditions using ERP components.

2.6.2 ERP COMPONENTS RELATED TO EMOTION AND MENTAL FATIGUE

These ERP components may show amplitude and latency variations in response to emotional stimuli, suggesting an emotional reaction from the brain. ERPs are helpful for researching the brain processes that underlie emotional processing. Important ERP elements related to emotion are P100, N100, P200, N200, P300, N300, and the Late Positive Potential (LPP).

a. P100

   A positive ERP component known as the P1 or p100 characteristic is one that appears about 100 milliseconds after the stimulus is presented (Hileman et al., 2011). The P100 ERP components are linked to the processing of emotional facial expressions with the result from patients exhibiting P100 deficiencies in response to a particular set of expressions or emotional states (Shah et al., 2018), and it was supported by the past study result that shows P100 amplitude to faces is consistently reduced in patients, indicating that face processing impairments in this population start earlier and providing evidence that these impairments are emotion-specific (Earls et al., 2016). Strong correlations for valence are obtained with P100 (Ding et al., 2017), and a previous study from Luo et al. (2010) discovered that emotions had a substantial impact on P100. Research has demonstrated that emotional stimuli, particularly those with high arousal levels, can increase the P100 component's amplitude, suggesting that emotional content affects early attentional processes.

b. N100

N100 is the negative peak of the electrical response that happens at approximately 100 milliseconds after the onset of the stimulus. It is shown in various functional paradigms, such as activities involving the senses, the body, behaviour, and cognition (Du et al., 2017). The work of Luo et al. (2010) demonstrated the considerable emotion modulation of N100, wherein scary faces elicited greater N100 amplitudes than happy and neutral expressions, for N100 viewed as a sensory component.

c. P200

The P200 ERP components represent a positive deflection that occurs 200 milliseconds after introducing the stimulus (Lithari et al., 2010). The P200 component is a positive deflection linked to subsequent visual processing, peaking 150–300 ms after stimulus onset and it was believed to represent the early capacity for attentional regulation brought about by emotional inputs from the outside during the onset of cognitive attention (M. Li et al., 2023).

d. N200

The N200 ERP components are a negative deflection that happens 200 milliseconds following the introduction of the stimulus to 300 milliseconds(Lithari et al., 2010; S. H. Patel & Azzam, 2005). The valence effect observed in our study was most prominent on N200 of Cz electrodes, with unpleasant pictures eliciting greater responses than pleasant ones(Lithari et al., 2010). P100–N200 ERP characteristics have been used to investigate emotional information processing in the frontal midline(Dennis & Chen, 2007). Conflict monitoring and cognitive control are associated with the N200. The N200 amplitude is sensitive to emotional stimuli, suggesting that processing emotionally charged information requires more cognitive control.

e. P300

The P300 wave, an event-related potential (ERP), emerged at around 300 milliseconds and was triggered by rare, task-relevant events (Thakur et al., 2011).

Emotion relation: The amplitudes of N300 and P300 most likely indicate additional analysis of data pertaining to a face's affective valence (Luo et al., 2010). P300 is a positive component that peaks after the start of an emotional stimulus and is associated with the response to it. Additionally, the components reacted differentially to the emotional content of the stimuli, suggesting that the emotionally relevant items' ability to engage attention may be reflected in emotional processing (Delplanque et al., 2006).

Mental fatigue relation: It was also stated by (Kemp et al. (2010) that the effects of mental fatigue and depression on attention have been studied using the N100, P200, N200, and P300 ERP components.P3 amplitude variations may indicate modifications in the cognitive resources linked to mental fatigue. Shorter latencies are associated with better mental performance than longer latencies; stronger P3 waves tend to result from increased attention since P3 amplitude reflects sensory information. (Sur & Sinha, 2009).

f. N300

The N300 is a component of the ERP, which appears 250–350 ms after the stimulus begins (Kumar et al., 2021). The amplitudes of N300 and P300 most likely indicate additional analysis of data pertaining to a face's affective valence (Luo et al., 2010).

g. Late Positive Potential (LPP)

LPP is a positive-going ERP component that can peak as early as 400 milliseconds and is observed for hundreds of milliseconds following the presentation of a stimulus (Gibney et al., 2020). Processing of emotional stimuli has a high correlation with the LPP, and the currently available research provides a wealth of evidence to support the effect of emotion on LPP (Ding et al., 2017). In event-related potential (ERP) paradigms, a popular measure for examining and assessing participants' emotional processes is the late positive potential (LPP) (Gibney et al., 2020; Hajcak et al., 2012). In order to investigate how emotions are processed and regulated throughout time, this element is widely used in emotion research. It was also stated by Kemp et al. (2010) that the effects of mental fatigue and feeling depression on attention have been studied using the N100, P200, N200, and P300 ERP components.

2.6.3 EEG and ERP features

Characteristic of mental fatigue human can be explained through EEG frequency bands. In the past study of EEG, mental fatigue can be detected through the power development in frontal theta and parietal alpha of EEG rhythms. This explains that mental fatigue can be analysed through the usage of the brain on doing some task it can influence the frontal midline theta and parietal alpha state (Trejo et al., 2015).

Another characteristic was found in another past study, which stated that there is a positive relationship between some symptom of fatigue which is boredom and sleepiness with mental fatigue where there was an increasing power of beta frequency band. It affected beta frequency band power in the right inferior and middle frontal gyri while performing a long and non-stop activity that can induce mental fatigue (Tanaka et al., 2014).

In another study, the common region of the alpha band that correlate to mental fatigue is parietal region, there was significant increase found in clustering coefficient around the parietal and occipital area of the brain (Chua et al., 2017). During a simulated driving task mental fatigue was found to be associated with increases in maximum alpha activity and increases in the sum of alpha amplitude. This was seen generally across the cortex and found to be significant in the Cz and P4 sites of the brain (Tran et al., 2014).

From previous study, relative power level (RPL) values from EEG based on 5 spectral were done but RPL for delta, theta, and gamma did not differ statistically between the two driving conditions. However, alpha and beta RPL values differed clearly in the two conditions which is state of alert and sleep deprived. (Ahn et al., 2016).

The main effects of session indicate that alpha and theta power spectra were significantly increased in the sleep deprivation condition as compared to the normal sleep condition. In contrast, beta power spectrum did not differ significantly between normal sleep and sleep deprivation conditions (Perrier et al., 2016).

Table 2.9 EEG and ERP features

Condition	Brain regions	Frequency band	References
Mental Fatigue	Frontal and parietal	Alpha and Theta	(Trejo et al., 2015)
Boredom and sleepiness (mental fatigue)	Right inferior frontal and middle frontal	Power beta	(Tanaka et al., 2014)
Mental fatigue	Parietal and occipital	Alpha	(Chua et al., 2017)
Mental fatigue	Cz Central and P4 Parietal	Alpha	(Tran et al., 2014)
Sleep-deprived condition	-	Alpha and theta significantly increased, and beta did not differ significantly	(Perrier et al., 2016)

The major findings from the literature show that EEG synchronizations in the alpha and theta bands in the frontal, central, occipital, and parietal regions are significantly related to mental fatigue conditions. In contrast, the beta band does not distinguish between normal and sleep-deprived conditions. Table 2.4 summarises EEG and ERP features of mental fatigue conditions.

2.7 CLASSIFICATION

When it comes to EEG (Electroencephalogram) signal processing, a classifier is a machine learning model or algorithm that uses the attributes of the EEG signal as input and produces a classification or prediction depending on the signal's properties. Finding patterns or characteristics in the EEG signal that are connected to particular cognitive states, emotions, or conditions like mental fatigue is the aim of an EEG classifier. This is the example of the classifier that the Matlab and its definition provided:

1. Binary Logistic Regression (BLR)

   A simple classifier which models the mean response as a function of the linear combination of predictors (The MathWorks Inc., 2022). Applied in situations when the answer is binary, meaning there are two viable paths. Binary logistic regression is used in the cracking example that was previously provided. This is the binary logistic regression formula provided by Harris (2021).

$$p\left(y\right) = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + b_2 x_2)}}$$

   Where:

   - p(y) stands for the probability of one category (sleep deprived and non sleep deprived condition) of the dependent variable
   - y and b are coefficients of the independent variables or predictors
   - x are the independent variables

2. Linear Support Vector Machine (Linear SVM)

   A support vector machine that makes a simple linear separation between classes using the linear separation between classes, using the linear kernel. It was the easiest support vector machine to interpret (The MathWorks Inc., 2022). This is the linear support vector machine formula provided by Berwick (2003).

$$\mathbf{w}^T\mathbf{x} + b = 0$$

Where:

- w is a weight vector
- x is input vector
- b is bias

3. A Multilayer Perceptron (MLP) is a fully linked multi-layer neural network. Multi-layer perceptron (MLP) comprises several layers of computing units and is utilised in many studies. It is a feed-forward neural network, and its weight is determined using the reverse propagation learning algorithm (Kotsiopoulos et al., 2021). Figure 2.7 illustrates how MLPs are integrated into every network layer and how each hidden neuron's output is distributed to every other neuron.

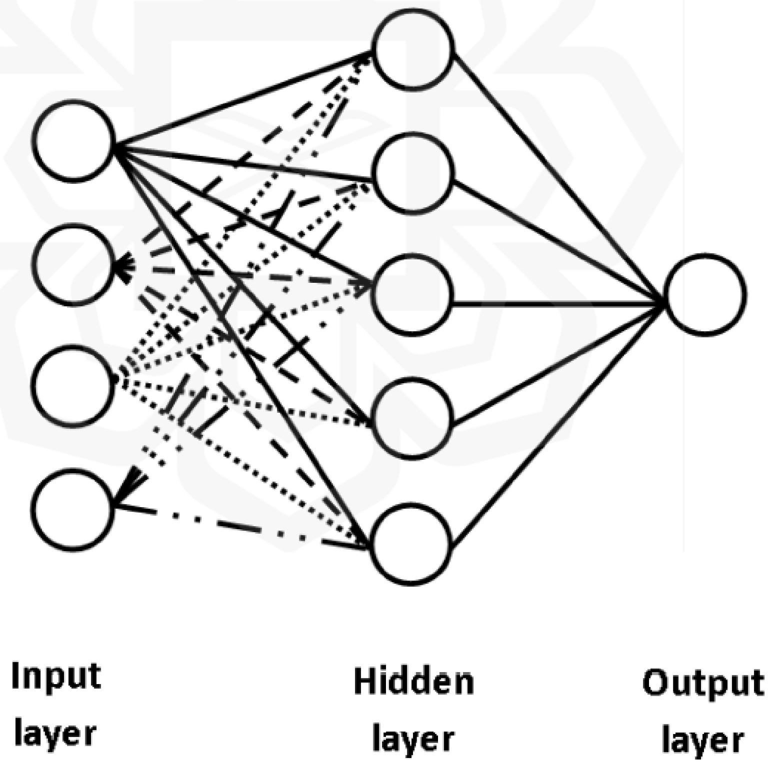

Figure 2.7 Multi-Layer Perceptron Structure (Yaacob et al., 2013)

The multi-layer perceptron (MLP) is a multi-layered artificial neural network technology (Yaacob et al., 2012). Narrow Neural Network (NNN), Medium

Neural Network (MNN) and Wide Neural Network are considered multi-layered artificial neural networks. Neurons with equal characteristics are found in the input layer, which is the first layer. Several hidden layers could make up the second layer. The number of hidden layers can be identified through the optimisation procedure. We have the output layer as the third layer. Supervised learning tasks, such as categorisation tasks, frequently employ this technique.

4. Narrow Neural Network (NNN)

   A neural network classifier with one fully connected layer of size 10 (The MathWorks Inc., 2022)

$$f(x) = (\sum_{i=1}^{n=10} w_i * x_i) + b$$

Where :

- n is the number of neurons in the previous layer,
- w is a random weight,
- x is the input value,
- b is a random bias.

5. Medium Neural Network (MNN)

   A neural network classifier with one fully connected layer of size 25 (The MathWorks Inc., 2022)

$$f(x) = (\sum_{i=1}^{n=25} w_i * x_i) + b$$

Where :

- n is the number of neurons in the previous layer,
- w is a random weight,
- x is the input value,
- b is a random bias.

6. Wide Neural Network (WNN)

   A neural network classifier with one fully connected layer of size 100 (The MathWorks Inc., 2022)

$$f(x) = (\sum_{i=1}^{n=100} w_i * x_i) + b$$

   Where :

   - n is the number of neurons in the previous layer,
   - w is a random weight,
   - x is the input value,
   - b is a random bias.

The literature has successfully used a number of machine learning classifiers on mental fatigue, each with various levels of performance, interpretability, and complexity. It is clear from the literature review compiled in Table 2.8 that a number of classifiers have been extensively used in time, frequency, and time-frequency domain research for the detection of mental fatigue using EEG signals. Multilayer Perceptrons (MLP), Binary Logistic Regression (BLR), and Linear Support Vector Machines (SVM) are a few of the frequently utilized classifiers.

These classifiers were regularly used in previous research due to their ability to detect patterns of mental fatigue and their resilience when processing EEG data. For example, MLP has been effectively used in many frequency-domain techniques, whereas Linear SVM has demonstrated excellent performance in spectral analysis. Despite its simplicity, logistic regression offers a trustworthy baseline model and makes it easy to evaluate classification findings.

Linear SVM, BLR, and MLP will be the main classifiers used in this study. This choice was made for two reasons:

1. Established use in literature – As indicated in Table 2.8, these classifiers have been regularly used in earlier studies on EEG-based emotion and mental fatigue identification, demonstrating their applicability in this field.

2. Performance comparison – The performance of several classifiers can be compared within the experimental framework and dataset. To ensure that the final model is both experimentally validated and based on accepted research practices, the best-performing classifier among the three will be selected based on evaluation measures like accuracy.

Therefore, this study not only aligns with proven methodologies in prior work but also ensures adaptability by determining the most effective classifier for the given data.

2.8 CHAPTER SUMMARY

A thorough examination of the research areas investigated in this study was provided in Chapter 2. This chapter has concluded that EEG will be used for the measurement of emotion in mental fatigue profiling. A review of the literature on the use of mental fatigue provides a detailed explanation of what mental fatigue is, its symptoms, and the causes and implications of mental fatigue for cognitive and emotional impact. This chapter also states why sleep deprivation is considered a subcomponent of mental fatigue. It also shows the analysis that was done using EEG on mental fatigue. The emotion that was related to mental fatigue is also discussed in this chapter.

This chapter can be summarized as follows:

1. Mental fatigue, also known as brain or cognitive fatigue, is a type of mental exhaustion that lowers individuals' emotional stability and cognitive function. Mental fatigue has been shown to be one of the main reasons for poor performance and cognitive function. When it comes to emotional symptoms, mental fatigue is positively correlated with negative emotions.
2. It is speculated that mental fatigue is a subcomponent of sleep deprivation. Lack of sleep lowers and impedes an individual's ability to give full attention and complete cognitive tasks. Emotions that are normally processed differently when sleep-deprived are also biased towards negative emotions.
3. A questionnaire has been the traditional method of measuring mental fatigue, but in recent years, psycho-dimensions like EEG have become more relevant.

4. The most appropriate emotional model for the thesis is a dimensional emotional model centred on the Affective Space Model emotion. The best emotional stimuli to evoke certain emotions in participants are IAPS (happy, calm, fear, and sad).
5. The human brain consists of the frontal, occipital, parietal, and temporal lobes. Based on past studies, the frontal, occipital, and parietal lobes are related to mental fatigue.
6. EEG channels ranging from 10 to 64 channels are highly comparable for an EEG study. The frequency bands for EEG are always represented as delta, theta, alpha, beta, and gamma.
7. The time-domain technique, event-related potential(ERP), is suitable for research involving internal or external events such as exposure to emotional stimuli. Mental fatigue and emotions are correlated with the ERP components N100, P100, N200, P200, N300, P300, and LPP.

The literature indicates that the majority of studies on mental fatigue have concentrated on frequency and time-frequency domain features, but ERP-based features remain underexplored despite their effectiveness in capturing time-locked brain responses. Prior studies predominantly utilise either a singular classifier or complex deep learning architectures, with insufficient comparative analysis of basic yet successful classifiers like Linear SVM, Binary Logistic Regression, and Multilayer Perceptron. This work seeks to fill existing gaps by utilising ERP characteristics and evaluating the performance of three classifiers to choose the most appropriate model for profiling emotional fluctuations during mental exhaustion.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 INTRODUCTION

This section outlines the research methodology and how the study will be conducted and constructed. In order to satisfy the objectives of the dissertation, quantitative research was performed instead of qualitative research. Its basic advantage, which also constitutes its basic difference with quantitative research, is that it offers a complete description and analysis of a research subject, without limiting the scope of the research and the nature of participant’s responses (Collis & Hussey, 2003). However, the effectiveness of qualitative research is heavily based on the skills and abilities of researchers, while the outcomes may not be perceived as reliable, because they mostly come from researcher’s personal judgments and interpretations.

The main characteristic of quantitative research is based on the aspect of quantity and sample group involving experimental method along with the analytical, mathematical and computational techniques (Mishra & Alok, 2017). The basic format for an experimental study is taking two randomly sampled groups and testing a treatment condition with one group versus a control condition (no treatment) with the other. Variations of this design include using more than one group or varying the data collection periods; however, the requirement of having randomly assigned treatment and control groups is essential. The random assignment minimizes additional influences and potential variation that could bias or confound the study (Biddix, 2018).

3.2 RESEARCH METHODOLOGY

The approach used to create a neurophysiological emotional profile model for mental fatigue is described in this chapter. The research methodology is divided into multiple important stages, starting with the literature review and problem analysis. These are followed by the creation of experimental protocols, data collection, and model building. The use of IAPS and driving stimuli, EEG data collecting, and emotional profiling are only a few of the particular tasks and instruments that are incorporated into each step to guarantee a methodical research. This study's general research technique is illustrated in Figure 3.1.

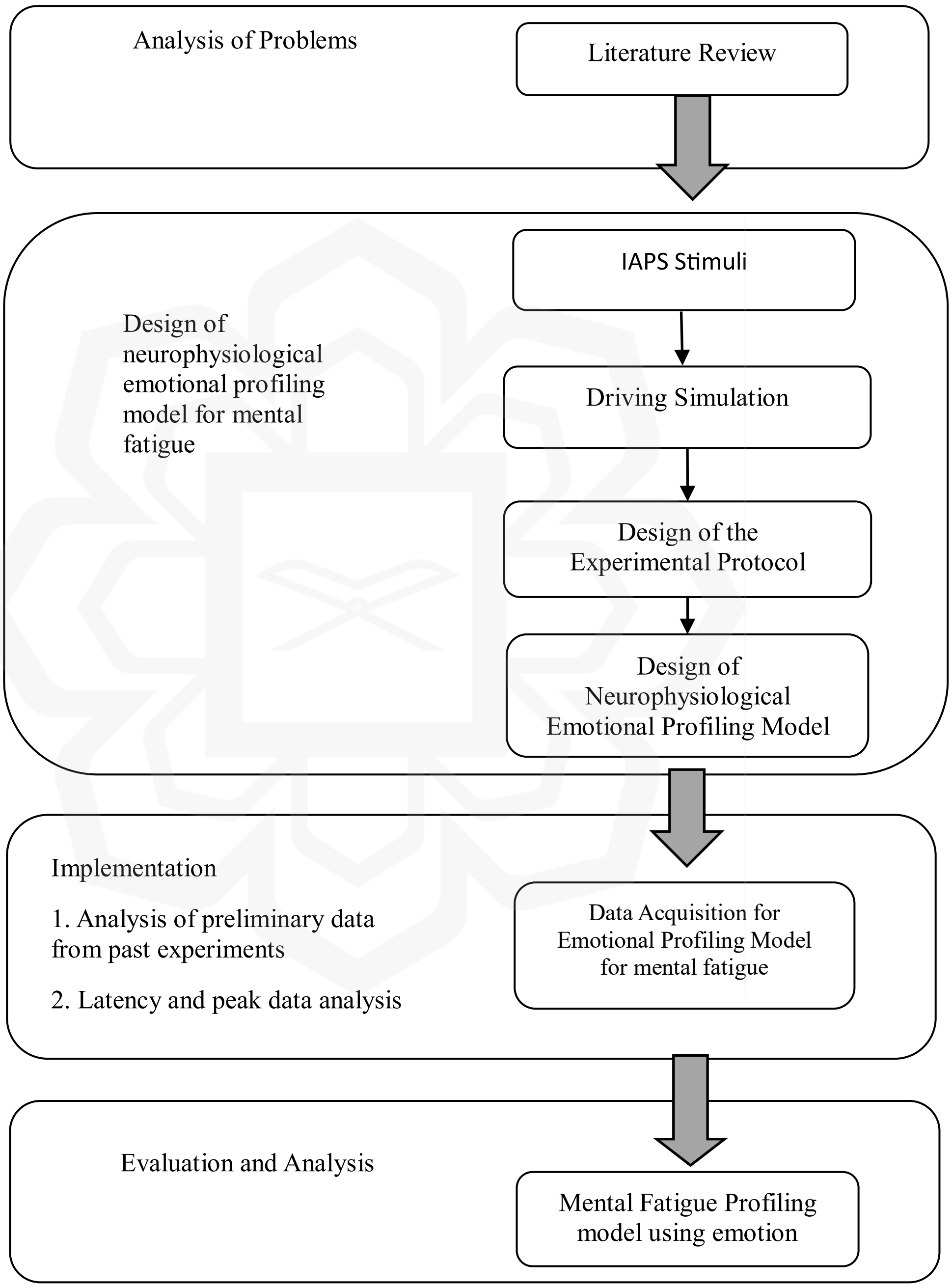

Figure 3.1 Research Methodology

Based on Figure 3.1, the research methodology is divided into four phases: analysis of the problem, design of the neurophysiological emotional profiling model for mental fatigue, implementation of the mental fatigue profiling model, and data evaluation and analysis.

a. Analysis of problems

   Phase 1 consists of identifying the fundamental challenges and difficulties, conducting a comprehensive literature review to identify the gaps in the current knowledge. By critically analysing the currently available literature, researchers can find gaps in the literature or topics that haven't been fully investigated. This aids in developing research topics that fill in these gaps and add fresh information. This is done using a literature review and preliminary data from an earlier emotion and mental fatigue research study. The literature review will gather the knowledge on the area of the thesis study:

   1. Definition of mental fatigue, symptoms, causes and its implications.
   2. Relationship of emotions and mental fatigue.
   3. Human brain and its correlation to mental fatigue
   4. EEG signal, features and its measurement on mental fatigue.

