



Faculty of Computer Science and Information Technology

***EEG ANALYSIS OF SLEEPY DRIVERS: IDENTIFYING KEY
BRAINWAVE INDICATORS OF FATIGUE***

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Bachelor of Software Engineering with Honors

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**EEG ANALYSIS OF SLEEPY DRIVERS: IDENTIFYING KEY BRAINWAVE
INDICATORS OF FATIGUE**

CRYSTAL SONG LEH SING

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requirements for the degree of
Bachelor of Software Engineering with Honors

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UNIVERSITI MALAYSIA SARAWAK

2025

**ANALISIS EEG PENGEMUDI YANG MENGANTUK: MENGENAL PASTI
PETUNJUK UTAMA GELOMBANG OTAK KELETIHAN**

CRYSTAL SONG LEH SING

Projek ini merupakan salah satu keperluan untuk
Ijazah Sarjana Muda Kejuruteraan Perisian dengan Kepujian

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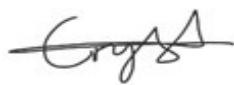
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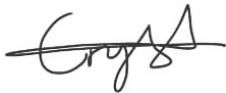
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DECLARATION

I hereby declare that this Final Year Project Report titled “EEG Analysis of Sleepy Drivers: Identifying Key Brainwave Indicators of Fatigue” is my original work and completed under the guidance of Dr. Liew Siaw Hong, Universiti Malaysia Sarawak (UNIMAS) this project work is submitted in the partial fulfillment of the requirements for the degree of Bachelor of Computer Science with Honors (Software Engineering). The findings presented in this thesis have not been submitted for consideration for a degree or certificate at any other university or institute.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
AUC	Area Under the Curve
CNN	Convolutional Neural Network
CSV	Comma-Separated Values
DFA	Detrended Fluctuation Analysis
DT	Decision Trees
EDA	Exploratory Data Analysis
EEG	Electroencephalogram
FFT	Fast Fourier Transform
FN	False Negatives
FP	False Positives
GB	Gigabyte
GPU	Graphics Processing Unit
Hz	Hertz
ICA	Independent Component Analysis
IDE	Integrated Development Environment

k-NN	k-Nearest Neighbors
LSTM	Long Short-Term Memory
ML	Machine Learning
SVM	Support Vector Machine
OS	Operating System
PSD	Power Spectral Density
RAM	Random Access Memory
RBF	Radial Basis Function
ReLU	Rectified Linear Unit
RF	Random Forest
RMS	Root Mean Square
RNN	Recurrent Neural Networks
ROC	Receiver Operating Characteristic
SampEn	Sample Entropy
SVM	Support Vector Machine
TN	True Negatives
TP	True Positives

ABSTRACT

Driver fatigue is considered a major cause of traffic accidents, injuring millions and killing many each year. The detection systems using existing methodologies based on external indicators, such as the movement of eyes or the pattern of the vehicle, are not very reliable and have low early detection capability. The present research investigates electroencephalogram (EEG) signals to identify a pattern of brainwaves that indicates fatigue, thereby improving real-time driver drowsiness detection systems. This study aims to apply machine learning techniques comprising Convolutional Neural Networks (CNN), Random Forest, and Support Vector Machines (SVM) to classify EEG data from alert and fatigued drivers; find important features in EEG signals related to fatigue that could be integrated into real-time driver monitoring system and test the accuracy of the developed models in detecting driver fatigue states. This study utilizes an open-access EEG dataset collected under controlled conditions, concentrating on the Delta, Theta, Alpha, and Beta frequency bands. Systematic methodology includes preprocessing, feature extraction, and classification modeling employed to analyze data. It is anticipated that specific EEG patterns, particularly those within the Theta and Alpha bands, will demonstrate a significant correlation with driver fatigue. The results are expected to provide the basis for developing robust and efficient drowsiness detection systems that will enhance road safety and reduce fatigue-related accidents. This research is important for the development of computer science, the improvement of transport safety, and the enrichment of human-machine interaction knowledge.

ABSTRAK

Keletihan pemandu diiktiraf sebagai penyumbang penting kepada kemalangan kenderaan, mengakibatkan kecederaan berjuta-juta dan kematian ramai setiap tahun. Sistem pengesanan semasa yang bergantung pada petunjuk luaran seperti pergerakan ocular atau corak kenderaan, menunjukkan kebolehpercayaan yang terhad dan mempunyai keupayaan pengesanan awal yang tidak mencukupi. Kajian ini meneroka isyarat EEG untuk mengetahui corak gelombang otak tertentu yang menunjukkan keletihan, dengan tujuan meningkatkan sistem pengesanan mengantuk pemandu masa nyata. Usaha penyelidikan ini bertujuan untuk melaksanakan metodologi pembelajaran mesin, termasuk CNN, Random Forest, dan SVM untuk mengklasifikasikan data EEG dari pemandu amaran dan keletihan; mengenal pasti ciri kritikal dalam isyarat EEG yang berkaitan dengan keletihan yang dapat dimasukkan ke dalam system pemantauan pemandu dalam talian; dan menilai ketepatan model yang dicadangkan dalam mengenali pelbagai tahap keletihan pemandu. Penyiasatan ini menggunakan set data EEG akses terbuka yang diperoleh dalam keadaan eksperimen terkawal, dengan fokus pada jalur frekuensi Delta, Theta, Alpha, dan Beta. Manuskrip ini menggariskan pendekatan analisis data komprehensif yang merangkumi prapemprosesan, pengekstrakan ciri, dan pemodelan klasifikasi. Dihipotesiskan bahawa corak EEG yang tersendiri, terutamanya dalam jalur Theta dan Alpha, akan menunjukkan korelasi yang besar dengan keletihan pemandu. Penemuan ini dijangka berfungsi sebagai asas untuk penciptaan sistem pengesanan mengantuk yang mantap dan berkesan, dengan itu mempromosikan keselamatan jalan raya dan mengurangkan insiden berkaitan keletihan. Penyelidikan ini mempunyai implikasi yang signifikan untuk kemajuan sains komputer, peningkatan keselamatan pengangkutan, dan pemahaman yang lebih mendalam mengenai interaksi manusia-mesin.

CHAPTER 1: INTRODUCTION

1.1 Introduction

Fatigue is one of the reasons why the driver is unable to focus on the drive, which leads to road accidents with injuries and deaths counting to millions every year (Shaik et al., 2021). According to the World Health Organization (2023), fatigue-related incidents account for about 100,000 road crashes worldwide. Consequently, research into physiological measures for the detection and prevention of drowsy driving has gained traction as a relevant area of focus in recent literature.

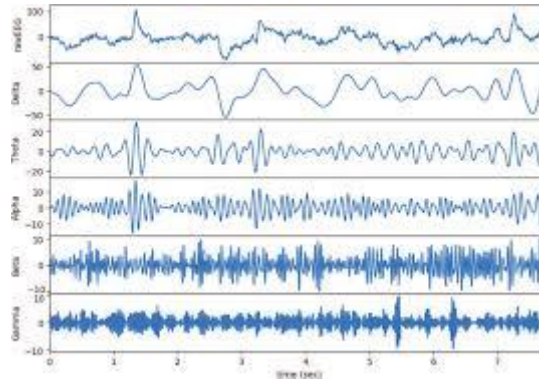


Figure 1: Example of EEG signals processing

EEG, which is known as Electroencephalogram testing analysis, is considered a useful tool in the measurement of driver fatigue due to its ability to non-invasively record brain signals. As opposed to traditional detection techniques, which generally rely upon environmental behavioural indicators, EEG provides a real-time and direct measure of cognitive states through the recording of the underlying changes in the brain. However, recent investigation has highlighted the potential of using EEG data signals to illustrate changes in brain signatures in order to identify targeted brainwave patterns that indicate fatigue and improve the accuracy of early warning systems designed to combat drowsy driving (Ibrahim et al., 2022).

The goal of this research project is to employ machine learning techniques to classify EEG signals that get progressively stronger while being recorded by individuals who drive with

varying signal data. This study aims to identify viable mechanisms in detecting the electroencephalography (EEG) patterns associated with changing states of mind, such as fatigue and alertness, by utilising machine-learning algorithms, including Convolutional Neural Networks (CNN), Random Forests, and Support Vector Machines (SVM). The results found are applicable in developing reliable and efficient driver fatigue recognition systems, thus ensuring that vehicle accidents occur and transport safety is improved.

1.2 Problem Statement

Driver fatigue is a major causative factor in road accidents, with millions of injuries and deaths worldwide each year. Most existing methods for detecting driver fatigue are based largely on visible outer signs, such as facial expressions, eye movements, and emissions from the vehicle, but these methods have significant limitations. So, this project proposes using EEG data to identify specific brainwave patterns indicative of fatigue, potentially leading to a more effective early warning system for drowsy driving. By focusing on EEG signals, this project aims to develop a deeper understanding of neural correlates of driver fatigue, potentially leading to more effective interventions and strategies for reducing drowsy driving incidents (AL-Quraishi et al., 2024).

1.3 Objectives

The objectives of this project are:

1. To implement machine learning techniques in classifying EEG data of alert versus fatigued drivers.
2. To identify the most important EEG characteristics of driver fatigue, potentially guiding the creation of real-time sleepiness detection systems.
3. To evaluate the classification performance of fatigued drivers using EEG signals.

1.4 Methodology



Figure 2: Research Methodology Workflows

This research project will adopt a systematic methodology which organized into four main stages.

Phase 1: Dataset Description

Phase one consists of data preprocessing and initial analysis of the EEG dataset. This phase will analyze the structure, features, and quality of data recorded from drivers in different states using EEG signals such as sleepy, not sleepy. Then, will perform the preprocessing for data to preprocess and clean data to prepare for analysis. The EEG dataset used in this study can be accessed at <https://www.kaggle.com/datasets/naddamuhhamed/sleepy-driver-eeg-brainwave-data/data>.