   It offers a strong basis for comprehending the present status of research on a certain topic. Researchers can better understand the topic by synthesising previous studies and learning about important theories, methodology, and findings. It will also highlight the major discoveries of these studies. It was proposed that the researcher provide a detailed classification of mental fatigue based on the existing literature. The classification may reveal interesting insights into the control parameters of mental fatigue and non-mental fatigue using emotion.

b. Design of neuro-physiological emotional profiling model for mental fatigue

   Phase 2 aims to explore the emotional differences based on varying complexity levels of the driving tasks. These complexities are reflected through three tasks: easy, medium, and hard. This phase will set up the experimental protocol to suit data collection for the emotional profiling of mental fatigue, including IAPS stimuli and driving simulation.. This phase identifies an appropriate emotional stimulus to be used. The other data that was needed for the analysis is the EEG signal of the emotions (i.e., happy, calm, fear, and sad) of the participant when they are in mental fatigue conditions, and what kind of induced technique is to be used to make the participant mentally fatigued (i.e., sleep-deprived and non-sleep-deprived). This study uses an experimentally controlled form of sleep deprivation to induce mental fatigue. The night before data collection, all the participants must have slept for fewer than six hours to ensure a constant and quantifiable level of sleep-deprived exhaustion among participants. Instead of examining the relationship between emotion and fatigue, the study aims to explore the emotional differences that come from mental fatigue. Also, the phase includes the design scenario of the driving tasks, design, and experimental protocol development, thus creating the development of a neuro-physiological emotional profiling model for mental fatigue (NPEMMF).

c. Implementation

This phase involves data collection based on the designed scenarios. Preliminary data collection and analysis will investigate and validate the early data collection process and its results. After gaining insight from the preliminary data and analysis, the actual data collection will be done, and some improvements will be made to the data collection and analysis.

d. Evaluation and analysis

The final stage is to evaluate and analyze the model based on mental fatigue using the IAPS emotional stimuli. The performance measures and their neuro-physiological states as measured by the EEG. The output of the evaluation and analysis phase is the proposed mental fatigue profile.

3.3 EQUIPMENT AND MATERIAL USED

3.3.1 EEG Machine

The 19-channel EEG DABO machine, as shown in Figure 3.2 below, will be used as a device to collect data for this study. The EEG DABO machine is a CE-certified, top-notch device that is a portable EEG device system suitable for research purposes. The system is very relevant for scientific research and other standard applications since the signal obtained from this gadget has an exceptionally high signal-to-noise ratio. This device requires a 12-volt power adaptor to function, weighing about one kilogram. The electrode cap comes with the EEG DABO Machine gadget as well. The participants' scalps will be equipped with EEG silver-silver chloride electrodes, positioned in accordance with the usual 10–20 electrode placement technique.

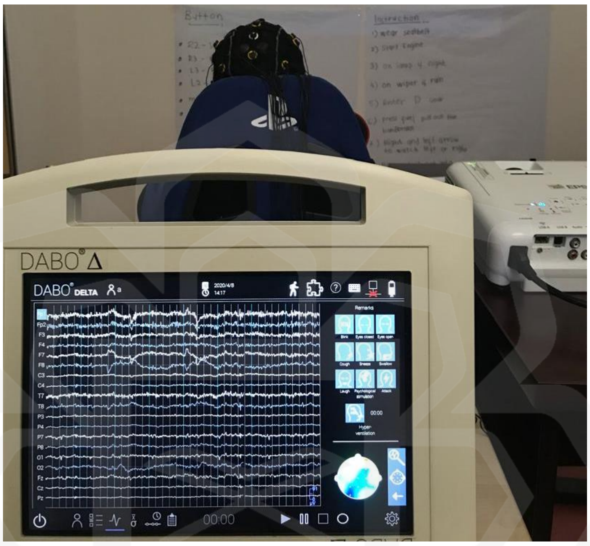

Figure 3.2 EEG DABO Machine

An EEG electrode is a tiny sensor used to gauge brain electrical activity. EEG equipment that captures electrical signals from the brain cannot function properly without these electrodes. The outermost layer of the head, the scalp, offers a surface on which electrodes for electroencephalograms (EEGs) can be placed for non-invasive brain activity monitoring. Electrodes for electroencephalography (EEG) are applied to the scalp to capture neural activity. Positioning is essential to get precise and consistent EEG readings. Figure 3.3 shows the EEG scalp and electrodes. EEG data from all 19 channels are utilized for the preliminary works. The most significant channel data will be selected for further analysis.

Figure 3.3 EEG Electrode and Scalp

3.3.2 Electrode and Skin Cleansing Gel

EEG electrode gel improves the contact between the scalp and EEG electrodes. It is sometimes referred to as conductive gel or paste. Because it improves electrical signal conductivity and lowers resistance at the electrode-skin contact, this gel is essential to the measurement of EEG recordings. The electrode gel that was used is Parker Signagel, as shown in Figure 3.4. Parker Signagel is a highly conductive, multi-purpose electrolyte that meets all the standards of the ideal saline electrode gel.

Figure 3.4 Parker Signa gel

The gel's main goal is to decrease the electrical resistance between the scalp and the electrode. High impedance can cause poor signal quality and more noise. The gel's additional purpose is to enhance conductivity, which ensures that electrical signals produced by the brain reach the electrodes efficiently.

Figure 3.5 Nuprep Gel

The scalp surface with high resistance signals will be applied with Nuprep gel, as shown in Figure 3.5. The Nuprep gel is applied using a cotton bud to remove the substances that prevent good connectivity between the EEG device and the brain. Nuprep gel can improve your tracings. Nuprep skin cleansing gel efficiently lowers impedance. Its slightly abrasive composition increases conductivity and aids in getting good signals from the EEG device.

3.4 EXPERIMENTAL PROTOCOL

The following Figure 3.6 shows the experimental protocol for this thesis. There will be a baseline recording in the first two minutes, followed by four minutes of emotion stimulation, fifteen minutes of driving simulation, and finally, a return to the baseline recording. This protocol is approved by the IIUM Research Ethics Committee (IREC No: KICT-RG20-007-0007).

Base Line		Emotional State				Task 1	Task 2	Task 3	Base Line Extension	
Eyes Closed (1 minute)	Eyes Open (1 minute)	Happy (1 minute)	Calm (1 minute)	Sad (1 minute)	Fear (1 minute)	Driving Simulation (Easy)	Medium	Hard	Eyes Closed (1 minute)	Eyes Open (1 minute)
2 minutes		4 minutes				5 minutes	5 minutes	5 minutes	2 minutes	

Figure 3.6 Experimental protocol

3.4.1 Baseline Recording (2 Minutes)

The EEG baseline recording, with the eyes closed and eyes open, is a resting state condition for the participant, which measures the electrical activity in the brain without any tasks occurring during the recording. This protocol measures the current condition of brain signals. EEG baseline recording resting-state intrinsic dynamic patterns in EEG signals may indicate the brain's flexibility, and these patterns may be used to forecast the brain's cognitive function during cognitive activities (Wan et al., 2023). The protocol is provided in Table 3.1:

Table 3.1 Baseline recording

Baseline Recording	Task	Description	Duration
Resting-state	Eyes Close	For one minute, participants will be instructed to keep their eyes closed and sit as still as possible in order to minimise movement artefacts in the EEG data.	1 Minute

	Eyes Open	For one minute, participants must remain still to avoid causing movement artefacts in the EEG readings. Participants will be required to view a black screen monitor image with a white "x" mark in the centre of the screen during this portion of the experiment.	1 Minute

3.4.2 IAPS Emotion Stimuli

Four sets of International Affective Picture System (IAPS) emotion stimuli which represent the four main emotions of happiness, fear, calm, and sadness were shown to the participants. For a minute, each emotion stimulus was shown to the participants as a series of frames on a computer screen. The duration of each frame on the screen was around 60000 milliseconds for each emotion; thus, the total duration is 240000 milliseconds. Table 3.2 outlines the process for eliciting emotions.

Table 3.2 IAPS emotive stimuli

Test	Evoke Emotion stimuli	Description	Duration	Emotion code
Emotion stimuli	Happy	Participants must remain static for one minute to avoid causing movement artefacts in the EEG readings. During this stage, participants will be required to see a computer screen that displays pictures of a happy scene.	1 minute	positive valence, positive arousal
	Calm	Participants must remain static for one minute to avoid causing	1 minute	positive valence,

		movement artefacts in the EEG readings. In this stage, participants will be required to view still photographs on a computer screen that depicts calm environments.		negative arousal
	Fear	Participants must remain still for one minute to avoid causing movement artefacts in the EEG readings. During this stage, participants must view a computer screen that displays images of fear scenarios.	1 minute	negative valence, positive arousal
	Sad	Participants must remain static for one minute to avoid causing movement artefacts in the EEG signal readings. During this stage, participants will be required to view a computer screen that displays pictures of sad scenarios	1 minute	negative valence, negative arousal

The current study's design used modern techniques, including exposure to the International Affective Picture System (IAPS) for emotion induction, to investigate this question.

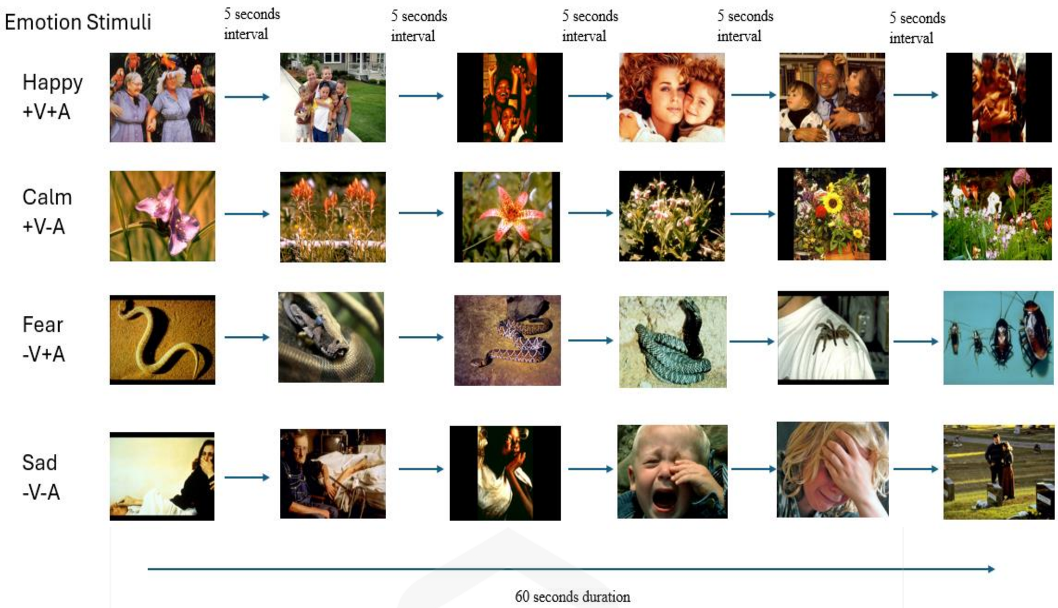

Figure 3.7 IAPS emotion stimuli

During this phase, the participant will be shown an IAPS picture of happy, calm, fearful, and sad. Each picture will have a 5-second interval before it changes to another picture to evoke an event in the brain. So, every five seconds of each Segment, there will be an interval of 5 seconds for the pictures to change automatically until they reach 60 seconds.

3.4.3 Driving Simulation (15 Minutes)

Participants at this level are required to complete a 15-minute test on a driving simulator with various driving tasks and scenarios (distracted driving). According to the (National Highway Traffic Safety Administration, 2015) driving is a major cause of death and serious injuries in the US. The three distinct stages for this phase are displayed in Table 3.3.

According to a prior study, executive control is crucial to the behaviour of distracted driving; moreover, people with higher executive problems also exhibited more distracted driving behaviours (Pope et al., 2017). Mental fatigue can also result from prolonged, continuous activity (Iampetch, S., Punsawad, Y., & Wongsawat, Y., 2012). Subjective weariness ratings rose over time, suggesting that mental fatigue increases as a result of task completion (Guo et al., 2016).

Table 3.3 Driving simulation task

Test	Task	Description	Duration
Driving Simulation	Easy	Participants will use the easiest road on the simulator while wearing EEG equipment for the first five minutes. To avoid waste movement artifacts in the signals, they must maintain a constant speed of 100 km/h while operating the car.	5 minute
	Medium	Participants will need to drive on a moderate road for the following five minutes, navigating easy problems, including rainy roads and minor distractions.	5 minute
	Hard	During the final five minutes, participants will encounter more distracted driving behaviour and use challenging roads, such as traffic roads, which require higher cognitive abilities.	5 minute

3.4.4 Baseline Recording (2 Minutes)

In this phase, the EEG baseline recording was performed, where the participant will do the eyes close and eyes open again. We will need to use this procedure to assess the brain's default state and check the state of the participants' current brain condition at the end of the experiments.

3.5 DEVELOPING A FRAMEWORK BASED ON AN EXISTING EEG EMOTION RECOGNITION MODEL

This study's primary objective is to examine quantitative measurements or indicators of emotional activity associated with mental fatigue. In this experiment, both sleep-deprived and non-sleep-deprived situations have already been inducers of mental fatigue.

The first step is sorting the data according to emotional reactions. A well-known model of the participant's emotional reactions is necessary for machine learning training. According to this paradigm, the participant's particular emotional valence must be induced through stimuli. Known emotional valence and arousal models can be obtained using feature extraction by capturing the EEG data of the participant's brain in a stimulated condition.

Second, a reference to the participant's other mental state is also required. For example, the brain's resting or starting state just before driving tasks can provide insight into how the game affects the participant's emotions and mental state. EEG data can be used to directly correlate the design and the participants' profile and capture the participant's initial/default state and other profiling constructs. The conceptual framework is based on these procedures:

1. The participants who provide EEG data from their sleep-deprived and non-sleep-deprived brain signals are volunteers who take part in this study.
2. Once the EEG device is attached to the patient's head, the patient is exposed to stimuli that elicit a specific emotion. Static images serve as the stimulus, evoking a particular emotional response in the viewer upon seeing them.
3. Following the emotional stimulation, the participant was simply put to undergo a driving simulation in three levels: easy, medium, and hard.
4. After the driving simulation, two types of EEG data will be acquired:
   i. Data with sleep-deprived emotional responses
   ii. Data with non-sleep-deprived emotional responses
5. The sleep-deprived and non-sleep-deprived data will be closely examined. The relationship between them can be learned and understood by analysing

the emotional responses within the sleep-deprived data and non-sleep-deprived data.

The classification process is separated into five classifiers (i.e. BLR, Linear SVM, NNN, MNN, and WNN): the best accuracy will be chosen to be the based classifier to measure emotional valence and arousal to detect mental fatigue. This idea can be implemented as a workable framework by using an existing approach as the foundation. Yaacob et al. (2019) have a comparable classification goal, and Figure 3.8 shows his approach to EEG emotion recognition based on the dimensional model of emotion.

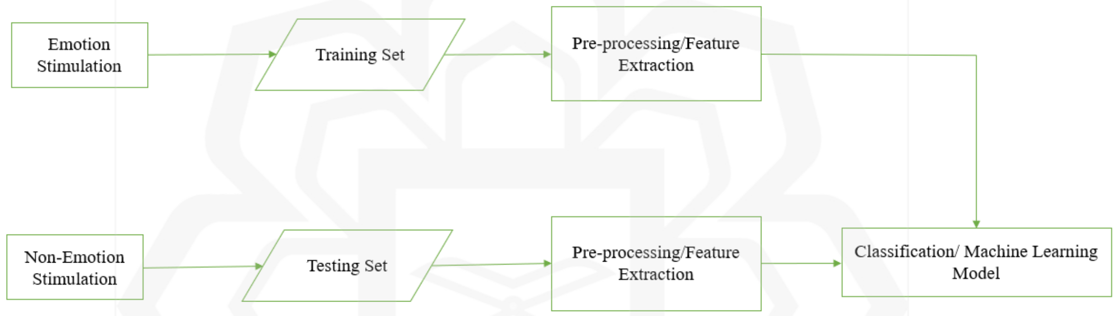

Figure 3.8 A working framework to establish an EEG emotion recognition based on the dimensional model of emotion (Yaacob et al., 2019)

In order to improve knowledge of the EEG emotion recognition system, the framework shown in Figure 3.9 was developed. The neurophysiological emotional profiling model will be strengthened by refining the current framework and incorporating it into an improvised framework structure. This framework has to be refined to meet this research's goals. Due to the similarity of the process, it is possible to add many similar processes for inputs originating from sleep-deprived and non-sleep-deprived data that represent states of mental fatigue. As a result, it is simpler to change the programming code to accomplish the study goals. Spreadsheets showing emotional reactions that occurred while the participant was sleep-deprived should be the final output of the framework.

The Neuro-Physiological Emotional Profiling Model of Mental Fatigue (NPEMMF) Framework, shown in Figure 3.9, is a novel working framework for classifying sleep-deprived and non-sleep-deprived data sets. It prepares the resulting emotional reactions in a valence and arousal spreadsheet. The emotional stimuli can then be statistically further examined to gain additional insight into the consequences of mental fatigue.

Adapting the NPEMMF architecture can accommodate other characteristics in addition to mental fatigue data. For example, the same framework can be used to classify the previously indicated resting state and brain performance activity that will be included in the data collection methodology. Classifying emotional responses from unstimulated activities is still done in the same way. The conceptual framework shown in Figure 3.10 serves as the conceptual foundation for this study and is the primary contribution to the fields of computer science, emotion, and mental weariness.