Phase 2: Data Preprocessing and Data Preparation

Exploratory data analysis of the EEG signals will be performed in the second phase. The research will analyze the EEG data using statistical analysis tools and investigate amplitude patterns, frequency distributions, and signals varying between different states. The visualization tools will be used to create meaningful representations of the results.

Phase 3: Feature extraction and Modelling

In the third phase, the dataset will be used for the identification and analysis of major EEG characteristics that correlate significantly to driver fatigue. The analysis will retrieve frequency-domain characteristics focusing on EEG frequency band changes. The analysis of variance will be conducted to test the significance of the observed patterns.

Phase 4: Performance Measurement

The last step of the project will consist of sorting through the research results and writing insights on EEG signatures of driver fatigue using the already analyzed dataset. This will comprise the identification of the most consistent EEG features linked to states of fatigue, an examination of the interactions between EEG measures of fatigue, and recommendations for future research in this area.

1.5 Project Scope

This research project focuses on analyzing pre-existing EEG datasets collected from drivers experiencing varying levels of fatigue. The scope includes the data collection of EEG signals recorded from drivers in controlled conditions. Research will focus on the analysis of traditional EEG frequency bands which is NeuroSky MindWave headset and their correlation with levels of driver fatigue. This analysis will be restricted to statistical and analytical analysis of the EEG data to look for significant patterns and correlations within the dataset. The scope includes analyzing data from adult drivers and is restricted to EEG recordings taken under controlled experimental conditions. While machine learning techniques will be discussed in the literature review, the project will not involve the development or implementation of these models.

This project aims to gain a deeper insight into and ultimately document the link between the EEG patterns of drivers and their levels of fatigue to assist further development of detection systems. Examining a small number of papers helps in ensuring that the available data is well analyzed while remaining within the clear boundaries of the study.

1.6 Significant of Project

The research project is significant important to several domains. From the computer science perspective, the application of advanced machine learning technique Convolutional Neural Networks (CNN) will be used to analyze complex EEG data signals representing an important stride in the field (Rajwal & Aggarwal, 2023). The efficient classification of the brain activity patterns indicative of driver fatigue states speaks to the potential of such computational methods in real-world sensing and monitoring applications. Most importantly, insight gained from key EEG features identified about fatigue can directly contribute to the development of innovative, computer-based systems for detecting drowsiness to enhance transportation safety. Beyond the immediate application, this research was wider implications for the research domain of human factors and human-computer interaction by providing substantial knowledge regarding the neural correlates of cognitive states and their relation to technological interventions. This would correspondingly relate to a three-in-one significance for computer science, transportation safety, and a better understanding of human-machine interface.

1.8 Expected Outcome

The current project will aim at isolating unique electroencephalogram (EEG) signals that are associated with the fatigue of drivers, therefore sharpening the understanding of how fatigue influences the activity of the brain. The study identifies the important EEG characteristics that can be used to detect fatigue by the use of machine learning methodologies. Such results provide important research and practical data. Further, by specifying these EEG signs, the study presents specific steps towards the installation of real-time drowsiness detection systems in automobiles. Therefore, the study forms a good baseline for future studies to be conducted on driver fatigue and EEG assessments, hence encouraging the search for practical methods of detection.

1.9 Project Outline

Chapter 1: Introduction

In this chapter, the global safety problem of driver fatigue is discussed, and explored the use of EEG technology in enhancing the detection of drowsiness. The discussion further explains why the current modes of detection are limited and why it is necessary to employ EEG-based modes of detection. It next presents the major objectives of the project, which are to classify the EEG signal to identify fatigue, before proceeding to explain the significance of the study to transport safety, define the scope, the dataset to be used, as well as the limitations of the project.

Chapter 2: Literature Review

In this chapter, the literature on the topic of driver fatigue, EEG technology, and machine learning techniques is reviewed. It summarizes papers published about fatigue detection, EEG signal processing, and applied machine learning using classification.

Chapter 3: Research Methodology

This chapter describes the design of the research, data collection procedures, and the technique employed in the analysis of EEG data. It specifies the method of preprocessing techniques, machine learning methods for signal classification, and explains the approach taken. It provides the details of the preprocessing methods used, the machine learning algorithms of signal classification, and the steps of analysis, including data cleaning, feature extraction, and validation.

Chapter 4: Implementation and Result Analysis

This chapter presents the findings of the EEG signal analysis, presents descriptive statistics of the results, and the results of the machine-learning classification and suggests relevant areas

for research. It compares various computational techniques, identifies key fatigue indicators, and discusses the implications of findings about the existing literature.

Chapter 5: Conclusion and Future Work

The concluding chapter encapsulates the principle of discoveries, affirms the hypothesis, and explores the wider implications of the research. It emphasizes the advancements made within the discipline, outlines potential practical uses, and suggests directions for future research, acknowledging both achievements and limitations of the study.

1.10 Summary

This research addresses driver fatigue, one of the major causes of accidents across the world, by appealing for the application of real-time fatigue detection using EEG technology. Contrary to the present techniques that are based entirely on external symptoms, EEG depends on brainwave patterns to define cognitive states. This research applies machine learning techniques in classifying EEG signals in establishing key features that are related to fatigue. The research aims to set up efficient systems for early detection of drowsiness to improve road safety. It explains the methodology, scope of the project, and what is expected during and at the end of the research, with the explanation of practical and theoretical contributions of the research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Driver fatigue detection using EEG signals falls under one of the most important and emerging areas of research in the field of transportation safety combined with biomedical engineering. The current chapter systematically reviews the related literature regarding EEG-based driver fatigue detection systems, analyzing in more detail the technologies in use in this area and the strategies of machine learning that could be further applied to improve detection accuracy. This review encompasses the methods, technologies, and results aimed at the establishment of efficient driver fatigue detection systems.

Driver fatigue is considered one of the major reasons for road accidents around the world (Che Hasan et al., 2021). On this basis, growing awareness of the problem has stimulated serious research efforts toward the development of reliable and accurate driver fatigue detection methods to help drivers before it goes out of control. The paper brings into focus the present position of EEG technology in fatigue detection and further integrations with machine learning techniques.

Recent advancements in both the EEG technology and the signal processing opened new possibilities for on-line monitoring of a driver's cognitive states. This literature review describes some of the recent theory and practice advancements that have occurred to build the current level of knowledge and development regarding EEG-based fatigue detection systems.

2.2 Review of Current Driver Fatigue Detection Systems

Currently, available driver fatigue detection systems can broadly be grouped into three main categories: driver behavioural-based systems, vehicle-based systems, and driver physiological-based systems (Jiao et al., 2022). All of these systems have some particular advantages and disadvantages concerning the driver fatigue detection aspect.

2.2.1 Driver Behavioural-Based Systems



Figure 3: Driver Behavioral-Based Detection Systems

Behavioural-based systems only been able to monitor detectable signs of fatigue, including:

- Eye movement and blinking behavior
- Facial expressions
- Head position and movement
- Yawning frequency

These systems are non-intrusive and relatively easy to implement, making them attractive to real-world applications. However, they face significant challenges and one of the main issues is their dependence on the lighting conditions, particularly if there is too little light or shine (Altameem et al., 2021). Additionally, individual differences play a crucial role, as everyone shows various kinds of fatigue, which can give rise to fallacies. Another challenge is the limited ability to detect driver fatigue, as behavioural changes can sometimes be subtle, making it not easy to detect, especially in the initial stages of fatigue during its incubation periods.

2.2.2 Vehicle-Based Systems

The various vehicle-based approaches monitor parameters like:

- Steering wheel movements
- Lane shift or departure patterns
- Speed variation
- Braking patterns

Although these systems reflect indirect information concerning the driver's state of fatigue, they are influenced by several factors. Road conditions can affect steering and lane deviation patterns, as variations in road type or roadwork may lead to different driving behaviors. Weather conditions such as rain or fog, may also result in erratic driving not caused by fatigue, further complicating the detection process. Moreover, the type of vehicle for example, size and suspension elements may reflect the differences in how fatigue manifests in driving behaviors and thus can lead to possible false alarms or missed detection.

2.2.3 Driver Physiological-Based Systems

EEG-based systems represent the most direct method of driver fatigue measurement due to their physiological basis. Which:

- Directly monitor patterns of brain activity
- Provide early detection of the onset of fatigue
- Highly sensitive to separate conditions of alert versus fatigued state
- Facilitate the continuous observation of cognitive states

Recent research showed that detection accuracies as high as 90% and above were achievable with EEG-based systems in controlled environments (Ardabili et al., 2024). Certain other, current EEG-based systems also faced challenges such as signal noise and artifacts, the need

for proper electrode placement, processing complexity, cost of implementation, and user comfort and acceptance.

These limitations have motivated continuous research toward the development of better EEG-based systems, focusing on noise reduction of the signal, easiness of the electrode setup, and embedding machine learning algorithms for better detection performance. Non-invasive EEG devices might provide better comfort and usability where monitoring is needed over a long period.