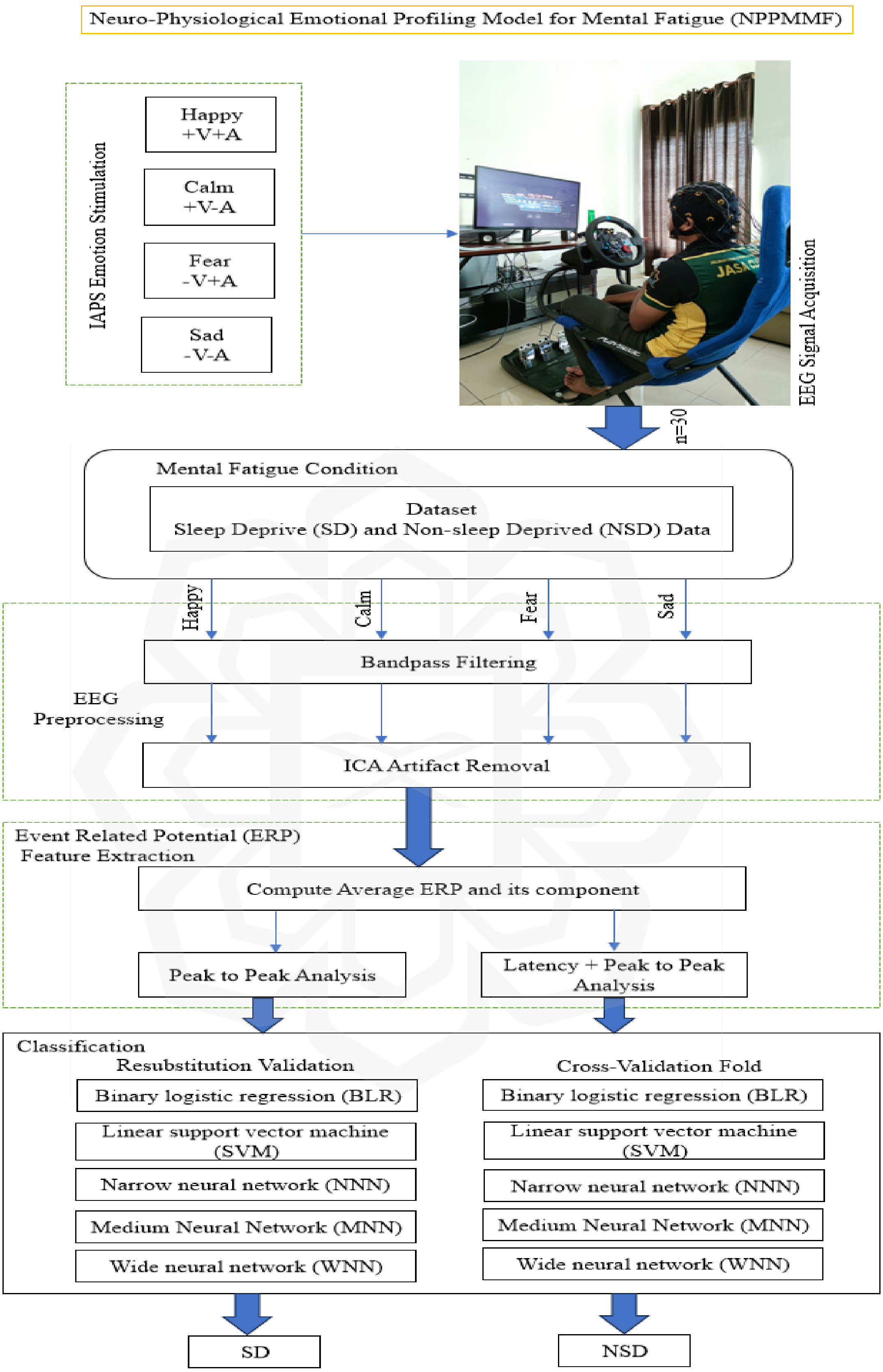

Figure 3.9 Neuro-Physiological Emotional Profiling Model for Mental Fatigue based on EEG emotion recognition on the dimensional model of emotion.

3.5.1 NPEMMF FEATURES AND SPECIFICATIONS

The NPEMMF framework is the data analysis plan for this research, which will be conducted as shown in Figure 3.9. First, data will be collected from the participants in (sleep-deprived and non-sleep-deprived conditions). The participants will then be exposed to the emotional stimuli named IAPS containing "Happy"," Calm"," Fear", and "Sad" stimuli. The data will be preprocessed and bandpass filtered into a certain frequency band for the next procedure.

On the feature extraction, the Event-Related Potential (ERP) was selected due to its capability in capturing emotional responses in high temporal resolution (Woodman, 2010). Then the feature-extracted data will be classified using five classifiers: Binary linear regression (BLR), linear SVM, Narrow neural network (NNN), Medium Neural Network (MNN), and Wide Neural network (WNN). This classifier is used in the feed-forward artificial neural network model classification process, which projects input data collection onto a set of suitable outputs. The study will use the best accuracy on the best classifier to quantify mental fatigue and non-mental fatigue.

The foundation of NPEMMF is from an existing framework (Yaacob, 2019). The elements that comprise NPEMMF are a combination of high-accuracy classification algorithms and feature extraction. This unique paradigm is anticipated to predict emotional responses. The design of NPEMMF is likewise modular. Comparable in flexibility to prefabricated building components, the framework can be applied to numerous other analysis constructs. The NPEMMF framework's different components can all be executed separately since it was built with Matlab. It is also feasible to run many participants in parallel, which expedites the categorization process for analysis.

3.5.2 NEURO-PHYSIOLOGICAL EMOTIONAL PROFILING MODEL FOR MENTAL FATIGUE WITH INTERNATIONAL AFFECTIVE PICTURES SYSTEM (IAPS)

This research uses five classifiers to classify mental fatigue EEG data with the individuals' emotional responses: Binary linear regression (BLR), linear SVM, Narrow Neural Network (NNN), Medium Neural Network (MNN), and Wide Neural Network (WNN). These five classifiers are used because they can provide accurate results.

The EEG data pertaining to the participants' emotional responses serve as the known variables in this instance. To obtain known emotional data, the participants must be stimulated to the intended emotional valence and arousal state while their EEG signals are being captured.

The International Affective Picture System (IAPS), a common emotional stimulus, is utilised to set up the emotional model. Following exposure to these stimuli, the participant's EEG signals corresponding to each distinct emotional valence and arousal are recorded. IAPS is a reputable image reference resource that elicits particular feelings and attention. Numerous studies have employed it, especially in psychology. As a result, it is an appropriate tool for this investigation.

The four primary emotions—happiness (positive arousal and positive valence), sadness (negative arousal and negative valence), calmness (negative arousal and positive valence), and fear (positive arousal and negative valence)—are represented by four sets of images in the IAPS material. The EEG Dabo Machine records brain signals while each category is exposed for a minute. The signal characteristics in these sets of EEG data match the recognised emotions. It is possible to develop a computer model for valence and arousal by using a feature extraction approach to these data.

The feature extraction method being used is known as the Event Related Potential (ERP). By analyzing the ERP of the emotional EEG data, the average signal frequency of the EEG signals can be characterized into distinguishable data sets. The result is the perceptron for classifying emotional valence and arousal. The computational model of the emotions is applied using a feedforward artificial neuro network to compare data of unknown emotional states. Consequently, EEG data collected during other activities – such as resting state, emotive stimuli, and driving simulation – will be used to analyse the emotional set of data to recognise their mental fatigue states. Correlation, classifications, and other statistical analyses can be analysed by curating emotional responses to emotive stimuli activities using mental fatigue participants.

3.5.3 Important IAPS Features

a. Elicitation of emotions:
   The IAPS is intended to evoke various emotions, including positive, negative, and neutral affective states. The images have been deliberately chosen to elicit several feelings, including happy, calm, fear, and sad.
b. Norms that are standardised:
   Based on ratings from a sizable sample of individuals, the IAPS offers standardised norms for the emotional reactions to the images. These standards are employed to guarantee that the images are uniformly assessed throughout various research projects and demographic groups.
c. Multidimensional illustration:
   Valence, arousal, and dominance are all included in the multidimensional space that the IAPS uses to express emotions. This makes it possible to comprehend emotions in greater complexity and nuance, which is useful for a variety of applications like affective computing and user experience design.

One of the most crucial elements of this study is the IAPS. It holds the key to obtaining a computational emotional model. One of the goals of this research is to statistically analyse mental fatigue by converting the participants' emotional responses (valence and arousal) into a numerical and measurable form. This is made possible by the development of EEG technology. The emotional valence and arousal computational models that will be used to categorise mental tiredness EEG data are constructed using these numerical data as building blocks. Developing a perceptron that can classify unknown data without the IAPS stimuli will be impossible.

3.7 CHAPTER SUMMARY

This chapter concludes the research methods and experimental techniques employed in this study. Novel frameworks are necessary for novel research. The NPEMMF framework was developed based on an operational framework already in place to guarantee the accomplishment of the study objectives. Thanks to the proven record of the current machine-learning classification technique, NPEMMF is anticipated to operate with high accuracy.

The NPEMMF consists of modular and adaptable components. Despite its lack of a user-friendly interface, its constituent parts are simple to run and debug. MATLAB Studio's elegant and simple architecture makes operating the source code without an interface easier.

The DABO EEG equipment is more than capable of collecting data in terms of hardware. On paper, its specifications are really good. However, its inability to be used when using an external power source and poor battery recharge rate could slow down the pace of data collection. Eventually, without a consistent stimulus, NPEMMF would not function. IAPS is crucial to this study because it provides well-known data to create a neuro-affective computational model. This paradigm is key to unlocking unclassified data, which is essential for accomplishing research goals.

The procedure and tasks are written in a checklist form to guarantee consistency in the execution of data collection for each session. In order to prevent errors and ensure that nothing is overlooked, checklists are crucial. The checklist in Table 3.4 is designed to make sure that the data collection is properly recorded, arranged, and labelled to facilitate future data analysis.

Table 3.4 Data Collection Protocol Checklist

Section	Activity	Remark	Duration
Part 1: Baseline Recording	Eyes closed (1 minute) To initiate the baseline for EEG data, participant will be required to sit still with eyes closed. This is to assess the default state of the brain.	- Total silence - No movements - Set time limit - Set task as Eyes Close	1 minute
	Eyes open (1 minute) Similar to eyes closed, but this time the participant will sit still with eyes open and staring at a blank white computer screen.	- As above - Blank screen with a center marking - Set time limit - Set task as Eyes Open	1 minute
Part 2: Emotion Stimuli	Emotion stimuli (4 minute, 1 minute for each different emotions) This procedure is to stimulate a particular emotion by exposing the participant with a specific picture. The recorded emotional signals reacting to the stimuli will serve as a model for this research to analyse the effects of mental fatigue in the later sessions. There are 4 emotions to capture; each will take 1 minute to record the EEG and PPG data.	- IAPS - Do not mention the emotions - Take note on the emotional sequences - Set time limit - Label suffix as emotion numbers - Set task as Others	4 minutes

Part 3: Driving Simulation	Easy Driving Task	- Use speakers for the driver to feel the driving situation - Use a projector to project the scenery of the road - Set 5 minute time limit for each task	5 minutes
	Medium Driving Task		5 minutes
	Hard Driving Task		5 minutes
Part 4: Baseline Recording	- Eyes closed (1 minutes) - Eyes open (1 minutes)	As on row 1 and 2 above	2 minutes
	TOTAL DURATION		23 minutes

CHAPTER FOUR

EXPERIMENTAL SETUP AND DATA ACQUISITION

4.1 INTRODUCTION

This chapter discusses the actual procedure for data acquisition, which lays out the experimental design. The way participants are handled during experiments is crucial in this respect. It was expected that proper handling would minimize participants' exhaustion throughout the lengthy procedures and therefore reduce errors. The consistency and efficiency of the data-collecting sessions were further enhanced using checklists.

In particular, the methods for selecting participants, the experimental activities used to create different degrees of mental fatigue, and the EEG acquisition protocols used to record brain activity are all covered in this chapter. To show how consistency and signal quality were preserved throughout the investigation, a detailed discussion of the EEG equipment configuration, electrode positioning, and recording settings is provided. To guarantee adherence to research standards, ethical issues and data handling practices are also covered. This chapter aims to give a thorough account of how the EEG data were methodically collected under carefully monitored circumstances in order to support the study's goals.

4.2 Participants

Data were gathered from targeted, randomly selected adult samples (N=30) aged between 20 and 30. Prior to the experiment, participants were briefed on the experimental protocol and were required to sign a consent letter. The form also included a questionnaire for the purpose of understanding participants' profiles, such as:

1. Personal information
2. Driving experience
3. Sleep conditions

4.2.1 Personal Information

These are the essential details about the participant's identification. Nonetheless, such data is kept private and was not disclosed to adhere to privacy regulations. The data gathered under this heading are:

i. Name
ii. Participant Number
iii. Gender
iv. Age range
v. Driving License
vi. Illness

During the thesis, the participants will only be referred to by their identifying numbers: SD1, SD2, NSD1, NSD2... until NSD15. The participants' data were labeled with an anonymous identifier to protect individual privacy in line with Personal Data Protection Act (PDPA) regulations. Participants who experienced sleep deprivation are denoted as SD, while those who did not are labeled as NSD. Individuals who suffer from past brain injury were excluded from the study because it might affect the wave of the brain signal and become another variable that differentiates the signal from another participant. However, this information only includes the most recent history of the participant's brain-related illnesses, not their unrelated illnesses. Heart rate, blood pressure, and body mass index (BMI) are a few examples of statistics that are not thought to be included in questionnaires because they have little effect on brain signal activity. Additionally, before the experiment was held, the participants were reminded not to consume coffee 24 hours before the trial or anything that included caffeine or take any medication that would affect brain activity 12 hours prior.

4.2.2 Driving Experience and Driving Simulator

All of the participants need to own a valid driving license and have at least two years of driving experience. This is important since there will undoubtedly be a difference between someone who seldom drives a car and someone who already has two years of driving experience.

4.2.3 Sleep-Deprived and Non-Sleep-Deprived

Participants will be divided into 2 groups:

1. Sleep-deprived

   Sleep-deprived participants get less than 6 hours of sleep per night (Gray et al., 2014). Sleep deprivation is the state of regularly not receiving enough sleep. It happens when a person does not get the necessary quantity of sleep, which is essential for their well-being and good functioning. All participants were required to sleep less than 6 hours to meet the condition for sleep deprivation.

2. Non-sleep-deprived

   Under the well-rested condition, participants were instructed to sleep at least 7 hours before the experiment, as sleeping seven or more hours is known to maintain healthy mental alertness (Kripke et al., 2002). A person who is "non-sleep deprived" or well-rested regularly obtains the recommended amount of sleep each night for their particular needs. All participants were required to sleep at least 7 hours so that the condition of non-sleep deprivation was met.

Warner (2007) claims that emotional responses are impacted by fatigue and sleep deprivation. Sleep appears to be crucial for regaining everyday functioning, even if lack of sleep makes us more emotionally sensitive (Vandekerckhove & Wang, 2018). People who do not get enough sleep will exhibit more emotionally illogical and unstable behaviour. Individuals who do not get enough sleep have sixty percent more mood swings and emotions. It would be helpful to know the participant's sleeping hours as this study focuses on emotional profiling of mental fatigue.

4.3 Experimental set-up

Due to careful preparation, the actual data collection proceeded without incident or major setbacks. Though a few minor glitches did arise from time to time, the session continued uninterrupted.

It should be emphasised that the data gathering was done in December 2021, after the COVID-19 pandemic phase 2 National Recovery Plan for the states of Selangor, Kuala Lumpur and Putrajaya. During this period, research activities were allowed on campus with additional safety measures. This fact explains how such a private setting and restricted physical contact may occur throughout the data collection sessions. The procedure needs to be modified by wearing face masks and gloves during the experiment process. If this process were to be used before the pandemic, then all procedures would not need to be modified.

The experiment was conducted in the Pervasive Computing and Brain Development Research Group Lab (PCBDG), International Islamic University Malaysia (IIUM). The experimental session started at 9.00 am until 4.00 pm. Each person was allocated an hour to complete the experimental test. Participants will be seated in a closed, lighted, and temperature-controlled room. EEG signals were captured using a 19-channel DABO machine. The sampling frequency was 250Hz, and the bandpass was filtered between 0.01 and 15 Hz. Data will be stored in the external hard drive of the research lab.

The setup of the EEG equipment was expected to take no more than 10 minutes. To guarantee that the 19 sensors connecting to the participant's scalp surface and the EEG amplifier are linked correctly, caution and attention to detail are needed while using the apparatus. Applying electrode and skin cleansing gel between the scalp surfaces and the electrode sensors can enhance the signal connection. The gel enhanced electrical conductivity without causing any hair damage to the wearer.

The protocol or the paradigm of the task sequence for the participant is divided into three main tasks, as discussed in the previous chapter. For each performed task, the participants were advised to minimize movements to reduce possible noises and enhance the quality of data signals. In addition, the following quality control procedures were performed for optimal EEG data acquisition:

1. Dimly lit room environment
   For dark rooms, the patient has to concentrate solely on the visual stimuli; the room has to have the ability to become entirely dim. But a windowless room might seem cramped, uncomfortable, and unsafe for the participant. Thus, the solution of a window blind.
2. Sound-attenuated environment
   There should be no background noise in the area. Any source of loud noises, such as busy activities, must be avoided.
3. Appropriate ventilation setup
   This is clear. However, using air ducts for conventional ventilation can allow outside sounds to enter the space. Better still, get a room with air conditioning.
4. Appropriate power supply setting and wiring
   This is also very important. The EEG equipment must be powered by an electrical outlet, as does the workstation for data storage and transfer, the tablet for questionnaire and profiling sessions, and the computer for the driving simulator.

4.4 EEG DATA PREPROCESSING

4.4.1 DATA VISUALIZATION AND EEG CHANNELS SELECTION

To find and choose possible ERPs and EEG channels, the ERP data was visualised prior to EEG channels selection (Muskan et al., 2022). Afterwards, data from particular ERPs and channels were preprocessed. The ERP data is first collected from the EEG signals by averaging many temporal segments, and it is then categorised into several channels and temporal segments. The connecting network of the channel's nodes was constructed using the retrieved binary matrix. Binary logistic regression (BLR) is the classification that will be used in this preliminary work. The accuracy and area under the curve (AUC) of the classification performance based on the chosen characteristics are compared and examined.

This ERP emotion analysis used 19 channels. Data were visualized according to the following regions: frontal (F), temporal (T), central (C), occipital (O), and parietal (P). Based on the visualization, it was revealed that all prefrontal and frontal pole areas were found to be of greater magnitude than other subregions (Figure 4.1).

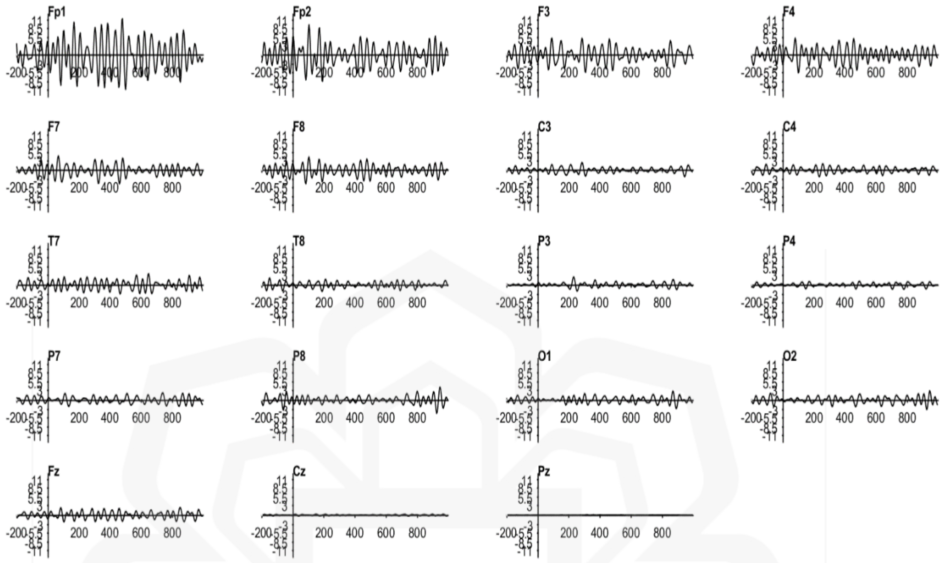

Figure 4.1 ERP Emotion Features from the 19-Channels DABO EEG

The substantial amplitude changes were found in the channels Fp1, Fp2, F3, F4, F7, and F8 of the frontal pole. This initial finding was consistent with a study of ERP coherence in both non-fatigued and fatigued states by X. Liu et al. (2017), as in their experimental studies, they found that the ERP alpha coherences at frontal regions (FP1-FP2 and F3-F4) were significantly higher than at central (C3-C4), parietal (P3-P4) and occipital (O1-O2) regions. Additionally, the other mental fatigue study shows an increase in both theta and alpha power over time, suggesting mental fatigue recovery following cognitively demanding tasks.

Considering the initial finding and the previous report, this explains the basis of utilising ERP emotion features; EEG channels Fp1, Fp2, F3, F4, F7, and F8 will be used for this study, thus resulting in Table 4.1, which shows the channels that will be used for this research purpose.

Mental fatigue significantly impacts EEG activity in the frontal and central regions of the brain (Tran et al., 2020). Strong brain networks between frontal and central regions are also demonstrated by connectivity research to exist when a person experiences mental fatigue (Fonseca et al., 2018; J. P. Liu et al., 2010; Sun et al., 2014). Thus, the electrode channels we are further analysing in this ERP research were Fp1, Fp2, F3, F4, F7, F8, and Cz due to their relation to emotion and mental fatigue.

Table 4.1 Related Channels for Emotion Analysis

Region	Channels
Frontal Area	Fp1, Fp2, F3, F4, F7, F8
Central Region	Cz

4.4.2 FREQUENCY BANDS FOR ERP EMOTION ANALYSIS

Upon selection of the EEG channel, the analysis proceeds with EEG frequency band selection. As seen in Figure 4.2, the initial examination of the EEG-frequency bands shows a burst-like oscillation of the beta band in Fp1. There is a possibility that sleep deprivation is more likely to be the cause of the altered amplitude in the other bands, even though the underlying mechanism cannot be confirmed at this stage of the investigation.