2.3 Review of Similar Existing EEG-Based Detection Systems

Table 1: Comparison of Existing EEG-Based Detection Systems

Type of Systems	Number of Channels	Accuracy	Real-time Processing	Cost	Implementation Complexity
NeuroSky MindWave-based Detection System	1	83.78%	Yes	Low	Low
Deep Learning-based EEG Analysis Systems	32	92.71%	Partial	High	High
Commercial EEG-based Driver Monitoring Systems - B-Alert X24	24	91%	Yes	High	Medium

2.3.1 NeuroSky MindWave-based Driver Fatigue Detection System

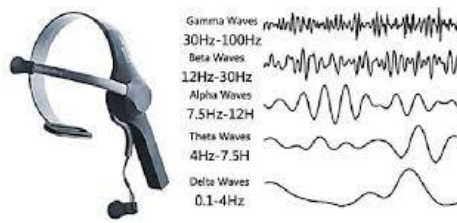


Figure 4: NeuroSky MindWave Headset

The NeuroSky MindWave-based Detection System is the easiest and cheapest way to detect driver fatigue in a commercial. The system employs a single-channel EEG headset with a dry electrode attached to the Fp 1 site to initiate the signal by transmitting it through the wearer's brain. The research revealed that it could correctly predict 83.78% of the time that the drivers were fatigued due to early warning signals given by the system (Kamti & Iqbal, 2022). The most attractive aspect of the application is the fact that the NeuroSky MindWave system is straightforward to operate and can solve real-world problems. On the other hand, the use of the single-channel device restricts the system's capability to capture higher spatial resolution on brain activities; hence, this single-channel setup might mask the sign of fatigue that multichannel systems can identify.

2.3.2 Deep Learning-based EEG Analysis Systems for Driver Fatigue

The cutting-edge deep learning solutions have come up with the best ways of handling fatigue problems using EEG data. One of the most influential systems is a multi-channel EEG setup trained with convolutional neural networks. The system exploits signals arising in EEG electrodes on all 32 channels for solving the task and can do so with an impressive accuracy of 92.71% in distinguishing between a person who is alert and one who is fatigued (Ren et al., 2021). This system can be ascribed as its core feature to its capacity to learn automatic feature extraction options, thus, there is no more necessity for a human interface that manipulates. The complexity and processing necessities of the system, however, become barriers to instant utilization of the system in vehicles.

2.3.3 Commercial EEG-based Driver Monitoring Systems

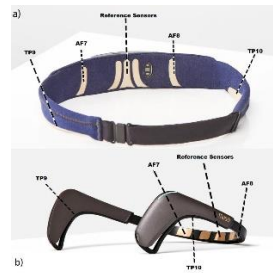


Figure 5: Muse 2 and Muse S Headset

Several commercial systems have been created as the solution for finding out which drivers are sleepy disorderly. A majority of these gadgets are so trained to automatically diagnose driver fatigue cases by combining almost all other registered devices with the brain readings. For example, Muse 2 and Muse S headsets have been developed to assess driver drowsiness by analyzing brain activity, providing a more precise and reliable method than traditional vehicle-based systems. These EEG devices equipped with dry electrodes, offer convenience and accuracy in detecting fatigue, potentially achieving performance comparable to clinical equipment. However, challenges such as higher costs and the complexity of integrating these systems into vehicles may limit their widespread adoption despite the effectiveness of detecting subtle changes in alertness (Rezaee et al., 2022).

2.4 Review of Machine Learning Techniques in EEG Analysis

Machine learning techniques have improved the analysis of EEG signals for finding driver fatigue. Traditional machine learning methods and deep learning architectures are the two major categories of this technique, both of which have different strengths that can be used in different parts of the clinical EEG system development and implementation.

Table 2: Comparison of Machine Learning Techniques in EEG Analysis

Machine Learning Techniques	Average Accuracy	Feature Engineering Required	Processing Speed	Model Complexity
SVM	96.42%	High	Fast	Medium
Random Forest	98.12%	Medium	Fast	Low
LSTM	97.42%	Medium	Moderate	High
CNN	98.13%	Low	Slow	High

2.4.1 Traditional Machine Learning Approaches

Traditional machine-learning approaches have demonstrated significant success in EEG-based fatigue detection through various algorithms. The application of SVM and Random Forests has also been quite useful in the detection of fatigue, which is generated using EEG. These methods usually require strict feature extraction and selection before the classification. SVM-based systems can reach a level of up to 96.42% if frequency-domain features that have been extracted diligently are applied. By contrast, Random Forests, powered by very smart programming, are good at detecting and catching the behavior of EEG signals that have been proven to be false. They scored around 98.12% in those studies, which were very controlled and solidified (Kumari et al., 2023).

k-Nearest Neighbors (k-NN) is one of the simple, efficient algorithms for classification in EEG; it has given excellent results for small datasets and with great success has also found

its way into some studies about EEG and fatigue states. k-NN could distinguish between alert and fatigued states with reasonable accuracy when combined with feature extraction techniques such as power spectral density. Decision Trees (DT) are another common choice for EEG-based fatigue detection due to their interpretability and low computational complexity. Decision trees identify key features with the most contribution to classification. Therefore, they are ideal for lightweight and real-time systems. But their susceptibility to overfitting is a big limitation unless combined with ensemble methods like Random Forest or Gradient Boosting (Altameem et al., 2021). Naïve Bayes classifiers are very common, especially in the case of smaller datasets, since they are straightforward and efficient. Though they assume independence of features, which may not be a good representation of the complex relationships that might exist in EEG signals, they provide a good baseline model to compare against (Hosseini et al., 2021).