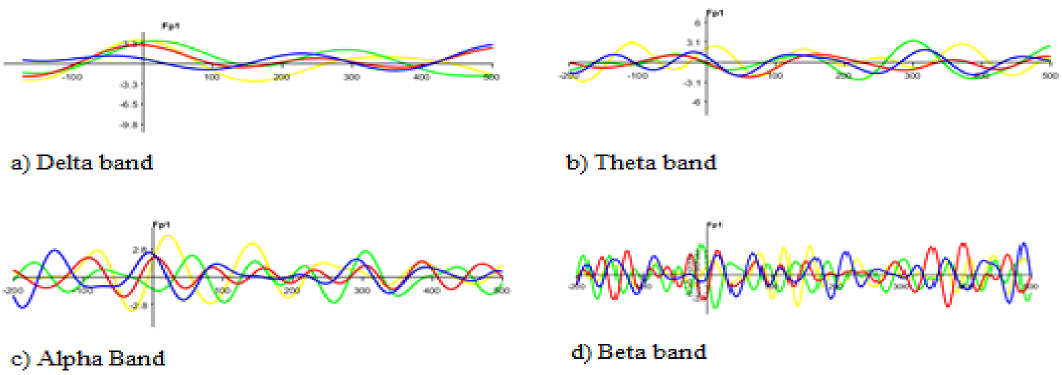

Figure 4.2 ERP Emotion Features for Each Frequency Band: A) Delta, B) Theta, C) Alpha, and D) Beta

Wu et al. (2021) observed that sleep deprivation and changes in alpha-band oscillations are closely related. Mental fatigue was shown to be correlated with significant increases in theta wave activity and somewhat large increases in alpha wave activity, while EEG spectral changes in beta wave activity proved to be imprecise and varied (Tran et al., 2020). To the best of the authors' knowledge, little research explains the alterations caused by sleep deprivation for the beta band (14–30 Hz).

Furthermore, a study of several frequency bands from a single channel (Fp1) demonstrated the beta band's burst-like activity (Figure 5.2). Some researchers view these fluctuations in the beta frequency as mysterious, and it is unclear how they might benefit emotion studies. Additionally, there was no discernible difference in the beta power spectrum between sleep deprivation and normal sleep (Perrier et al., 2016).

4.5.5 Bandpass Filtering for Event-Related Potential (ERP) Data

Preprocessing is an essential stage in the analytic pipeline, as several kinds of noise often taint ERP data, as shown in Figure 4.3, the unfiltered data of ERP. A popular preprocessing method is bandpass filtering, which makes it possible to separate the precise EEG signal frequency components that are most important for ERP analysis.

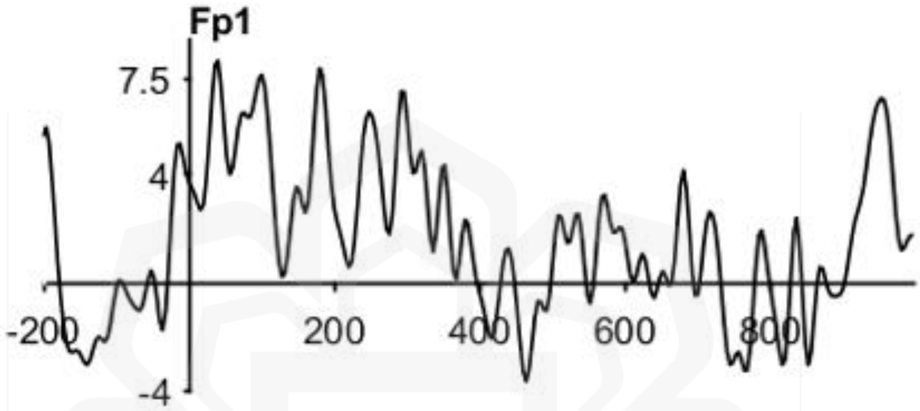

Figure 4.3 Unfiltered ERP data

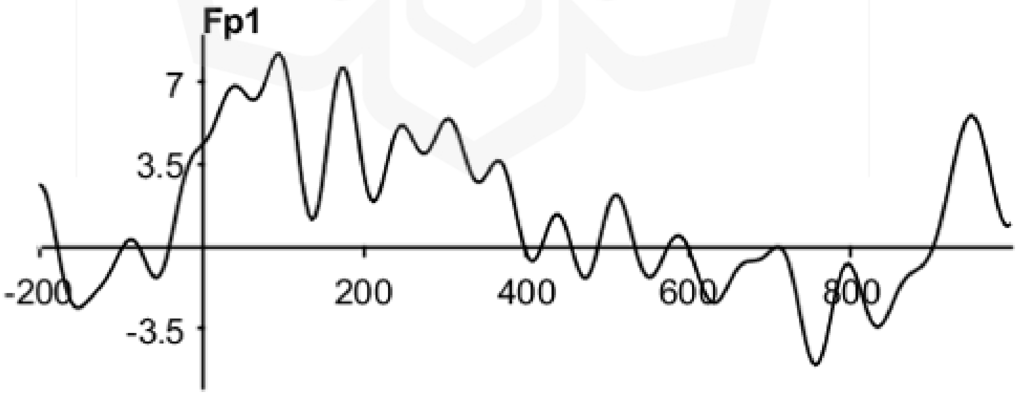

Figure 4.4 Bandpass filtering 0.01 Hz to 15 Hz or ERP data

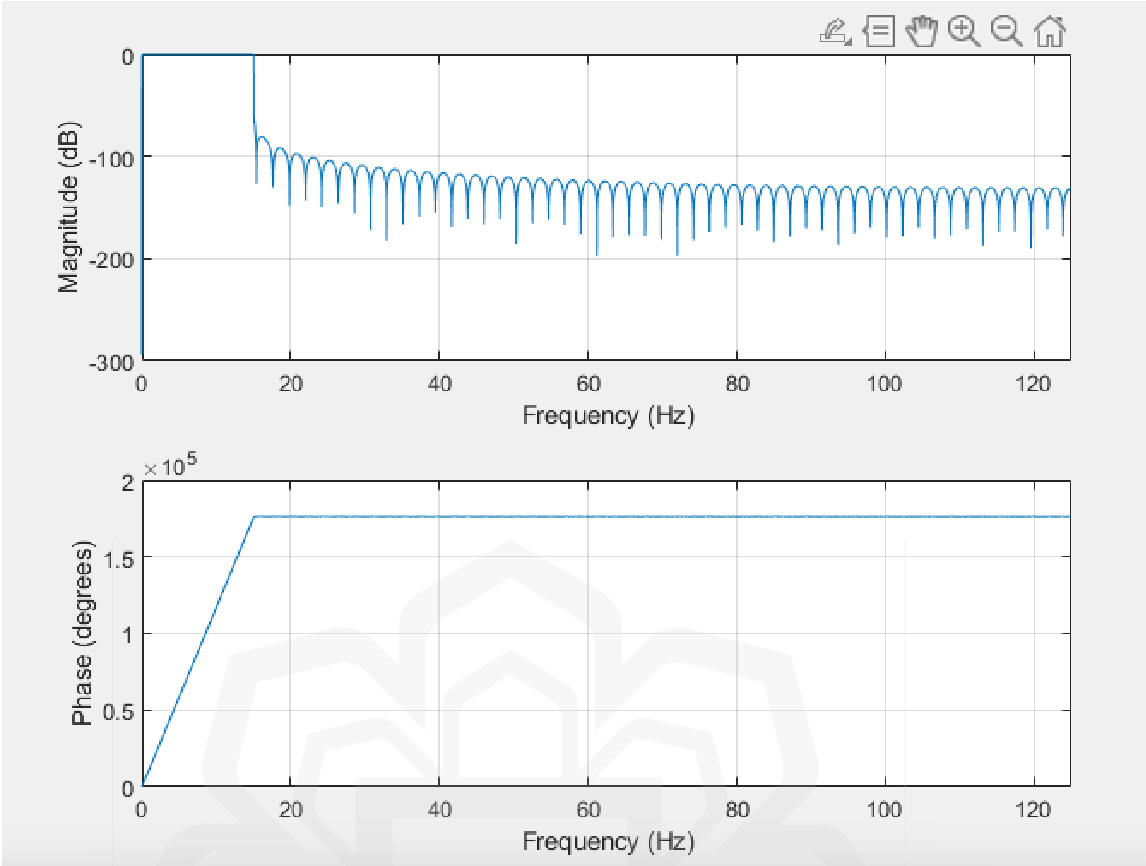

Figure 4.5 Filter design 0.01 – 15 Hz bandpass filter

A signal processing method called bandpass filtering reduces frequencies outside of a certain range while allowing frequencies within that range to pass through. This research study uses a normal frequency range of interest for ERP data which is from 0.01 Hz to 15 Hz, as shown in Figure 4.4 and Figure 4.5, as the analysis only intended to capture the delta, theta and alpha frequency bands.

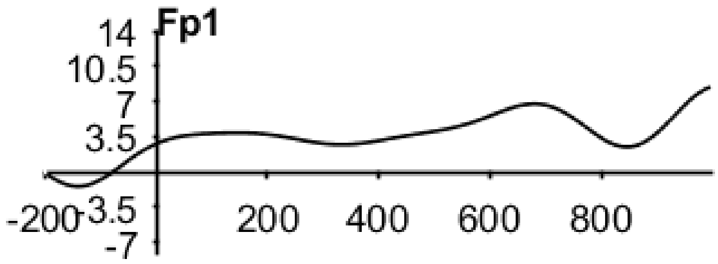

Figure 4.6.a Filtered ERP data of Delta Band

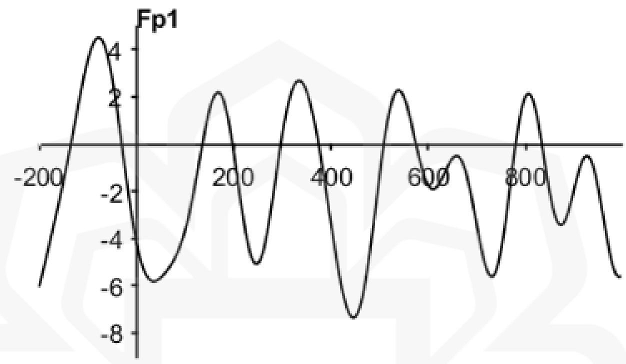

Figure 4.6.b Filtered ERP data of Theta Band

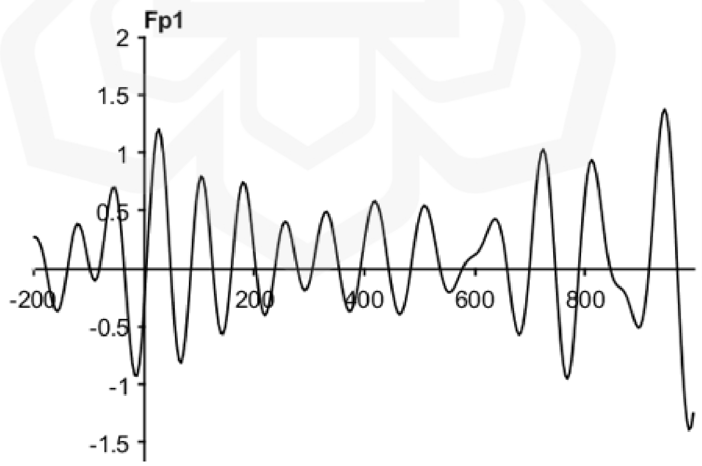

Figure 4.6.c Filtered ERP data of Alpha Band

This step enabled component isolation as different cognitive processes are associated with specific frequency ranges. Filtering helps isolate these components, making studying the underlying cognitive processes easier. Additionally, filtering ensures that the data across different participants and sessions are standardised, reducing variability unrelated to the experimental manipulations.

The ERP data signal in Figure 4.6a was filtered exclusively using the delta band range of 0.5–4 Hz, the ERP data signal in Figure 4.6b was filtered exclusively using the theta band range of 4–8 Hz, and the ERP data signal in Figure 4.6c was filtered exclusively using the alpha band range of 8-13 Hz.

As illustrated in the above figure, there are many differences between the filtering process focusing only on a specific frequency band (Figures 4.6a, 4.6b, and 4.6c) and the bandpass filtering from 0.01 to 15 Hz as in Figures 4.4. Based on this observation, this analysis focused on specific wave bands due to the concern of losing important information within the ERPs.

From the visualizations, it was concluded that the best components for emotion and mental fatigue analysis consisted of the ERPs of delta, theta, and alpha bands. Thus, the bandpass filtering of ERP data, ranging from 0.01 to 15 Hz, was selected for reducing the noise and obtaining all the frequency bands related to emotion and mental fatigue data.

The alpha, delta, and theta bands have been the subject of much research on the social and emotional development of both sleep-deprived and non-sleep-deprived individuals because these bands are associated with mood and sleep quality. As a result, only the alpha, delta, and theta bands were used to evaluate the ERP feature patterns for each location.

The ERP signal in this study is the reference EEG signal for Neurophysiological profiling of mental fatigue in non-sleep-deprived and sleep-deprived conditions. When discussing event-related potentials (ERP), the average waveform that results from averaging the EEG data from several participants or trials is referred to. The brain's reaction to a particular event or stimulus is deduced from the ERP signals. Attention, memory, and emotion are examples of cognitive processes that variations in the amplitude or latency of ERP components may impact.

4.5.6 Independent Component Analysis (ICA) Artifact Removal

An efficient computational method, independent component analysis (ICA), can divide an EEG signal into beneficial, independent components. This method is especially helpful for signal processing applications like EEG signal analysis. Figure 4.7 shows the signal of an EEG signal before and after using ICA decomposition.

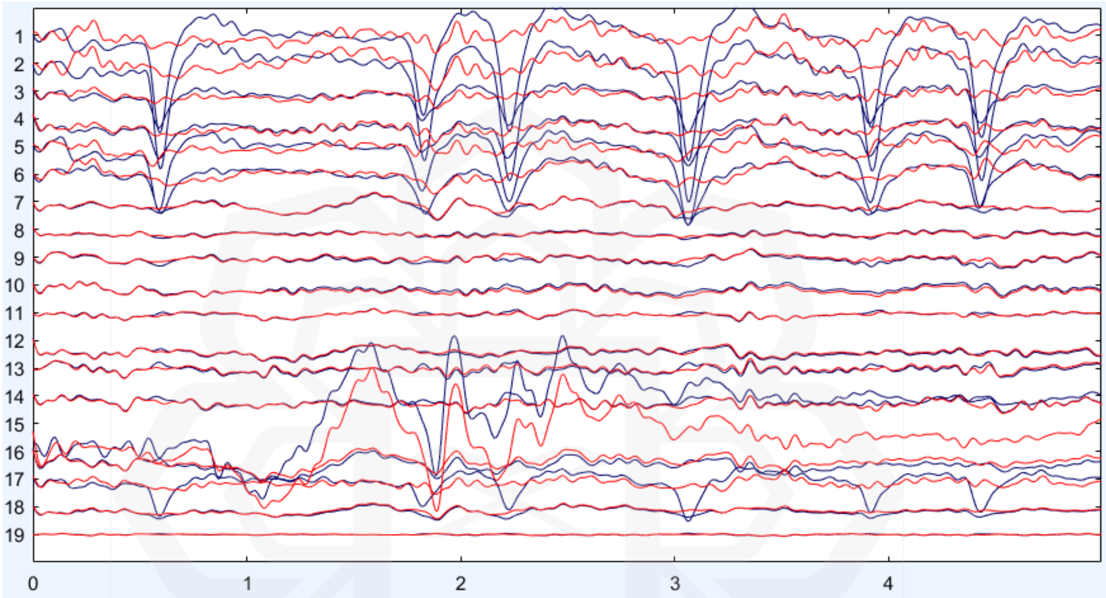

Figure 4.7 EEG Signal of one participant, blue represents the EEG signal before ICA decomposition, and red represents the EEG signal after ICA decomposition

The blue-coloured EEG signal in Figure 4.7 contains various types of noise and artefacts that further complicate the task of identifying the underlying sources. This is due to certain moving artefacts and eye-blinking artefacts. Thus, the signal needs to undergo ICA decomposition, where we remove the eye movement artefacts.

Following the EEG signal's ICA decomposition, the noise signal is diminished, as shown in the red-coloured EEG signal (Figure 4.7). ICA can aid in noise reduction by identifying and isolating separate components. A cleaner signal results from the removal or suppression of components that are identified as noise. ICA often yields

EEG signal components that are easier to interpret, as shown in red-coloured signals. The benefits of ICA decomposition are:

1. Enhanced Signal Clarity: ICA improves the signal's clarity by dividing its sources, facilitating analysis and interpretation.
2. Artefact Removal: ICA is useful in eliminating artefacts from signals, such as eye blinks or muscle movements, in EEG data to produce cleaner data for analysis.
3. Improved Analysis: Separating sources offers more precise insights into the signal's fundamental elements, enabling improved analysis in various applications.

Signals undergo a remarkable transition through ICA decomposition from a complicated, entangled mixture to a collection of separate, comprehensible components. Signals were difficult to analyse before ICA due to their complexity, correlation, and noise content. The signals are clearer and easier to interpret after ICA decomposition, which improves the capacity to examine and comprehend the underlying events. This transformation is especially helpful in this NPEMMF model, where clean and independent signals are essential for precise analysis and diagnostics. ICA is a vital tool in contemporary signal processing because of its capacity to isolate sources and reduce noise.

4.6 EVENT-RELATED POTENTIAL AS FEATURE EXTRACTION

The brain reacts to a particular sensory, cognitive, or motor event as an event-related potential (ERP). In neuroscience and psychology, event-related potentials (ERPs) are useful instruments for deciphering the order and timing of brain functions in response to certain stimuli. Event-related potentials (ERP) are brain-generated electrical potentials associated with certain external or internal events, such as stimuli, reactions, or decisions (Luck, 2012). The electroencephalogram (EEG), which measures brain activity, is the source to measure event-related potentials (ERP).

4.6.1 Average ERP Plot

For the purpose of feature extraction, average ERP plots were generated to yield the main components of ERPs. These three main ERP components are:

1. Latency

   The term "latency" describes the elapsed time between a stimulus's presentation and the occurrence of an ERP component. Milliseconds (ms) are used to measure this. The amount of time that passes before the brain reacts to emotional stimuli is known as latency. As shown in Figure 4.8, latency quantifies the duration between the beginning of a visual input and the corresponding ERP response, for instance. There are distinct latencies among the various ERP components.
2. Peak-to-peak analysis

   The ERP waveform's peak is the location where, for positive peaks, the amplitude reaches its highest or, for negative peaks, its minimum. The ERP waveform's highest (positive peak) or lowest (negative peak) point after a stimulus is used to identify peaks. They serve as essential indicators in the definition of the ERP elements.

Figure 6.5 shows the ERP data signal analysis results of peak-to-peak analysis. As illustrated in Figure 6.5, the peak ERP components included in this study were P100, N100, P200, N200, P300, N300, and six LPP components. Furthermore, latency of each peaks were extracted from the ERPs resulting in twelve latency features per subject per channel.

For identifying the substantial contribution of these identified features, we combined these components into several configurations as shown in Table 4.2. The features are arranged into a feature matrix consisting of the ERP components as the columns and the participants as the row instances. The column features were arranged according to channels in 4 parts: Fp1 and Fp2 (prefrontal region), F3 and F4 (frontal region), F7 and F8 (frontal region), and Cz (central region). Overall, this resulted in 24 feature matrices ranging from a total of 6 to 48 ERP features. These matrices were formed for each emotion dataset of calm, fear, happy, and sad.

Table 4.2 Feature combinations for NPEMMF model. All ERP components consist of P100, N100, P200, N200, P300, N300, six LPP components, and their respective latencies 2. P100, N100, P200, N200, P300, N300, and their respective latencies 3. Six LPP components and their respective Latencies.

Emotion dataset	Features	Feature combination	Number of features per participant per channel	Channel combinations	Total features per participant
Happy Calm Fear Sad	All ERP components	Peak to peak + latency	24	FP1, FP2	48
		Peak to peak only	12		24
		Peak to peak + latency	24	F3, F4	48
		Peak to peak only	12		24
		Peak to peak + latency	24	F7, F8	48
		Peak to peak only	12		24
		Peak to peak + latency	24	Cz	24
		Peak to peak only	12		12
	Early ERP components and latency	Peak to peak + latency	12	FP1, FP2	24
		Peak to peak only	6		12
		Peak to peak + latency	12	F3, F4	24
		Peak to peak only	6		12
		Peak to peak +	12	F7, F8	24

		latency			
		Peak to peak only	6		12
		Peak to peak + latency	12	Cz	24
		Peak to peak only	6		12
	Late ERP components and latency	Peak to peak + latency	12	FP1, FP2	24
		Peak to peak only	6		12
		Peak to peak + latency	12	F3, F4	24
		Peak to peak only	6		12
		Peak to peak + latency	12	F7, F8	24
		Peak to peak only	6		12
		Peak to peak + latency	12	Cz	24
		Peak to peak only	6		12

Understanding various levels of emotional processing is possible with each ERP component because, as highlighted in Chapter 2, each of the studied ERP components relates to emotion and sleep deprivation.

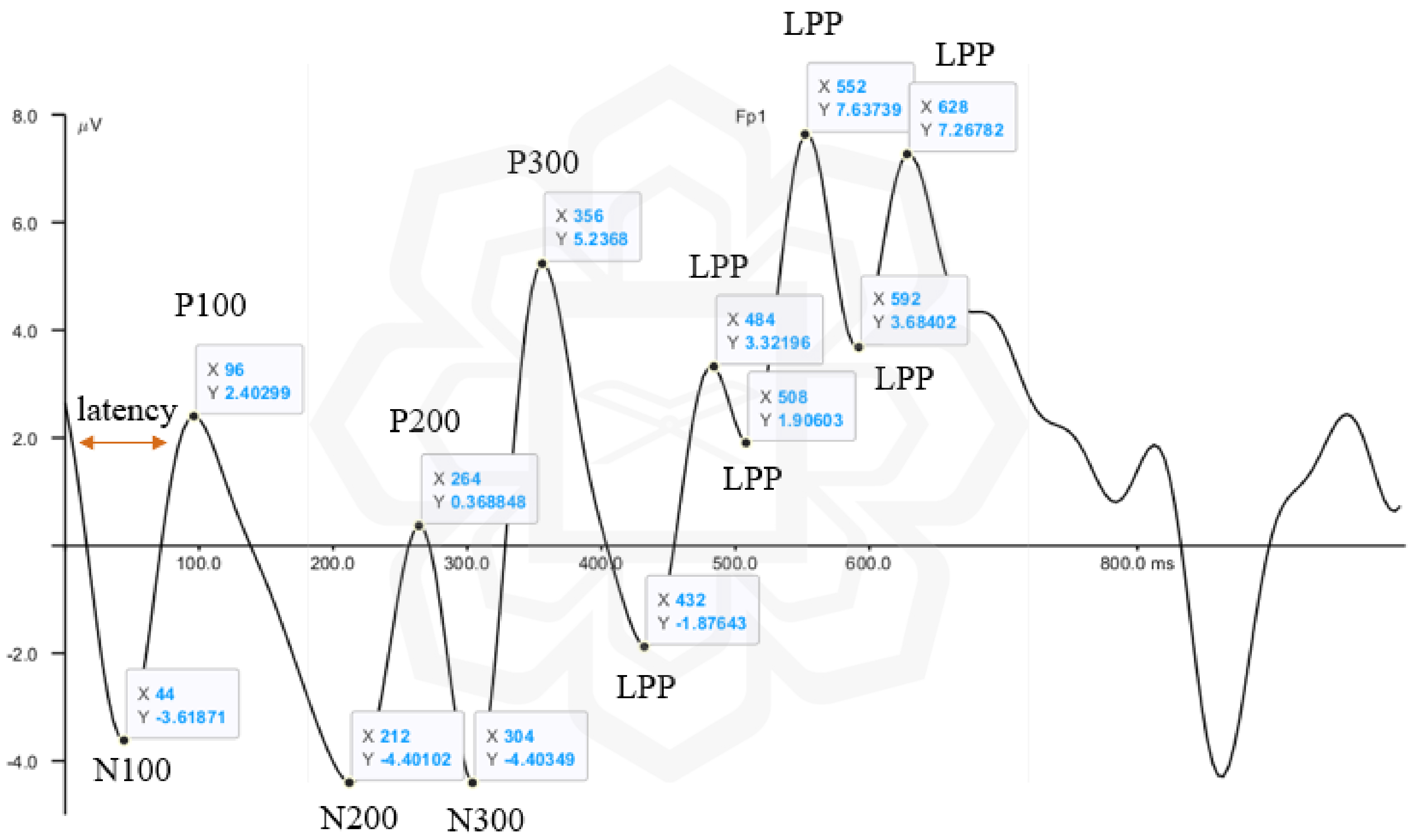

Figure 4.8 Peak-to-peak analysis of ERP data signal for one participant

4.7 CLASSIFICATION AND ITS PERFORMANCE VALIDATIONS

A classifier is a machine learning model or algorithm used in EEG (electroencephalogram) signal processing that takes the signal's attributes as input and generates a classification or prediction based on the signal's characteristics. The purpose of an EEG classifier is to identify patterns or features in the EEG data that are associated with specific cognitive states, emotions, or conditions such as mental fatigue. In this study, we will be using five classifications:

1. Binary logistic regression
2. Linear support vector machine
3. Narrow neural network
4. Medium neural network
5. Wide neural network

In statistical modelling and machine learning, assessing a model's performance is essential to ensure its accuracy and applicability to new data. Cross-validation and resubstitution validation are two popular methods for this. While each of these techniques provides a different way to estimate a model's potential to do well on fresh, untested data, their methods and the accuracy of their findings vary greatly. Accuracy analysis is one of the most crucial parts of the research process. The correlation between emotional valence and arousal and the recorded EEG data is verified. Without understanding how brain signals relate to emotional context, this research would not have been possible in any case.

1. Cross-validation folds
   Protects against overfitting by partitioning the data sets into folds and estimating accuracy on each fold (The MathWorks Inc., 2022).
2. Resubstitution folds
   No protection against overfitting. The application uses all the data for both training and validation (The MathWorks Inc., 2022).

Table 4.3 Resubstitution validation technique for latency + peak in (N1-P3 and LPP)

	AVERAGE
Binary Logistic Regression	0.99
Linear SVM	0.70
Narrow Neural Network	0.94
Medium Neural Network	0.99
Wide Neural Network	0.99

Table 4.4 Cross-validation folds technique for latency + peak in (N1-P3 and LPP)

	AVERAGE
Binary Logistic Regression	0.49
Linear SVM	0.40
Narrow Neural Network	0.42
Medium Neural Network	0.48
Wide Neural Network	0.50

Table 4.5 Resubstitution validation technique for only peak (N1-P3 and LPP)

	AVERAGE
Binary Logistic Regression	0.99
Linear SVM	0.82
Narrow Neural Network	0.99
Medium Neural Network	0.98
Wide Neural Network	0.98

Table 4.6 Cross-validation folds technique for only peak (N1-P3 and LPP)

	AVERAGE
Binary Logistic Regression	0.51
Linear SVM	0.6
Narrow Neural Network	0.59
Medium Neural Network	0.56
Wide Neural Network	0.63

Although Tables 4.3 and 4.5 show that the resubstitution validation technique has a higher average than cross-validation folds in every aspect of the result, this does not mean it is more reliable. When assessing the performance of classification models, cross-validation—especially k-fold cross-validation—is usually preferable to resubstitution validation. This is a thorough justification of why cross-validation is preferable.

An overview of validation for resubstitution validation involves using the complete dataset to train a model and then using the same dataset to assess the model's performance. Tables 4.3 and 4.5 show that the average results of each classification using the resubstitution validation technique are high. The lowest average is 0.70, followed by 0.82, 0.94, 0.98, and 0.99. This method, in which the model is tested using data it has already seen, frequently results in optimistic performance estimations.

Table 4.4 and Table 4.6 show that the average results of each classification using the cross-validation fold technique are not as high as resubstitution validation. Table 6.2 shows ERP components' latency plus peak value (N1-P3 and LPP). With BLR at 0.49, Linear SVM at 0.40, NNN at 0.42, MNN at 0.48, and WNN at 0.50. Meanwhile, Table 6.4 shows ERP components' only peak value (N1-P3 and LPP), with BLR at 0.51, Linear SVM at 0.60, NNN at 0.59, MNN at 0.56, and WNN at 0.63. Thus, WNN is already being decided as a classification process, and the result needs to be addressed on a 0.63 average. Although the average is only 0.63, it is considerably higher. Cross-validation is a robust and widely used technique for model validation that involves partitioning the dataset into multiple subsets or "folds." The model is trained on a portion of these folds and tested on the remaining fold, with the process being repeated multiple times. This approach mitigates the risk of overfitting and provides a more reliable estimate of the model's performance by ensuring that every data point is used for training and validation. Common variants of cross-validation include k-fold cross-validation.

On the other hand, resubstitution validation is a simpler and less computationally intensive method where the same dataset used to train the model is also used to evaluate its performance. While this technique is straightforward and easy to implement, it tends to provide overly optimistic estimates of the model's accuracy, as it does not account for its ability to generalize to new, unseen data. This lack of external validation often leads to overfitting, where the model performs exceptionally well on the training data but poorly on new data.

Cross-validation fold techniques are much better because the model's performance is evaluated using the same training data set. Resubstitution validation may result in overfitting. Accordingly, the model might function well on training data but badly on unobserved data. Consider using a dataset to train a sophisticated model. When assessed on the same dataset, it may pick up on the noise and finer points of the training data, resulting in high accuracy but poor generalization to fresh data. To provide a more accurate evaluation of the model's generalisation performance, cross-validation evaluates the model on various subsets of the data it has not seen during training.

Using cross-validation, the model's performance can be estimated more reliably and steadily by averaging the results over k distinct folds. This is especially crucial for small datasets because of the potential for large performance variance. For instance, dividing a dataset of 100 samples into 10 folds, each with 10 samples, and executing the model 10 times yields 10 distinct performance estimates. The specifics of any one fold are unlikely to impact the average of these calculations.

In resubstitution validation, the full dataset is used for testing and training, which may provide a distorted picture of the model's performance. Cross-validation, conversely, guarantees that each data point is used for testing and training, but never simultaneously. For example, in 10-fold cross-validation, 100 samples are used for validation, and 900 samples are used for training for a dataset of 1000 samples. Every sample appears in the validation set precisely once over tenfold.

The model's performance varies with different subsets of the data, and cross-validation helps to explain this variation. This fluctuation is essential for evaluating the model's stability and robustness. For instance, significant variability suggests that the model may not be robust if it performs well on some folds but badly on others. Cross-validation can help to find these differences.

Cross-validation provides a more thorough and trustworthy approach when evaluating a model's performance than resubstitution validation. It lessens the bias caused by overfitting, offers a more accurate performance estimate, makes better use of the data, and aids in comprehending model variability. Because of these benefits, cross-validation is a recommended technique in machine learning for assessing categorization models. This cross-validation technique will be used for the research classification process.

For preliminary analysis, classification targets were set as 0 for sleep-deprived and 1 for non-sleep-deprived. From the results, it was indicated that the best performing classifiers were the 3 configurations for MLP, consisting of WNN, MNN, NNN, Linear SVM, and BLR. For simplicity, standard hyperparameter settings were utilized for all classifiers according to MATLAB’s classification learner toolbox.

4.8 SUMMARY OF EXPERIMENTAL SET-UP AND DATA ACQUISITION

The process of gathering the data proceeded really easily. All of the necessary data are obtained in the intended manner for analysis. Thirty EEG data sets have been saved for each person who participated in the session, consisting of 15 sleep-deprived participants and 15 non-sleep-deprived participants. The preliminary data collection was first done to gain insight into the process and data; then, the actual data collection was done based on the preliminary data collection and analysis. Naturally, there were a few issues, but they were not major roadblocks in the process of collecting the data; rather, they were unplanned. In the event that this research paradigm is used in future studies, several of the data collection techniques can be improved.

CHAPTER FIVE

RESULTS AND DISCUSSION

5.1 INTRODUCTION

This chapter covers the findings and data analysis. The objective of the analysis is to thoroughly examine the characteristics, traits, variations, features, and neural correlates of emotional processing using EEG readings to correlate with mental fatigue. The amplitude and latency of particular ERP components linked to emotional stimuli were investigated by analysing the ERP data.

Raw EEG data are irrelevant without using a well-known machine learning model. As covered in Chapter 3, this study uses emotional stimuli to create a perceptron that distinguishes between data indicating mental fatigue caused by sleep deprivation and data that is not. To clarify how IAPS stimuli convert raw EEG data into emotional reactions, accuracy analysis examines the outcomes of data modeling.

The model's accuracy in separating different emotional responses in Event-Related potential and classification determines whether the data training is successful and justified for use in this research's analysis. The model's ability to distinguish between various emotional reactions in Event-Related Potential and classification is what establishes whether or not the data training is effective and appropriate for use in the analysis of this research

5.2 RESULT

The analysis focuses on ERP data using the cross-validation folds technique. The data are divided into latency + peak analysis of all ERP components, only peak analysis of all ERP components, latency + peak of (N1-P3) ERP components, and only peak analysis of (N1-P3) ERP components. This analysis for Table 5.1 and 5.2, includes all of ERP components from N100 until LPP ERP components.

Table 5.1 Cross-validation folds technique for only latency + peak (N1-P3 and LPP) ERP components

	Percentage of Accuracy (%)				
Classification	HAPPY	CALM	FEAR	SAD	AVERAGE
Binary Logistic Regression	46.7	55	53.3	43.3	49
Linear SVM	41.7	45	45	31.7	40
Narrow Neural Network	50	45	45	28.3	42
Medium Neural Network	50	55	50	35	48
Wide Neural Network	51.7	53.3	53.3	43.3	50
AVERAGE	48	51	49	36	

Table 5.1 shows the result of data using the cross-validation folds technique consists of latency combining with peak analysis data of the ERP. The highest value for happy are using WNN with 51.7 percent, for calm using BLR and MNN with 55 percent, for fear using WNN and BLR with 53.3 percent and lastly for sad using BLR and WNN with 43.3 percent. For this table it can be concluded for latency + peak using all ERP component it shows that WNN is the most suitable for the analysis with the average of 50 percent.

Table 5.2 Cross-validation folds technique for only peak (N1-P3 and LPP) ERP components

	Percentage of Accuracy (%)				
Classification	HAPPY	CALM	FEAR	SAD	AVERAGE
Binary Logistic Regression	50	50	46.7	60	51
Linear SVM	60	63.3	56.7	60	60
Narrow Neural Network	60	66.7	46.7	63.3	59
Medium Neural Network	60	53.3	56.7	56.7	56

Wide Neural Network	63.3	66.7	60	60	63
AVERAGE	59	60	53	60	

Table 5.2 shows a result of data using cross-validation folds technique consist only peak to peak analysis data of the ERP. The highest value for happy are using WNN with 63.3 percent, for calm using WNN with 66.7 percent, for fear using WNN with 60 percent, and lastly for sad by using WNN with 60 percent. For this table it can be concluded that for only peak analysis using all ERP components WNN is the most suitable with average of 63 percent.

Table 5.3 Cross-validation folds technique for only latency + peak (N1-P3) ERP components

	Percentage of Accuracy (%)				
Classification	HAPPY	CALM	FEAR	SAD	AVERAGE
Binary Logistic Regression	50	55	50	56.7	52
Linear SVM	56.7	51.7	45	33.3	46
Narrow Neural Network	53.3	55	55	46.7	52
Medium Neural Network	53.3	61.7	53.3	43.3	52
Wide Neural Network	55	58.3	53.3	38.3	51
AVERAGE	0.53	0.56	51	43	

From the table 5.3 The highest value for happy are by using linear SVM with 56.7 percent, for calm using MNN with 61.7 percent, for fear using NNN with 55 percent and lastly for sad by using BLR with 56.7 percent. Thus we can conclude that by studying latency + peak for (N1-P3) ERP components, BLR, NNN and MNN is the most suitable with average of 52 percent.

Table 5.4 Cross-validation folds technique for only peak (N1-P3) ERP components

	Percentage of Accuracy (%)				
Classification	HAPPY	CALM	FEAR	SAD	AVERAGE
Binary Logistic Regression	56.7	66.7	40	56.7	55
Linear SVM	66.7	66.7	33.3	50	54
Narrow Neural Network	80	73.3	36.7	56.7	61
Medium Neural Network	66.7	66.7	33.3	50	54
Wide Neural Network	63.3	73.3	33.3	53.3	55
AVERAGE	66	69	35	53	

Table 5.4 shows a result of data using cross-validation folds technique consist only peak to peak analysis data of the ERP while latency data are excluded. The highest value for happy are by using NNN with 80 percent, for calm using NNN and WNN wit 73.3 percent, for fear using BLR with 40 percent and lastly for sad by using BLR and NNN with 56.7 percent. Thus we can conclude that by studying only peak analysis for (N1-P3) ERP components, NNN is the most suitable with average of 61 percent.

Table 5.5 Cross-validation folds technique for only latency data combining with peak to peak data using only LPP ERP components

	Percentage of Accuracy (%)				
Classification	HAPPY	CALM	FEAR	SAD	AVERAGE
Binary Logistic Regression	55	40	53.3	41.7	47
Linear SVM	38.3	45	40	30	38
Narrow Neural Network	48.3	51.7	51.7	55	47
Medium Neural Network	48.3	51.7	53.3	38.3	47
Wide Neural Network	51.7	50	51.7	48.3	50
AVERAGE	48	47	50	42	

This analysis includes LPP for the ERP components while excluding N100, P100, N200, P200, N300, and P300. Table 6.9 shows a result of the highest value for happy are by using WNN with 51.7 percent, for calm using NNN and MNN with 51.7 percent, for fear using MNN with 53.3 percent and lastly for sad by using NNN with 55 percent. Thus we can conclude that by studying latency + peak analysis for (LPP) ERP components, WNN is the most suitable with average of 50 percent.

Table 5.6 Cross-validation folds technique for only peak to peak data using LPP ERP components

	Percentage of Accuracy (%)				
Classification	HAPPY	CALM	FEAR	SAD	AVERAGE
Binary Logistic Regression	40	30	46.7	50	41
Linear SVM	60	63.3	56.7	73.3	63
Narrow Neural Network	53.3	53.3	46.7	56.7	59
Medium Neural Network	56.7	56.7	63.3	60	59
Wide Neural Network	46.7	53.3	63.3	70	58
AVERAGE	51	51	0.55	62	

Table 5.6 shows the result of data using the cross-validation folds technique, which consists only of peak-to-peak analysis data of the ERP, while latency data are excluded. The results shows that the highest value for happy are by using linear SVM with 60 percent, for calm using linear SVM with 63.3 percent, for fear using MNN and WNN with 63.3 percent and lastly for sad by using linear SVM with 73.3 percent. Thus we can conclude that by studying only peak analysis for (LPP) ERP components, linear SVM is the most suitable with average of 63%.

5.2.1 Selection of Classification

The best classifier need to be appoint for performance validation to standardise the results. Tables 5.1, 5.2, 5.3, 5.4, 5.5, and 5.6 show that in classification applications, particularly those involving complicated and non-linear data, wide neural networks provide significant advantages over other classifications such as binary linear regression, linear SVM, narrow neural networks, and medium neural networks.

There are some results in the data analysis where in BLR, linear SVM, NNN, and MNN performance is a little bit higher than WNN, but in terms of consistency, the performance validation of WNN is more consistent. Table 5.6 provided evidence that the average of BLR is 41 percent; meanwhile, in Table 5.5, the linear SVM average result is 38 percent; for NNN in Table 5.1, the average result is 42 percent, and lastly, in Table 5.5, the average result of MNN is 47 percent. The table above shows that WNN consistently produces results with an average of at least 50 percent and a high of 63 percent. Thus, WNN was decided to use as the primary classification method instead of BLR, linear SVM, NNN, and MNN.

WNN can get more precision and reliable performance because of its enhanced expressiveness and model capability. Wide neural networks are an ideal option for difficult classification problems due to their benefits in terms of consistency and accuracy of classification. They are the recommended model over the other 4 classifications in this study's machine learning applications because of the empirical data and practical reasons highlighting their efficacy. A wide neural network has been chosen for this study's classification for its consistent results on all emotional stimuli. The classifier chosen for this study is a wide neural network, and the accuracy of each emotion was consistently high during the data analysis.

5.2.2 Result of Wide Neural Network Classification on Certain Channels

The study's classification will use a wide neural network for performance validation. In this subchapter, we will focus on the study in more detail, focusing on each different channel for each emotion stimulus to gain insights into which channel and which brain region will play the biggest role in the mental fatigue condition using the four emotion stimuli (happy, calm, fear, and sad). In this subchapter, we will also learn whether latency + peak or peak-to-peak analysis is better for research usage on mental fatigue.