Most traditional ML algorithms show their best performance, which heavily relies on the quality of the extracted features. Although SVM and Random Forest often have higher accuracy, their dependency on well-engineered features increases the complexity of preprocessing. Comparatively, simpler algorithms like k-NN and Naïve Bayes provide faster predictions but may sacrifice some accuracy. In general, combining features from multiple domains, such as time, frequency, and time-frequency enhances the robustness of traditional ML methods applied to EEG-based fatigue detection systems.

2.4.2 Deep Learning Architectures

Deep learning architectures revolutionized EEG-based fatigue detection, largely due to their capabilities for automatic extraction and learning of features from raw EEG data, hence eliminating feature engineering. The main deep learning techniques being employed include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and hybrid models that combine a couple of deep learning techniques.

CNN designed for EEG signal processing are becoming popular with strengthening the patient's brain signal. Their non-linear nature allows them to find features well even from raw EEG data. The most recent applications of CNNs have been found to give high accuracy with the help of less preprocessing and feature engineering (Salvi et al., 2020). RNN, along with their variant LSTM, is very effective in the analysis of temporal dependencies within EEG signals. LSTM models have proven to be great at modelling sequential relationships and temporal variations in brain activity. Research by Yousefi et al. (2023) showed that LSTM networks achieved high accuracy when processing time-domain EEG features. The research indicates the potential of the LSTM network in dealing with the dynamically altering aspect of the temporal fatigue states. With this ability, the heavy computational resource requirement makes LSTM networks not applicable for real-time use in a vehicular environment.

Hybrid techniques of CCN and RNN architectures have been found to be very useful in enhancing fast, accurate classification. CNN layers focus on extracting spatial features, whereas RNN or LSTM layers capture the temporal dynamics of EEG signals. For example, Khan et al. (2024) implemented a hybrid CNN-LSTM model to achieve a classification accuracy exceeding 99.82% in driver fatigue detection using physiological data. The combinations of spatial and temporal feature learning enable these models to outperform single deep learning architectures in fatigue classification tasks.

While deep learning methods, especially CNNs and LSTMs, have shown much better performance in classification compared to other traditional machine learning techniques, their computational complexity and resource consumption have increased accordingly. This presents a challenge in implementing real-time systems on vehicles, especially when multi-channel EEG systems are employed. However, with continuous improvement in hardware and optimization techniques, deep learning is still one of the great approaches to EEG-based driver fatigue detection due to its high accuracy and automation in feature learning.

To illustrate the use of these algorithms in the context of this study, the RF model was selected due to its interpretability and performance in handling EEG data that contains diverse feature types. This model proved particularly skilled at detecting the relevance of features and performed better when used on both statistical and engineered features. The SVM, based on sound theoretical foundations as a classifier with significant capability in handling high dimensionality, was utilized as a supporting model to determine stable decision boundaries across the EEG feature space. Finally, CNN was used due to its ability to detect sophisticated spatial patterns in raw EEG features, although with high computational complexity. Together, these models brought distinct strengths to the analysis of EEG data, and their comparative assessments played a key role in validating the consistency of critical EEG indicators related to fatigue.

2.5 Analysis of EEG Signal Processing Methods

Fatigue detection through the EEG signals' processing includes several standpoints that heavily affect the efficiency of the whole system. Knowing those steps is crucial for creating fatigue detection systems that will work with the same precision as they do in real traffic conditions.

2.5.1 Signal Preprocessing

Preprocessing of the EEG signal is the most basic technique to ensure the precision of fatigue detection, especially in all vehicular environments where signal quality is a problem due to many factors. The proper preprocessing, specifically when dealing with vehicle-induced artifacts, can improve classification accuracy (Chaddad et al., 2023). The main preprocessing techniques are the following:

Bandpass Filtering: This technique removes high-frequency muscle artifacts and low-frequency drift. It is especially effective in filtering out vehicle vibration noise while preserving important neural brain activity signals linked to fatigue states.

Independent Component Analysis (ICA): ICA helps with separating and removing artifacts such as eye movements and blinks, which is essential in the situation of the car being driven with frequent eye movements. This technique makes it possible to keep the signal in good quality during functional driving behaviours.

Artifact Removal: This technique is directed to improving certain problems typical of vehicular conditions, like head movement artifacts, electromagnetic interferences produced by the vehicle's electronics, as well as environmental noise from the road.

2.5.2 Feature Extraction and Selection

The machine learning methods used in EEG rely heavily on the quality of the features derived from EEG signals. Feature extraction techniques can be broadly categorized into time-domain, frequency-domain, and time-frequency methods, each offering unique insights into brain activity patterns associated with fatigue states.

Time-domain features include statistical parameters such as mean, variance, skewness, and kurtosis, which describe the overall behavior of EEG signals. Advanced metrics like Hjorth Parameters for signal mobility and complexity, while Sample Entropy (SampEn) and Detrended Fluctuation Analysis (DFA) enable sophisticated analysis of signal complexity and long-range correlations within the signals. Temporal characteristics such as peak-to-peak amplitude variations, zero-crossing rate for frequency content changes, and Root Mean Square (RMS) values for signal energy analysis have been proven particularly effective in capturing the dynamic aspects of fatigue-related EEG patterns.

Frequency-domain features focus on the spectral properties of EEG signals, providing crucial insights into different brainwave states associated with varying levels of alertness. Techniques such as the Fast Fourier Transform (FFT) and Welch's method are employed to compute the power spectral density, which reflects signal power across various frequency bands. Relative band power analysis uses the Theta band (4-8Hz) as drowsiness indicators, the Alpha band (8-13Hz) reflects relaxation states and the Beta band (13-30Hz) serves as a reliable indicator of alertness. Advanced spectral measures, including spectral entropy for irregularity quantification, coherence analysis between channels, and phase synchronization indices, have significantly enhanced the precision of EEG signal analysis in fatigue detection systems.

The integration of time-frequency features, such as wavelet coefficients and short-time Fourier transforms, gives a complete representation of the signal characteristics across different time scales. Contemporary research has shown that combining complementary data from three domains – time, frequency, and time-frequency may result in improving the classification accuracy up to 5% when compared to results obtained from a single-domain approach (Stancin et al., 2021). While increasing the dimension increases the accuracy, the increased computational complexity and processing time make it a very crucial trade-off in the implementation of real-time systems for EEG-based driver fatigue detection.

2.6 Comparison Between Existing Detection Systems

The effectiveness of EEG-based fatigue detection systems varies significantly based on the design approach and implementation. Understanding these differences is crucial for selecting appropriate systems for specific applications.

Table 3: Comprehensive Comparison of Detection Systems

Parameters		Traditional EEG Systems	Single-Channel Systems	Multi-Channel EEG-Based Systems
Number of Channels		Multiple (usually 16-32 channels)	Single Channel	Multiple (typically 16-256+ channels)
Accuracy		High (depending on number of electrode)	Lower (limited to one region)	High (improved with more channels, better resolution)
Response Time		2-3 seconds	<1 seconds	1-2 seconds
Ease of Use		Complex setup, trained operator required	Simple, self-applicable	Moderate, basic training needed
Reliability in Vehicle		Moderate (sensitive to movement)	High (robust to movement)	High (with advanced noise cancellation)
Real-time Capability		Limited by the processing time	Yes, immediate feedback	Yes, with minimal delay
Setup Time		>30 minutes	<5 minutes	15-20 minutes

Key Findings from System Comparison

Each system types present distinct advantages and limitations for real-world applications:

Table 4: Comparative Analysis of Advantages and Limitations of Systems

Systems	Advantages	Limitations
Traditional EEG Systems	- Capable of comprehensive brain activity monitoring - Can process brain signals for fatigue detection	- Slow response time than other systems - Complex setup and interpretation requiring trained operator - Only moderate reliability and sensitive to movement - Needs regular maintenance and calibration
Single-channel Systems	- Quick setup ideal for daily use - Minimal training requirements - Cost-effective solution for individual drivers	- Lower spatial resolution - Limited detection of complex fatigue patterns - May miss subtle fatigue indicators
Multi-channel EEG-based Systems	- Higher accuracy crucial for safety-critical applications - Comprehensive brain activity monitoring - Advances noise cancellation capabilities	- High-cost limits widespread adoption - Requires regular maintenance and calibration - Complex setup process

Implementation Challenges

The real-world implementation of EEG-based driver fatigue detection systems faces several key challenges. One of the key challenges is maintaining signal quality. Movements within the vehicle can change the contact of electrodes, leading to signal deterioration. Additionally, environmental factors such as temperature and humidity can introduce noise or distortion, impacting the performance of the EEG device. Over time, wear and tear on the sensors can also degrade performance, causing inconsistent readings and necessitating regular maintenance (Soufineyestani et al., 2020).

Another very important factor in terms of cost-effectiveness. When the system applies data processing with high-end techniques of detecting through the use of EEG, the cost may even be very high. The financial load is expanded not only through the initial payment but also with the ongoing maintenance and replacement costs in addition to the original costs. Besides, user training is essential, which may be time-consuming and costly for more complex systems.

Finally, these systems run with real-time processing needs. The best aspect is the transmission of information quickly. However, the more complex the algorithms, the longer the lag of a real-time decision. Moreover, EEG systems are required to work for extended time scales without using vehicle power supplies, power consumption is an issue. The integration of these systems with existing vehicle technologies can be challenging, as it requires seamless communication between the EEG system and other onboard systems, such as the vehicle's computer and safety systems. These challenges highlight the need for continued development to make EEG-based fatigue detection systems more viable in practical, real-world applications.