Table 5.7 Cross-validation folds technique using a wide neural network classification only on all channels (FP1, FP2, F3, F4, F7, F8, and Cz)

	Percentage of Accuracy (%)				
ERP components	Happy	Calm	Fear	Sad	Average
All ERP component (Peak-to-peak + latency)	45	50	53.3	38.3	46
N1, P1, N2, P2, N3, P3 (Peak-to-peak + latency)	55	58.3	53.3	38.3	51
LPP ERP Component (Peak-to-peak + latency)	51.7	50	51.7	48.3	50
All ERP component (Peak to peak only)	63.3	56.7	53.3	60	58
N1, P1, N2, P2, N3, P3 (Peak to peak only)	63.3	73.3	33.3	53.3	55
LPP ERP Component (Peak to peak only)	46.7	53.3	63.3	70	58

This analysis will focus on all the channels used (FP1, FP2, F3, F4, F7, F8, and Cz). Table 5.7 shows the results of cross-validation folds techniques using wide neural network classification on all channels.

The first part of the analysis is the study of peak-to-peak data, combined with latency data. Also, with the combination of all ERP components on this data, using happy stimuli resulted in 45 percent, calm with 50 percent, fear with 53.3 percent, sad with 38.3 percent, and the average for this is 46 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy is 55 percent, calm is 58.3 percent, fear is 53.3 percent, and sad is 38.3 percent, with an average of 51 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 51.7 percent, calm is 50 percent, fear is 51.7 percent, and sad is 48.3 percent, with an average of 50 percent.

The second part of the analysis studies peak-to-peak data only, with the exception of latency data. With the combination of all ERP components on this data, using happy stimuli resulted in 63.3 percent, calm with 56.7 percent, fear with 53.3 percent, and sad with 60 percent, with an average of 58 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy are 63.3 percent, calm is 73.3 percent, fear is 33.3 percent, and sad is 53.3 percent, with an average of 55 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 46.7 percent, calm is 53.3 percent, fear is 63.3 percent, and sad is 70 percent, with an average of 58 percent.

The highest performance validation and accuracy for happy emotional stimuli for all channels is achieved by using only peak-to-peak analysis on (N1-P3) ERP components, with 63.3 percent accuracy. For calm emotional stimuli, the highest performance accuracy is also achieved by using peak-to-peak analysis on (N1-P3) ERP components, with 73.3 percent accuracy. Meanwhile, on fear emotional stimuli, the highest accuracy performance was achieved by peak-to-peak analysis on only LPP ERP components with 63.3 percent accuracy. Lastly, on sad emotional stimuli, peak-to-peak analysis on LPP ERP components achieved the highest accuracy performance with 70 percent accuracy. Thus, we can conclude from Table 6.11 that peak-to-peak analysis is way better than latency + peak analysis for the percentage of accuracy.

Table 5.8 Cross-validation folds technique using wide neural network classification, only focusing on FP1, FP2 channels

	Percentage of Accuracy (%)				
ERP component	Happy	Calm	Fear	Sad	Average
All ERP component (Peak-to-peak + latency)	53.3	63.3	38.3	53.3	52
N1, P1, N2, P2, N3, P3 (Peak-to-peak + latency)	53.3	50	36.7	46.7	46
LPP ERP Component (Peak-to-peak + latency)	56.7	63.3	50	41.7	52
All ERP component (Peak to peak only)	43.3	53.3	46.7	40	45
N1, P1, N2, P2, N3, P3 (Peak to peak only)	66.7	70	30	43.3	52
LPP ERP Component (Peak to peak only)	53.3	43.3	50	43.3	47

This analysis will focus on only certain channels and exclude all the others. Table 5.8 shows the results of cross-validation folds techniques using a wide neural network focusing only on the FP1 and FP2 channels.

The first part of the analysis is the study of peak-to-peak data combination with latency data. Also, with the combination of all ERP components on this data, using happy stimuli resulted in 53.3%, calm with 63.3%, fear with 38.3%, and sad with 53.3% with an average of 46%. With the combination of only N1, P1, N2, P2, N3, and P3 ERP component the result for happy is 53.3%, calm is 50%, fear is 36.7%, sad is 46.7% with average of 41%. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 56.7%, calm is 63.3%, fear is 50% and sad is 41.7 % with an average of 52%.

The second part of the analysis studies peak-to-peak data only, with the exception of latency data. With the combination of all ERP components on this data, using happy stimuli resulted in 43.3 percent, calm with 53.3 percent, fear with 46.7

percent, and sad with 40 percent, with an average of 45 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy is 66.7 percent, calm is 70 percent, fear is 30 percent, and sad is 43.3 percent, with an average of 52 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 53.3 percent, calm is 43.3 percent, fear is 50 percent, and sad is 43.3 percent, with an average of 47 percent.

The highest performance validation and accuracy for happy emotional stimuli for FP1 and FP2 channels is achieved by using peak-to-peak analysis on (N1-P3) ERP components, with 66.7 percent accuracy. The highest performance accuracy for calm emotional stimuli is achieved by using peak-to-peak analysis on (N1-P3) ERP components, with 70 percent accuracy. Meanwhile, on fear emotional stimuli, the highest accuracy performance was achieved by peak-to-peak analysis on only LPP ERP components with 50 percent accuracy. Lastly, on sad emotional stimuli, Latency + peak analysis on all ERP components achieved the highest accuracy performance with 53.3 percent accuracy. Thus, we can conclude from Table 5.8 that peak-to-peak analysis is way better than latency + peak analysis for the percentage of accuracy.

Table 5.9 Cross-validation folds technique using a wide neural network classification only on F3, F4 channels

	Happy	Calm	Fear	Sad	Average
All ERP component (Peak-to-peak + latency)	58.3	56.7	43.3	51.7	52
N1, P1, N2, P2, N3, P3 (Peak-to-peak + latency)	53.3	55	53.3	55	54
LPP ERP Component (Peak-to-peak + latency)	70	45	58.3	56.7	57
All ERP component (Peak to peak only)	66.7	50	46.7	60	55
N1, P1, N2, P2, N3, P3 (Peak to peak only)	70	56.7	50	36.7	53
LPP ERP Component (Peak to peak only)	63.3	46.7	66.7	50	56

This analysis will focus on only certain channels and exclude all the others. Table 5.9 shows the results of cross-validation folds techniques using a wide neural network focusing only on the F3 and F4 channels.

The first part of the analysis is the study of peak-to-peak data, combined with latency data. Also, with the combination of all ERP components on this data, using happy stimuli resulted in 58.3 percent, calm with 56.7 percent, fear with 43.3 percent, and sad with 51.7 percent, with an average of 52 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy are 53.3 percent, calm is 55 percent, fear is 53.3 percent, and sad is 55 percent, with an average of 54 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 70 percent, calm is 45 percent, fear is 58.3 percent, and sad is 56.7 percent, with an average of 57 percent.

The second part of the analysis studies peak-to-peak data only, with the exception of latency data. With the combination of all ERP components on this data, using happy stimuli resulted in 66.7 percent, calm with 50 percent, fear with 46.7 percent, and sad with 60 percent, with an average of 55 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy are 70 percent, calm is 56.7 percent, fear is 50 percent, and sad is 36.7 percent, with an average of 53 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 63.3 percent, calm is 46.7 percent, fear is 66.7 percent, and sad is 50 percent, with an average of 56 percent.

The highest performance validation and accuracy for happy emotional stimuli for F3 and F4 channels is achieved using peak-to-peak analysis on (N1-P3) ERP components, with 70 percent accuracy. Other than that, for happy emotional stimuli, the highest result can also be achieved by using latency with peak-to-peak analysis on LPP ERP components with 70 percent accuracy. The highest performance accuracy for calm emotional stimuli is achieved by using latency + peak analysis of all ERP components and peak-to-peak analysis of (N1-P3) ERP components, with 56.7 percent accuracy. Meanwhile, on fear emotional stimuli, the highest accuracy performance was achieved by peak-to-peak analysis on only LPP ERP components with 66.7 percent accuracy. Lastly, on sad emotional stimuli, latency + peak-to-peak analysis on

LPP ERP components achieved the highest accuracy performance with 56.7 percent accuracy. Thus, we can conclude from Table 5.9 that certain emotional stimuli accuracy is high in latency with peak analysis, and some accuracy is high in only peak-to-peak analysis.

Table 5.10 Cross-validation folds technique using a wide neural network classification, only focusing on F7, F8 channels

	Percentage of Accuracy (%)				
ERP component	Happy	Calm	Fear	Sad	Average
All ERP component (Peak-to-peak + latency)	63.3	65	48.3	38.3	53
N1, P1, N2, P2, N3, P3 (Peak-to-peak + latency)	58.3	50	55	55	54
LPP ERP Component (Peak-to-peak + latency)	51.7	50	51.7	65	54
All ERP component (Peak to peak only)	70	80	36.7	53.3	60
N1, P1, N2, P2, N3, P3 (Peak to peak only)	53.3	66.7	50	50	55
LPP ERP Component (Peak to peak only)	43.3	56.7	53.3	60	53

This analysis will focus on only certain channels and exclude all the others. Table 5.10 shows the results of cross-validation folds techniques using a wide neural network focusing only on the F7 and F8 channels.

The first part of the analysis is the study of peak-to-peak data, combined with latency data. Also, with the combination of all ERP components on this data, using happy stimuli resulted in 63.3 percent, calm with 65 percent, fear with 48.3 percent, and sad with 38.3 percent, with an average of 53 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy are 58.3

percent, calm is 50 percent, fear is 55 percent, and sad is 55 percent, with an average of 54 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 51.7 percent, calm is 50 percent, fear is 51.7 percent, and sad is 65 percent, with an average of 54 percent.

The second part of the analysis studies peak-to-peak data only, with the exception of latency data. With the combination of all ERP components on this data, using happy stimuli resulted in 70 percent, calm with 80 percent, fear with 36.7 percent, and sad with 53.3 percent, with an average of 60 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy are 53.3 percent, calm is 66.7 percent, fear is 50 percent, and sad is 50 percent, with an average of 55 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 43.3 percent, calm is 56.7 percent, fear is 53.3 percent, and sad is 60 percent, with an average of 53 percent.

The highest performance validation and accuracy for happy emotional stimuli for F7 and F8 channels is achieved by using only peak-to-peak analysis on all ERP components, with 70 percent accuracy. For calm emotional stimuli, the highest performance accuracy is also achieved by using peak-to-peak analysis on all ERP components, with 80 percent accuracy. Meanwhile, on fear emotional stimuli, the highest accuracy performance was achieved by latency with peak-to-peak analysis on (N1-P3) ERP components with 55 percent accuracy. Lastly, on sad emotional stimuli, latency with peak-to-peak analysis on LPP ERP components achieved the highest accuracy performance with 65 percent accuracy. In this table, it can be seen that the happy and calm stimuli are really high, but it seems inconclusive, as in this table, only the results have high accuracy. Thus, it can be concluded from Table 6.14 that certain emotional stimuli accuracy is high in latency with peak analysis, and some accuracy is high in only peak-to-peak analysis.

Table 5.11 Cross-validation folds technique using a wide neural network classification focusing only on on Cz channels

	Percentage of Accuracy (%)				
ERP component	Happy	Calm	Fear	Sad	Average
All ERP component	53.3	63.3	40	50	51
N1, P1, N2, P2, N3, P3 (Peak-to-peak + latency)	50	61.7	48.3	41.7	50
LPP ERP Component (Peak-to-peak + latency)	58.3	50	51.7	53.3	53
All ERP component (Peak to peak only)	43.3	66.7	46.7	50	51
N1, P1, N2, P2, N3, P3 (Peak to peak only)	63.3	73.3	43.3	50	57
LPP ERP Component (Peak to peak only)	60	63.3	50	70	60

This analysis will focus on only certain channels and exclude all the others. Table 5.11 shows the results of cross-validation folds techniques using a wide neural network focusing only on the Cz channels.

The first part of the analysis is the study of peak-to-peak data, combined with latency data. Also, with the combination of all ERP components on this data, using happy stimuli resulted in 53.3 percent, calm with 63.3 percent, fear with 40 percent, and sad with 50 percent, with an average of 51 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy are 50 percent, calm is 61.7 percent, fear is 48.3 percent, and sad is 41.7 percent, with an average of 50 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 58.3 percent, calm is 50 percent, fear is 51.7 percent, and sad is 53.3 percent, with an average of 53 percent.

The second part of the analysis studies peak-to-peak data only, with the exception of latency data. With the combination of all ERP components on this data, using happy stimuli resulted in 43.3 percent, calm with 66.7 percent, fear with 46.7 percent, and sad with 50 percent, with an average of 51 percent. With the combination of only N1, P1, N2, P2, N3, and P3 ERP components, the results for happy are 63.3 percent, calm is 73.3 percent, fear is 43.3 percent, and sad is 50 percent, with an average of 57 percent. Meanwhile, using only the LPP ERP component, the result for happy stimuli is 60 percent, calm is 63.3 percent, fear is 50 percent, and sad is 70 percent, with an average of 60 percent.

The highest performance validation and accuracy for happy emotional stimuli for Cz channels is achieved by using only peak-to-peak analysis on (N1-P3) ERP components, with 63.3 percent accuracy. For calm emotional stimuli, the highest performance accuracy is also achieved by using peak-to-peak analysis on (N1-P3) ERP components, with 73.3 percent accuracy. Meanwhile, on fear emotional stimuli, the highest accuracy performance was achieved by peak-to-peak analysis on only LPP ERP components with 50 percent accuracy. Lastly, on sad emotional stimuli, peak-to-peak analysis on LPP ERP components achieved the highest accuracy performance with 70 percent accuracy. Thus, it can be concluded from Table 6.15 that peak-to-peak analysis is better than latency + peak analysis for the percentage of accuracy.

From all the tables that were provided above, we can see the comparison of the results from the combination of latency with peak data and only peak-to-peak data. If the results are compared across all the tables, we can see that the results of only peak-to-peak data analysis are getting much consistently higher accuracy. Thus, the results seemed much better when the early ERP components (N1-P3) and LPP components were separated. It can be seen that there are some patterns where happy and calm stimuli result in (N1-P3) ERP components that are much more accurate. Meanwhile, the results towards LPP ERP components are much higher for fear and sad emotion stimuli. It can be concluded from the tables above that happy and calm stimuli are reacting more towards early components of ERP, while fear and sad emotional stimuli are reacting towards late ERP components.

5.3 SUMMARY OF RESULTS AND DISCUSSION

This chapter can be summarized as follows:

1. Cross-validation fold techniques are much better than the resubstitution validation technique
2. For classification, the wide neural network (WNN) was chosen for the performance validation due to its performance consistency.
3. Combining Peak and Latency Data: The researcher analyse data on both peak-to-peak and latency data. The results, which show significant subject variability in latency, make the analysis more difficult. Due to the additional noise from latency variability, the composite measure exhibits fewer distinct differences between conditions, leading to inconsistency, and the results are not consistent compared to only peak-to-peak analysis.
4. Stand-alone Peak-to-peak data analysis typically produces more reliable and consistent findings in ERP research, even if latency and peak data offer useful information. Due to their lower variability, simplicity, and resilience, peak-to-peak analysis measurements are a better method of choice when examining brain responses to stimuli, and the results are much more consistent.
5. Separating the channels gives insights into which EEG channels and brain regions are suitable for studying mental fatigue. Separating the early ERP components and the late ERP components also gives us the knowledge on which emotion stimuli are suitable for studying mental fatigue.

CHAPTER 6

CONCLUSION

6.1 INTRODUCTION

Measurements, statistical analyses, and graph plotting have all been done, but ultimately, it all comes down to the meaning of emotional profiling of mental fatigue as a whole. Discussion and compilation of the results and analyses conducted in the aforementioned sections follow. Meaningful facts and information must be derived from numerical data interpretation.

This part must address the research objectives and meet the research goals. The mental fatigue model's emotional profiling will incorporate fresh information. We will also discuss recommendations for the future, particularly for comparable EEG studies conducted in other settings. This chapter contextualises and synthesizes the data analysis results so that other researchers can make sense of them and utilise this body of knowledge. This chapter's final recommendation may not be a how-to manual for designing well, but it should help you make design choices that are more objective and task-specific than just reading widely.

This chapter ends with an understanding of the Neuro-Physiological Emotional Profiling Model for Mental Fatigue (NPEMMF). Emotions provide the framework for this complete research examination. As such, the results represent a small portion of the larger picture of how emotion might influence and investigate mental tiredness in the audience. This research and thesis aim to refine and add value to people's well-being by laying the groundwork for future studies examining every aspect, from emotion to mental fatigue. The concept of using EEG and machine learning to maximise emotional potential can raise the bar for measuring the mental fatigue process globally.

6.2 AN ATTEMPT TO UNDERSTAND THE EFFECT OF EMOTIONAL STIMULI TO MENTAL FATIGUE

Before combining the data analysis findings into a new body of knowledge, the most evident and crucial step is to validate the hypothesis. It must be established that applying emotional stimuli can, in fact, show changes in the ERP signals that can be consistently detected after being classified via machine learning in order to comprehend the effects of mental tiredness on the human mind and emotions.

Using data sets from the stimulated emotions session, a computational model for valence and arousal responses is created as the initial stage in analysing the EEG data. Since each person exhibits a unique brain wave pattern when experiencing the same emotion (much like a fingerprint), each participant will have a computational model that is combined with the models of all other participants to classify them according to their data sets related to mental fatigue.

The Event-Related Potential (ERP) of the EEG data recorded during emotional stimulation is analysed using several MATLAB computations. The procedure entails identifying ERP features and converting numerical data into valence and arousal models from the EEG files. The term "feature extraction process" refers to this. This results in the conversion of all 19 channels of brain signals coming from the patient's scalp into a range of arousal and valence ratings.

The same emotional EEG data can be utilised to train and assess the accuracy of the emotional model once it has been developed. The success rate of the emotional model in forecasting a known set of emotional data can be used to gauge its accuracy. Although a 100% success rate is ideal, mistakes and flaws are inevitable in real life. This is caused by things like disruptions in the EEG data collection process, the effectiveness of the scalp-to-electrode signal detection method, or small inconsistencies in the feature extraction procedure used to create the emotional model itself. Because of this, it's critical to assess the model's correctness before applying machine learning classification to data on mental fatigue.

From the data that were collected, all 30 participants gave accuracy results of higher than 66.7 percent. The highest accuracy reading is 73.3 percent. This is considerably high for using the cross-validation folds technique in the classification process, where if the researcher used unobserved and untrained data, the data could still have a high accuracy. These data might be useful for analysis.

One would wonder what the benchmark percentage deemed "usable" is. How can the model's suitability for use in the machine learning classification process be justified? Numerical evidence by itself is insufficient to support the model's use when benchmarking the precise accuracy %. To justify a model as adequate, more precise criteria must be examined. Numerical values in science must be interpreted in light of their context and with respect to a standard. Hence, validating the emotional model aims to determine if it can differentiate between different emotions rather than just statistically predict the available data. A plot of valence vs arousal gives a more accurate view of the emotions model's correctness, even though the numerical value may be an objectively acceptable explanation for its applicability.

To refresh your memory, valence is defined as either positive or negative affectivity, and arousal is the degree of calmness or excitement associated with the subject matter. The arousal value is on the horizontal axis, and the emotional valence value is on the vertical axis. The combination of the two values (valence and arousal) yields the four fundamental emotions. Tables 6.1 and 6.2 provide an overview of the participants' data results.

6.3 RESULTS SUMMARY

Table 6.1 shows the Summary result of the cross-validation folds Technique, Which Uses a wide Neural network classification, only focusing on the Latency + peak characteristic study on all aspects of channels on N1, P1, N2, P2, N3, P3, and the LPP ERP component.

Combining Peak and Latency Data: Researchers collect data on both peak-to-peak and latency. The results, which show significant participant variability in latency, make the analysis more difficult. Due to the additional noise from latency variability, the composite measure exhibits fewer distinct differences between conditions, leading to inconsistency.

Table 6.1 Summary of cross-validation folds technique using wide neural network classification, only focusing on latency + peak characteristic study on all aspects of channels on N1, P1, N2, P2, N3, P3, and LPP ERP component.

	Percentage of Accuracy (%)				
Channel	Happy	Calm	Fear	Sad	ERP component
ALL Channel	55%	58.3%	53.3%	38.3%	N1, P1, N2, P2, N3, P3
ALL Channel	51.7%	50%	51.7%	48.3%	LPP
FP1/FP2	53.3%	50%	36.7%	46.7%	N1, P1, N2, P2, N3, P3
FP1/FP2	56.7%	63.3%	50%	41.7%	LPP
F3/F4	53.3%	55%	53.3%	55%	N1, P1, N2, P2, N3, P3
F3/F4	70%	45%	58.3%	56.7%	LPP
F7/F8	58.3%	50%	55%	55%	N1, P1, N2, P2, N3, P3
F7/F8	51.7%	50%	51.7%	65%	LPP
Cz	50%	61.7%	48.3%	41.7%	N1, P1, N2, P2, N3, P3
Cz	58.3%	50%	51.7%	53.3%	LPP

Table 6.2 shows the Summary result of the cross-validation folds Technique, which uses a wide neural network classification, only focusing on the peak characteristic study on all aspects of channels on N1, P1, N2, P2, N3, P3, and LPP ERP components.

Peak data analysis typically produces more reliable and consistent findings in ERP research, even if latency and peak data offer useful information. Due to their lower variability, simplicity, and resilience, peak-to-peak analysis measurements are a better method of choice when examining brain responses to stimuli.

Table 6.2 Summary of Cross-validation folds Technique Using a wide Neural network classification, only focusing on peak characteristic study on all aspects of channels on N1, P1, N2, P2, N3, P3, and LPP ERP component.

	Percentage of Accuracy (%)				
Channel	Happy	Calm	Fear	Sad	ERP Component
ALL Channel	63.3	73.3	33.3	53.3	N1, P1, N2, P2, N3, P3
ALL Channel	46.7	53.3	63.3	70	LPP
FP1/FP2	66.7	70	30	43.3	N1, P1, N2, P2, N3, P3
FP1/FP2	53.3	43.3	50	43.3	LPP
F3/F4	70	56.7	50	36.7	N1, P1, N2, P2, N3, P3
F3/F4	63.3	46.7	66.7	50	LPP
F7/F8	53.3	66.7	50	50	N1, P1, N2, P2, N3, P3
F7/F8	43.3	56.7	53.3	60	LPP
Cz	63.3	73.3	43.3	50	N1, P1, N2, P2, N3, P3
Cz	60	63.3	50	70	LPP

Peak Data Analysis: Researchers measure the greatest amplitude (positive and negative deflections that occur) in the N1, P1, N2, P2, N3, P3, and LPP ERP components. In contrast to latency combined with peak-to-peak data, where no meaningful results are obtained, they discover that a familiar and significant result is obtained for each of the emotion stimuli in the peak-to-peak data analysis.

In this study, refer to Table 6.3; we will illustrate the table in the graph, where the details on the important data that relate to the emotional stimuli, channels, and also the ERP components.

From figures 6.1, 6.2, 6.3, and 6.4, it can be seen that the emotional model can identify which ERP components and channels are important to certain stimuli. Thus, we can segregate the emotional data into four separate emotion clusters. Since these data are of known variables, the plots can be made multi-coloured or signed just to distinguish each emotion from the other. To justify whether the NPEMMF model is good enough to be used in machine learning, the accuracy of the results must not overlap, and only the highest accuracy data must be considered. A clear separation of each emotion must be observed.

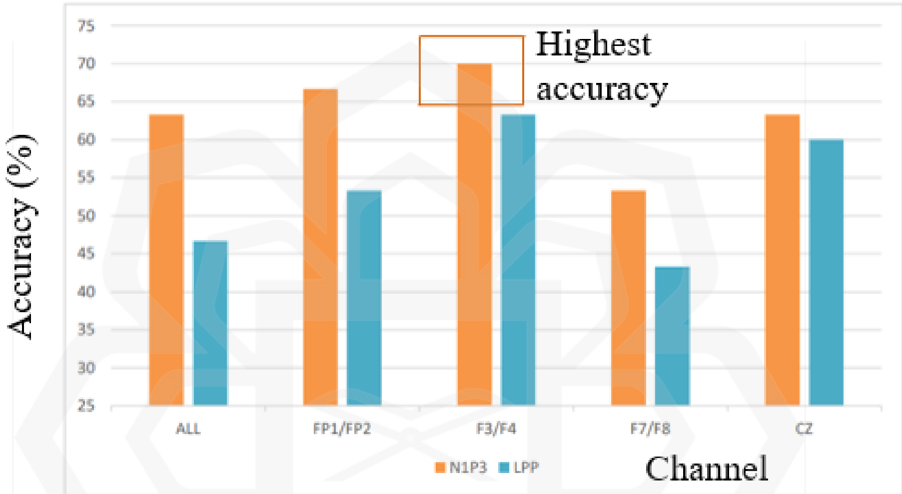

Figure 6.1 Graph of Happy emotion stimuli on certain channels differentiates between N1-P3 and LPP components

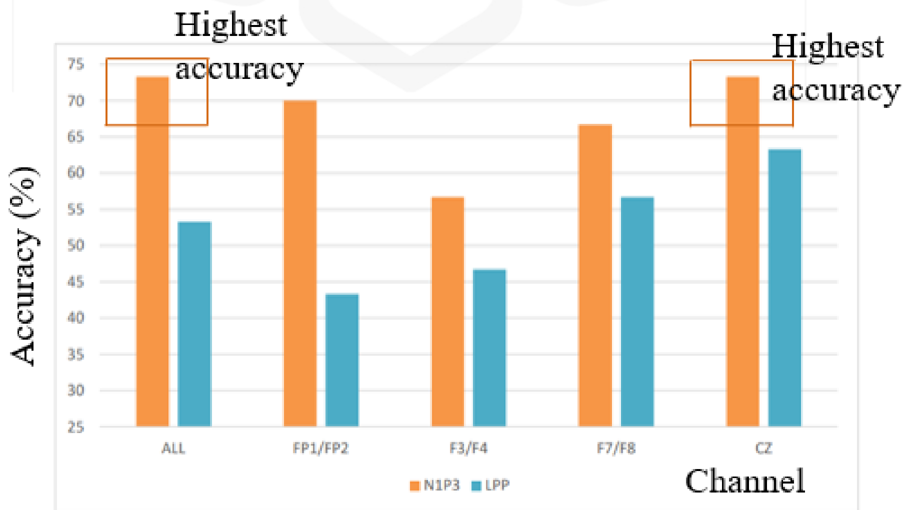

Figure 6.2 Graph of Calm emotion stimuli on certain channels differentiates between N1-P3 and LPP components

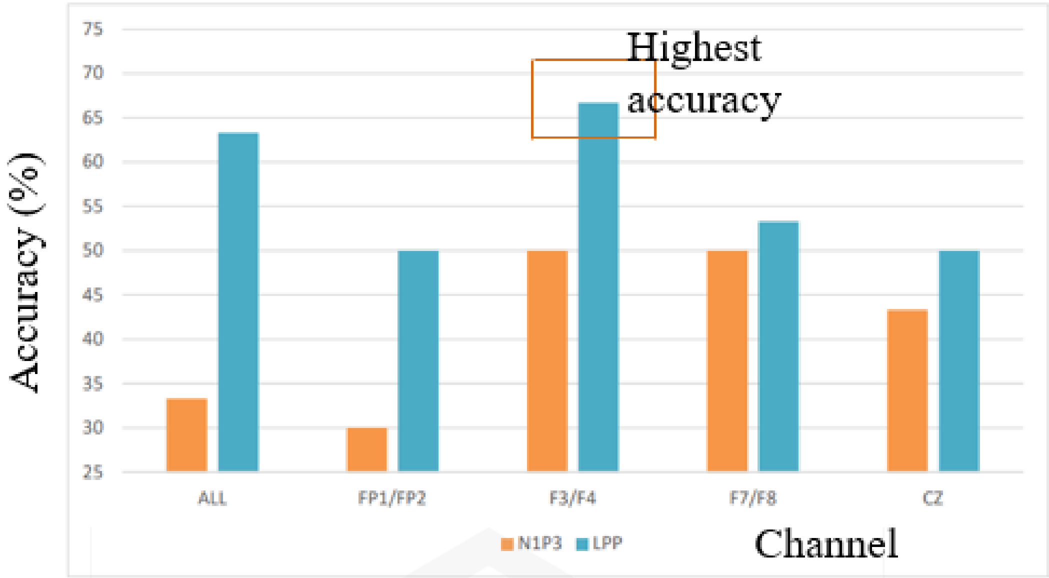

Figure 6.3 Graph of Fear emotion stimuli on certain channels differentiates between N1-P3 and LPP components

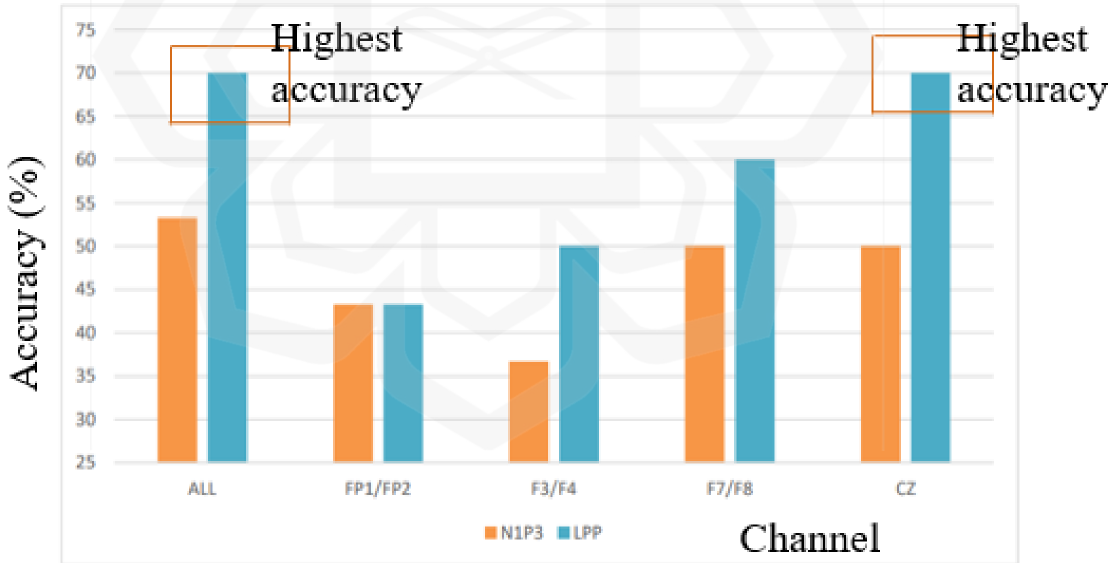

Figure 6.4 Graph of Sad Emotion stimuli on certain channels differentiates between N1-P3 and LPP components

6.4 NPEMMF MODEL RESULTS AND ACCURACY

Table 6.3 NPEMMF Result

Emotion	Channel	ERP components	Percentage of accuracy (%)
HAPPY	F3/F4	N1, P1, N2, P2, N3, and P3	70
CALM	Cz	N1, P1, N2, P2, N3, and P3	73
FEAR	F3/F4	LPP	66.7
SAD	Cz	LPP	70

We have successfully profiled emotional stimuli using IAPS for mental fatigue using the NPEMMF framework. By using Happy emotion stimuli, we can gather information related to the subject's sleep-deprived and non-sleep conditions with an accuracy of 70 percent. The accuracy of the happy profiling can be achieved at 70 percent by using ERP components from N1, N2, N3, P1, P2, and P3. From the 7 channels we chose from all frontal lobes and Cz, we identified that the best channel to profile happy emotional stimuli is using only two combined channels: the F3 and F4 channels. By using both channels, we can achieve an accuracy of 70 percent to differentiate between sleep-deprived and non-sleep-deprived subjects.

Similarly, by using calm emotion stimuli, we can gather information related to the subjects' sleep-deprived and non-sleep conditions with an accuracy of 73 percent. The accuracy of the happy profiling can be achieved at 73 percent by using ERP components also from N1, N2, N3, P1, P2, and P3. From the 7 channels that we chose from all frontal lobes and Cz, we identified that the best channel to profile calm emotional stimuli is the Cz channel to differentiate SD and NSD.

We may obtain information on the subject's sleep-deprived and non-sleep states with an accuracy of 66.7 percent for the Fear emotion stimuli. Using ERP components from LPP allows for a 66.7 percent accuracy rate in fear profiling. We found that using the F3 and F4 channels to distinguish between SD and NSD is the best channel to profile fear emotional stimuli out of the seven channels we selected from all frontal lobes and Cz.

Finally, we can get information on the subject's sleep-deprived and non-sleep states for the sad emotion stimuli with 70% accuracy. When ERP components from LPP are included, sad profiling can be completed with 70% accuracy. Out of the seven channels we selected from the frontal lobes and Cz, we found that the Cz channel is the most effective channel to profile sad emotional stimuli, as it can distinguish between SD and NSD.

6.5 CHANNEL ANALYSIS IN AFFECTIVE SPACE MODEL

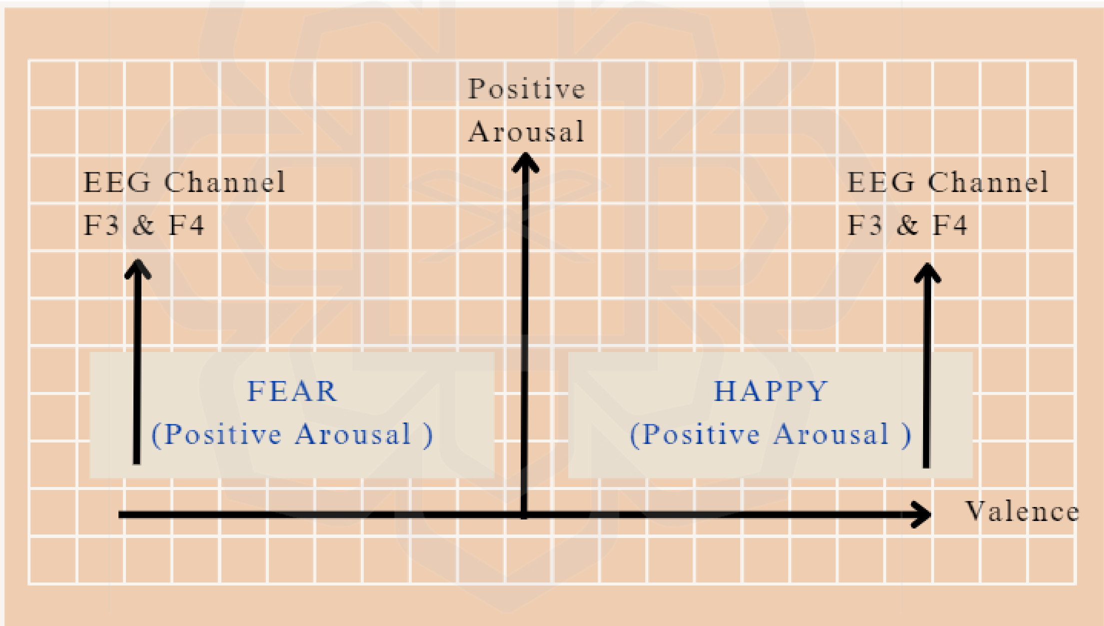

Figure 6.5 Channel Analysis for Positive Arousal

Figure 6.5 and Figure 6.6 referencing Figure 2.2 represent the affective space model emotion valence and arousal model, positive arousal (happy and fear), whereas negative arousal (sad and calm).

Figure 6.5 shows the result related to Positive arousal. Both happy and fear are from the positive arousal dimension. From the result obtained, the data analysis shows some similarities in the pattern, as seen in Figure 7.5. For the positive arousal dimension, we can see that the same pattern channel can be used to study and detect mental fatigue: the EEG from the F3 and F4 electrode channels.

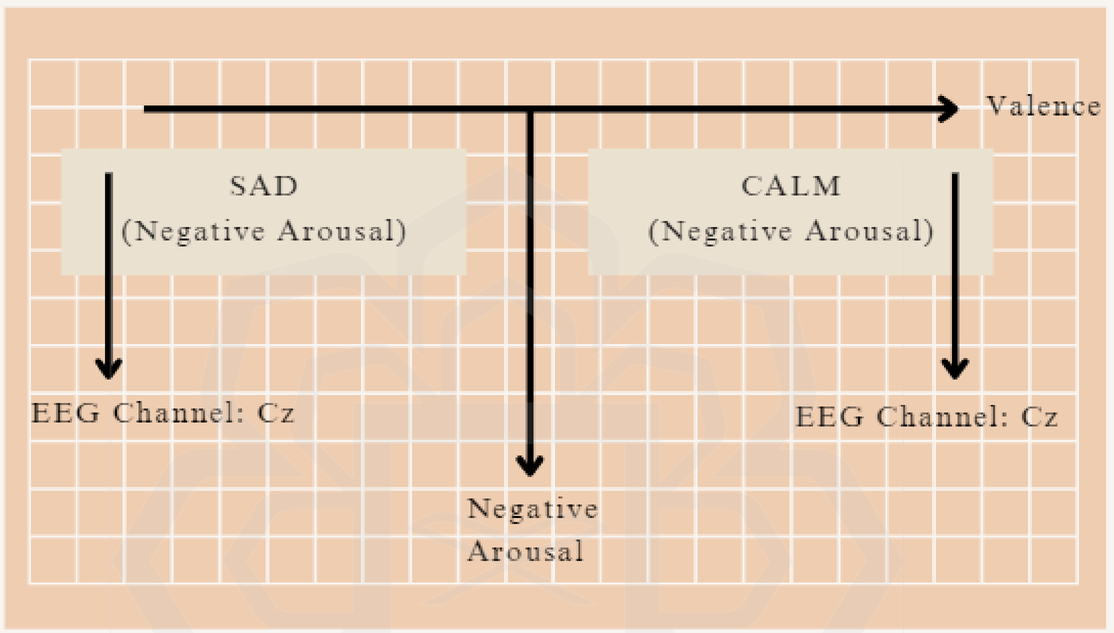

Figure 6.6 Channel Analysis for Negative Arousal

Meanwhile, Figure 6.6 shows the result related to the negative arousal dimension. Both calm and sad are from the negative arousal dimension. From the result obtained, the data analysis also shows some similarities in the pattern, as seen in Figure 6.6. For the negative arousal dimension, we can see that the same pattern channel can be used to study and detect mental fatigue: the EEG from the Cz channel.

Thus, channel localisation can be further studied in the brain region on channels F3 and F4 for positive and negative arousal; we can use the channel from the Cz region. Brain channel localisation will be one of the founding pieces of knowledge for emotional profiling of mental fatigue.

6.6 ERP COMPONENTS IN AFFECTIVE SPACE MODEL

Figure 6.7 shows the result related to Positive valence. Both happy and calm are from the positive valence dimension. From the result obtained, the data analysis shows some similarities in the pattern, as seen in Figure 6.8. For the positive valence dimension (happy and calm), we can see the same result pattern regarding ERP components. The result shows that ERP components that are suitable to study and detect mental fatigue on the positive valence dimension are ERP components that start from N100, P100, N200, P200, N300, and P300.

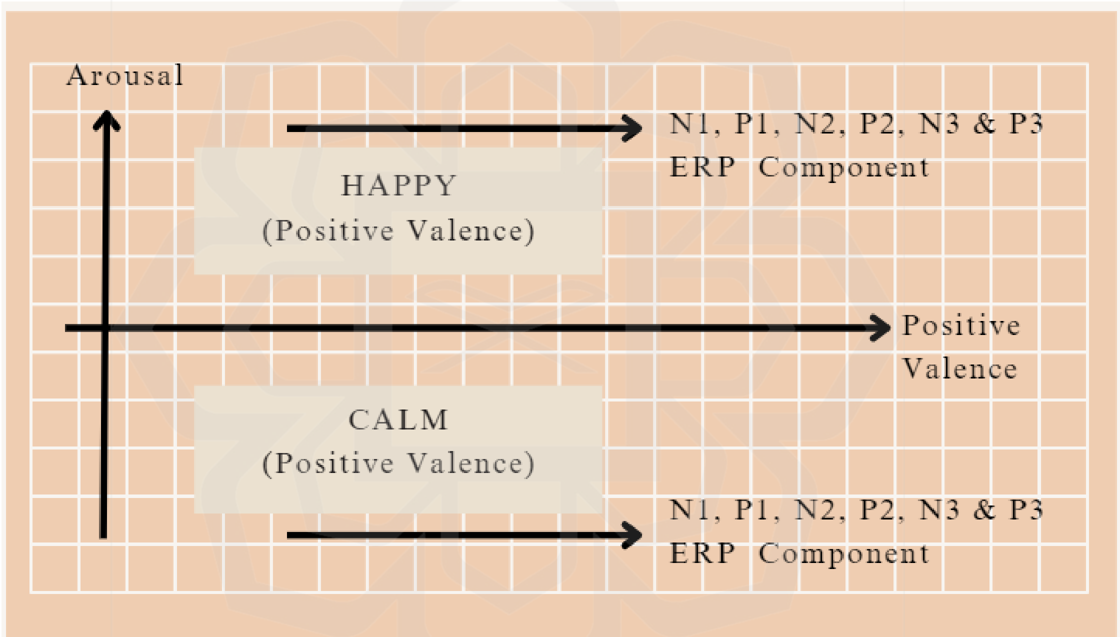

Figure 6.7 ERP components for positive valence

Meanwhile, Figure 6.8 shows the result related to Negative valence. Both fear and sad are from the negative valence dimension. From the result obtained, the data analysis shows some similarities in the pattern, as seen in Figure 6.8. We can see the same result pattern regarding ERP components for the negative valence dimension (fear and sad). The result shows that ERP components that are suitable for studying and detecting mental fatigue on the negative valence dimension are ERP components that are related to Late Positive Potential (LPP) components.

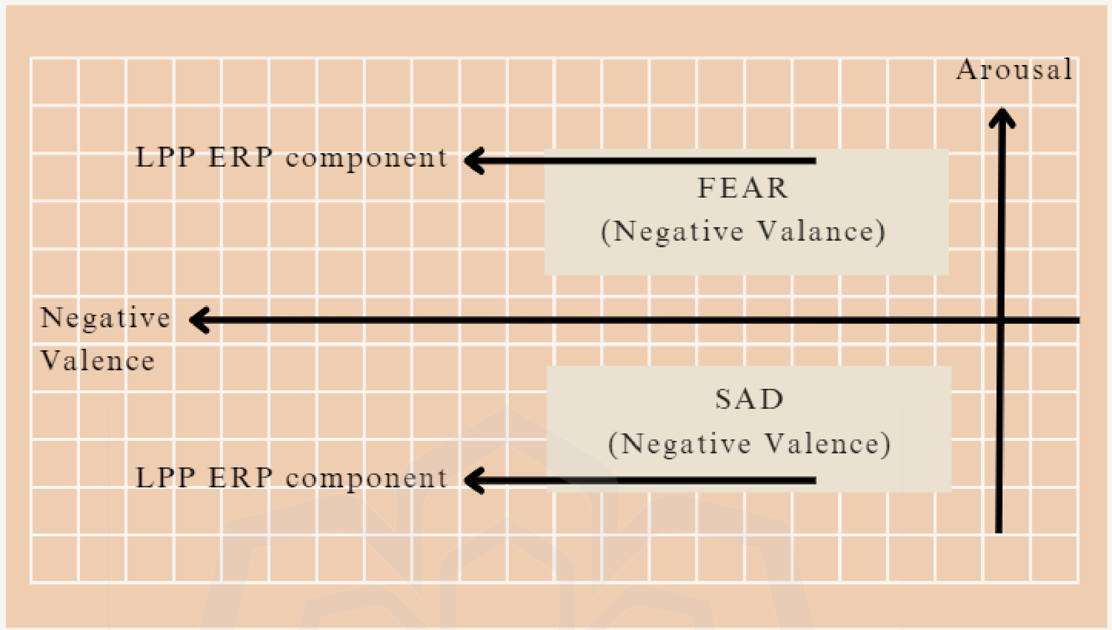

Figure 6.8 ERP components for negative valence

Thus, detecting mental fatigue related to ERP components can be further studied using specific ERP components for positive valence N100, P100, N200, P200, N300, and P300 ERP components will be used, and for negative valence, LPP components will be used. This will be one of the founding pieces of knowledge regarding ERP components for emotional profiling of mental fatigue.

6.7 SUMMARY OF FINDINGS AND DISCUSSION

This data analysis uses emotional stimuli to classify EEG mental fatigue data gathered from individuals into emotional valence and arousal responses. It is also important to note that, should the classification procedure be successful, the data can be categorised according to how mental fatigue affects valence and arousal. It is believed that the findings of the final analysis will help clarify what is necessary to realise the full promise of emotional research on mental fatigue.

The accuracy study further demonstrates the efficacy of the Event-Related Potential (ERP) feature extraction method in this research study, where we gain valuable information on the IAPS emotional stimuli for mental fatigue subjects. The valence and arousal plot indicates the impact of the IAPS instrument, which was employed to elicit strong emotions in the respondents, in addition to the previously described elements. Without the triggers employed, the emotional reactions would not have been measurable. The efficacy of the IAPS instrument is demonstrated by this research's approach, which successfully produced the perceptron for machine learning.

The initial step in this study's quantitative analysis was accuracy analysis. Doubts about other parts of this research analysis would have existed if the computational model's validity had not been confirmed. More than 66.7 percent prediction success for the emotional model and beyond may seem like great accuracy, but without the analysis, raw data have no significance and are hard to interpret. When accuracy and the emotion affective space model are combined, the outcome improves significantly and shows a meaningful pattern in the valence and arousal models.

A major step forward in comprehending and measuring mental fatigue using objective, quantitative metrics is the creation of a Neuro-Physiological Emotional Profiling Model for Mental Fatigue (NPEMMF). With the help of neuro-physiological data, such as ERP and EEG, this model can generate a thorough profile of a person's emotional and cognitive states, making it an effective tool for identifying mental fatigue.

6.8 RESEARCH OBJECTIVES ACHIEVED

The study objectives have been accomplished and the research questions have been addressed thanks to the analytical results and conclusions. Using machine learning classification, brain wave data obtained from an EEG equipment were divided into categories such as emotional valence and arousal responses. Emotional fluctuations, now measured and quantified to identify mental fatigue.

Table 6.4 Research objectives and the outcomes

Research objectives	Outcome
1) To identify the relationship between mental fatigue and its consequences on human emotion.	This objective was achieved by studying past literature reviews, as discussed in Chapter 2. Brain and cognitive fatigue are frequently linked to mental fatigue. The factors contributing to mental fatigue include stress, lack of sleep, and extended periods spent using one's mental and cognitive abilities without taking a break. High levels of mental fatigue always have the negative effects of impairing emotional control and lowering motivation for task completion.
2) To develop a neurophysiological emotional profiling model for mental fatigue based on ERP features.	The conceptual framework covered in Chapter 3 served as the basis for this research. The way we quantify mental fatigue is by analyzing mental fatigue using EEG signals. The research model was built on an existing framework and designed to categorise emotional reactions using visual stimuli to detect mental fatigue. The stimulation pictures used for analyzing happy, calm, fear, and sad emotions were based on the well-known IAPS stimuli. The Neuro-physiological emotional profiling model for mental fatigue (NPEMMF) is based on the existing framework and was improvised to

	suit this research.
3) To evaluate the performance of the neurophysiological profiling model based on affective space model for detecting the underlying emotions in mental fatigue.	EEG data were classified via the Wide Neural Network (WNN) algorithm for high accuracy capability. The computational model acquired for data classification was obtained through Event-Related Potential (ERP) for feature extraction. Classified data in the form of numerical values allows the observation of their pattern in the affective space model using a valence-arousal plane. The data analysis was being done by separating the early and late ERP components. The data analysis is also being repeated using difference channel on every emotional stimuli to investigate the accuracy analysis on each channel towards mental fatigue.

6.9 RESEARCH LIMITATIONS

This is the limitation that we face in this research:

1. The barely enough quantity of EEG data that was obtained from participants is one of the main problems with the study. The current model's generalizability may be limited across various demographics, cultures, and contexts due to its calibration to particular groups or tasks. Male volunteers in a comparable age range were the participants of the EEG investigation. In order to have a more thorough understanding, a more varied population sample that includes female participants may be explored. Additionally, the EEG research ignored other attributes that can impact the participants' mental health, such as their cultural background, and instead just examined the participants' emotional state.

2. Restricted Emotional Metrics: Although the model includes emotional profiling, it could not be comprehensive enough to adequately represent the variety of emotional states that impact mental fatigue. Since emotional experiences are complex and ever-changing, it is difficult to measure them fully.

6.10 FUTURE WORKS AND RECOMMENDATIONS

New queries and gaps in the literature were discovered throughout the course of this study. They pose a new challenge and possibility for future research, even if they are outside of the scope of this study.

This is the recommendation for future work in related to this field:

1. As the findings showed, the NPEMMF model found a significant, meaningful pattern in the EEG channels and the emotion stimuli pattern for mental fatigue. Thus, we can still consider studying each component, focusing on one ERP component itself instead of many ERP components directly.
2. Extending emotional and cognitive measurements: Future models must include more emotional and cognitive measurements, which would offer a more thorough evaluation of mental fatigue.

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APPENDIX A: Consent Form

Consent Form

Neuro-physiological Profiling Model for Mental Fatigue in Driving Tasks

This document contains three parts:

1. A consent form with information sheet
2. Additional Consent Form

1. CONSENT FORM

This consent form is for the volunteers to participate in a research on driver's mental fatigue titled "Neuro-physiological Profiling Model for Mental Fatigue in Driving Tasks."

Marini binti Othman, Assistant Professor,
Department of Information Systems,
Kulliyyah of Information & Communication Technology,

This statement of consent has two parts:

i. **Information Sheet**
ii. **Consent Form – to record your agreement**

You will be given a copy of the full statement of content

Part 1: Information Sheet

Purpose Of The Research

Mental fatigue is a condition induced by prolonged intense mental activity, which leads to sleepiness, distraction, poor concentration, lack of energy, and affects performance. Heavy workload and long working hours are the key factors of developing mental fatigue. As Covid-19 continues to threaten every country, society, and family, citizens worldwide are forced to adapt to a new normal of working from home, travel restrictions, home-schooling, financial distress, and lack of physical contacts. These mental workloads can be extremely taxing on one's mental health, with the lack of support on mental health may result in self-harm, increased levels of alcohol and drug use, suicidal thoughts, insomnia, and anxiety.

At present, measurement of brain activities during driving using EEG has become an emerging interest among researchers. However, this research is still limited to self-reported data, and attempts to correlate and profile the patterns of the EEG signal with mental fatigue remains inconclusive. To address this issue, we propose a neurophysiological profiling model for mental fatigue with the emphasis on driving tasks as a use case. It is hypothesized that there are specific parameters that underlying mental fatigue among drivers specifically during the Covid-19 pandemic. These drivers eventually diminishing their ability for timely response to emergent situations while dealing with daily mundane tasks.

In this work, EEG and PPG recording will be collected from 30 male participants with sleep-deprived and non-sleep deprived conditions. This work will utilize signal analysis, machine learning, and statistical approaches to form a neurophysiological profiling model for mental fatigue. Findings from this research may provide a better understanding and elevate awareness of mental fatigue, particularly in the area of transportation. Quantitative assessments of electroencephalography (EEG) and

Photoplethysmogram (PPG) can be a promising accurate indicators of mental fatigue.

Type of Research Intervention

EEG is a device that records brainwaves by attaching nodes to the participants head. The nodes are attached to the participants head via harmless gel that allows brainwave signals to be received and captured. These signals can thus be analyzed to study the correlation between EEG signal and drivers mental fatigue.

This research will look at the emotion aspects of the brain. Participant's emotional response during driving while in mental fatigue state activities will be recorded. To establish the study that correlate both EEG and PPG signal on driver's mental fatigue, a working protocol will be conducted. Overall, the data collection session is safe, non-intrusive, and does not alter any part of the participant's body.

We invite you to volunteer in this research and contribute to the data collection. However, as a standard procedure, we will need your permission to gather information about you in the context of your mental condition, sleepiness and driving activity. You will be profiled based on your mental and sleepiness condition before your brain and heart signals while driving using driver simulator are captured for our research.

Participant Selection

This research requires the study of randomly selected 30 male people aged between 18 to 40 years old. Participants will be divided into 2 groups sleep-deprived and non-sleep deprived participants. Under the well-rested condition, subjects were instructed to sleep at least 7 h before the experiment, as sleeping seven or more hours is known to maintain healthy mental alertness. Sleep-deprived participants are defined as those having less than 6 hours of sleep per night. It is also required for all participants to have a valid driving license.

Procedures

This research requires about 30 participants. Before the EEG and PPG recording session begins, a briefing will be given followed by filling the consent form attached with this document. Personal particulars, mental fatigue condition, and agreement to participate will be documented. Participants will be referred to as subjects of this study.

Once the participant agrees and ready for the experiment, the 19-channels non-invasive Electroencephalogram (EEG) sensor or cap will be placed on the subject`s head. There will be the assistant that will aid on donning the EEG cap to the participants. Additionally, a conductive gel is applied on the scalp to enhance brain signal detection. The gel are non-damaging to the hair and can be rinsed easily. Meanwhile for the PPG devices the subject will be wearing it around the hand palm. The experiment will be conducted in the Pervasive Computing and Brain Development Research Group Lab (PCBDG), International Islamic University Malaysia (IIUM).

The procedure for EEG and PPG recording is divided into six parts:

Part 1: Sleepiness Task

- In this procedure, subjects will be given a questionnaire known as KSS (Karolinska Sleepiness Scale) to measure their sleepiness scales. This questionnaire is to be completed within three to four minutes.

Part 2: Baseline recording

Eyes closed (1 minute): To initiate the baseline for EEG data, Participants will be asked to close their eyes and sit as still as possible and visualize on how to drive on the highway for 1 minute. This is a procedure for assessing the default state of the brain and to check the state of Alertness for the current time Participants have to sit as still as possible to prevent movement artefacts in the signals for 1 minutes.

- Eyes open (1 minute): Similar to eyes closed, but this time the Participants have to sit as still as possible to prevent movement artefacts in the signals for 1 minute. In this phase, participants will be asked to look at a computer screen by looking at a blank image with an X at the centre.
- Emotion stimuli (4 minute, 1 minute for each different emotions): This procedure is to stimulate a particular emotion by exposing the subject with a specific video. The recorded emotional signals reacting to the stimuli will serve as a model for this research to analyse the effects of playing video games in the later sessions. There are 4 emotions to capture, each will take 1 minute to record the EEG and PPG data.

Part 3: Emotionally related stimuli (4 minutes)

- This task requires the participant to watch video clips. Each clip has one minute and half emotional stimulus (happy, sad, fear and calm). The effect of clips may help the participant to change his/her feeling.

Part 4: Driving Simulation

- In this stage, participants need to perform a 15-minute test on driving simulator under different driving tasks and conditions (distracted driving)
- For the first 5 minutes, participants will be wearing EEG and PPG equipment and need to drive the simulator by using the easiest road. Participants will need to drive the car in the constant speed which 100km/h as to prevent waste movement artefacts in the signals.
- On the next 5 minute, participants will need to drive using the moderate road which faces simple obstacle such as rainy road and simple distraction.
- For the last 5 minute, participants will be using the hard driving road such as drive in the traffic road that requires higher thinking skills and will be facing more distracted driving behaviour.

Part 5: Baseline Recording Closing Session

- Finally, an eyes-closed and eyes-open session similar to part 1 earlier will be the closing stage of the EEG and PPG recording session.

Part 6: Sleepiness and Mental Fatigue Tasks

- In this procedure, subjects will be given again a KSS questionnaire to assess their sleepiness at current time. This questionnaire is to be completed within one minute.
- In addition there will be another questionnaire that will be given to the participant known as MFS (Mental Fatigue Scale). The mental fatigue scale (MFS) is a multidimensional questionnaire containing 15 questions. The questions concern fatigue in general, lack of initiative, mental fatigue, mental recovery, concentration difficulties, memory problems, slowness of thinking, sensitivity to stress, increased tendency to become emotional, irritability, sensitivity to light and noise, decreased or increased sleep as well as 24-hour symptom variations. This questionnaire is to be completed within two minutes

Total duration of this voluntary experiment is around 30 minutes.

Risks

There are no risks in this experiment. The EEG and PPG devices are passive systems and non-intrusive to the human brain and body.

Benefits

Your participation will give us insights to the way the brain reacts to how mental fatigue effect on the driver's performance. Thus, it is our job to correlate EEG and PPG signal of driving while in mental fatigue states. This will provide a useful information on how mental fatigue can effect on the drivers ability.

Confidentiality

The research being done in the community may draw attention and if you participate you may be asked questions by other people in the community. We will not be sharing information about you to anyone outside of the research team. The information that we collect from this research project will be kept private. Any information about you will have a unique number on it instead of your name.

We will also ask you and others in the group not to talk to people outside the group about what was said in the group. We will, in other words, ask each of you to keep what was said in the group confidential. You should know, however, that we cannot stop or prevent participants who were in the group from sharing things that should be confidential.

Sharing the Results

Nothing that you tell us today will be shared with anybody outside the research team, and nothing will be attributed to you by name. The knowledge that we get from this research will be shared with you and your community before it is made widely available to the public.

Each participant will receive a summary of the results. The results of this research study may be presented at meetings or in publications. Your identity will also not be disclosed in those presentations.

Right to Refuse and Withdraw

The participation in this research study is voluntary. Refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You are free to withdraw from the study at any time without penalty.

Who to Contact

If you have any questions, you can ask now. If you wish to have any enquiries later, you may contact any of the following:

Principal Investigator:
Marini bt Othman omarini@iium.edu.my

Co-researchers:
Abdul Wahab bin Abdul Rahman abdulwahab@iium.edu.my
Raini Bt Hassan hrai@iium.edu.my
Nur Hafizah Mahri nurhafizahm@iium.edu.my

Student researchers:
Muhammad Afiq'Ammar bin Kamaruzzaman afiqammar91@gmail.com

Part 2: Certificate of Consent

I have been invited to participate in research about analysis on "Neuro-physiological Profiling Model for Mental Fatigue in Driving Tasks".

I have read the foregoing information, and understand the conditions of this project. I have had the opportunity to ask questions about it and any questions I have been asked have been answered to my satisfaction. I hereby acknowledge the above and give my voluntary consent to participate in the study.

Print Name of Participant____________________________________

NRIC____________________

Signature ___________________ Date ___________________________

Day/month/year

Statement by the researcher/person taking consent

I have accurately read out the information sheet to the parent of the potential participant, and to the best of my ability made sure that the person understands that the following will be done:

1. Baseline Recording(2 minutes)
2. Emotionally related stimuli (4 minutes)
3. Driving Simulation (15 minutes)
4. Closing Baseline recording (2 minutes)
5. KSS and MFS questionnaires (3 minutes)

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

A copy of this ICF has been provided to the participant.

Print Name of Researcher/person taking the consent________________________

Signature of Researcher /person taking the consent__________________________

NRIC of Researcher /person taking the consent__________________________

Date _________________________ Day/month/year

2. ADDITIONAL CONSENT FORM

Additional Consent to Neuro-physiological Profiling Model for Mental Fatigue in Driving Tasks

This statement of consent has two parts:

i. **Information Sheet**
ii. **Consent Form – to record your agreement**

You will be given a copy of the full statement of content

Part 1: Information Sheet

EEG and PPG measurements are non-invasive and non-intrusive method of obtaining brain and blood volume changes in the microvascular bed of tissue. The devices harness and electrodes are harmless and painless to wear. By sampling electrical signals naturally occurring in a human head, it is possible to observe reactions of the human mind towards their brainwave activity on driving. Other method of observing such reaction exists, but their result can often be distorted by false reading and inaccuracy. EEG and PPG opens up an opportunity to look directly into the brain and the data can be measured, analyzed, and synthesized with machine learning algorithm.

This research project studies the correlation between EEG and PPG signal on driving in mental fatigue states. Other profiling criteria will also be taken for analysis. The findings will contribute to the community for developing more safety way and alert driver to be more caution when driving in that state,

Right to Refuse and Withdraw

The participation in this research study is voluntary. Refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You are free to withdraw from the study at any time without penalty.

Confidentiality

The results of this research study may be presented at meetings or in publications. Your children identity will not be disclosed in those presentations. All participants will be identified based only on their unique identifying number. Only the investigators and experimenters involved in the research will have access to these identifying numbers.

Part 2: Certificate of consent

I give my consent to use my EEG data for the purpose of this research. Once the research has been completed, whether or not my data is used, I hereby… (tick where appropriate)

- ☐ Wish my EEG and PPG data to be destroyed and no duplicates shared with anyone.
- ☐ Allow my EEG and PPG data to be reserved only for ______ years for future works. The data shall be destroyed thereafter.
- ☐ Give permission for my EEG and PPG data to be stored indefinitely but not shared
- ☐ Give permission for my EEG and PPG data to be stored indefinitely and shared with other researchers

AND

- ☐ I want my identity to be removed from my EEG and PPG data.
- ☐ I want my identity to kept with my EEG and PPG data.

AND (if the data is allowed for future works)

- ☐ I give my consent to use my EEG and PPG data for any research which has been approved.
- ☐ I give my consent to use my EEG and PPG data only in the same context and field of study similar to the current research.

I have read the information, or it has been read to me. I was given the opportunity to ask any enquiries regarding this research and my questions have been answered to my satisfaction. I consent voluntarily to have my EEG and PPG data stored in the manner and purpose indicated above.

Name of Participant: ____________________

Signature of Participant: _____________________

NRIC of Participant: _____________________

Date: _________________(dd/mm/yyyy)

Statement by the researcher/person taking consent

I have accurately read out the information sheet to the parent of the potential participant, and to the best of my ability made sure that the person understands that the following will be done:

1. Baseline Recording(2 minutes)
2. Emotionally related stimuli (4 minutes)
3. Driving Simulation (15 minutes)
4. Closing Baseline recording (2 minutes)
5. KSS and MFS questionnaires (3 minutes)

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

A copy of this ICF has been provided to the participant.

Print Name of Researcher/person taking the consent________________________

Signature of Researcher /person taking the consent__________________________

NRIC of Researcher /person taking the consent__________________________

Date ___________________________ Day/month/year