2.7 Summary

A thorough review of EEG-based fatigue detection systems reveals significant technological evolution from diagnostic methods to sophisticated machine learning. These advancements demonstrate the improved capability of EEG systems compared to behavioural and vehicle-based detection methods, offering more direct physiological monitoring of brain activity. The progression from single-channel systems, represented by NeuroSky MindWave, to multi-channel deep learning implementations using CNNs and LSTMs highlights the field's development toward more precise and reliable fatigue detection, with traditional machine learning techniques, like Random Forest, showing promising results through careful feature engineering.

Despite their technological promise, the practical deployment of EEG-based systems faces serious challenges that must be addressed for real-world deployment. Key barriers include the fundamental trade-off between system complexity and usability, where sophisticated multi-channel systems provide higher accuracy but require greater technical expertise and cost financial investment. Signal quality maintenance in vehicular environments remains an ongoing challenge due to movement artifacts, electromagnetic interference, and environmental factors, while balancing cost-effectiveness and performance remains crucial for widespread adoption in consumer vehicles. Future research should prioritize bridging the gap between laboratory performance and real-world application through enhanced signal preprocessing techniques, efficient real-time processing algorithms, and adaptive learning systems. Developing more comfortable and user-friendly EEG devices for extended wear and implementing cost-reduction strategies without sacrificing accuracy. EEG-based solutions can be most effective in improving traffic safety solely by overcoming the complex technical, economic, and usability issues through the adoption of standardized procedures and seamless integration with existing automobile technologies.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter expands on a thorough understanding of the research methodology in EEG data analysis of the factors for identifying brainwave indicators associated with driver fatigue. This methodology can be divided into four stages: dataset description, data preprocessing and preparation, feature extraction and modeling, and performance measurement.

3.2 Research Design

The research adopts a quantitative approach, utilizing machine learning techniques to analyze EEG data. The EEG signals from drivers in different alertness states will be processed and analyzed with the aim of identifying EEG recordings that indicate brainwave patterns indicative of wearer fatigue.

3.2.1 System Overview Diagram

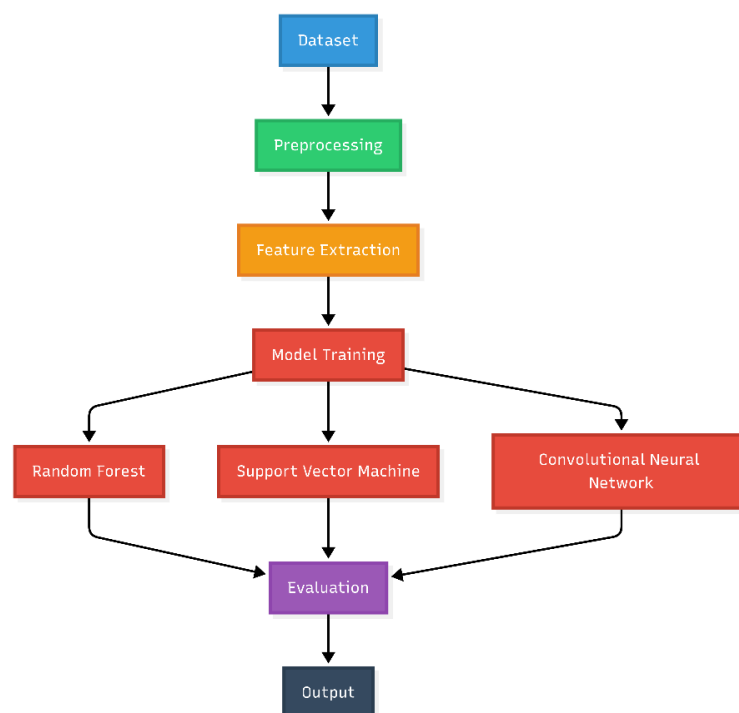


Figure 6: System Flow Diagram

The diagram above explains the overall architecture of the driver fatigue detection system that employs EEG technology. The framework is provided to bridge the theoretical methods discussed in Chapter 2 with the practical solutions provided in Chapter 4. The diagram maps the entire process, from the initial EEG data acquisition to the final classification step. Moreover, it creates an explicit connection between the literature review and its application in practice by showing the incorporation of the machine learning methods discussed in Chapter 2 on the operational process.

3.2.2 Dataset Description

The extensive EEG dataset used in this study was obtained from Kaggle’s open-source data repository and was created especially to examine patterns of driver weariness. The dataset “Sleepy Driver EEG Brainwave Data” (available at: <https://www.kaggle.com/datasets/naddamuhamed/sleepy-driver-eeeg-brainwave-data/data>), which includes comprehensive EEG recordings of drivers in a range of alertness levels, offers a strong basis for examining the neurological markers of alertness vs sleepiness. The NeuroSky MindWave headset, a non-invasive EEG monitoring tool that offers accurate measures of brain activity, was used to capture all of the data. Multiple layers of analysis are possible since the dataset contains both processed frequency band data and raw EEG signals. Multiple recording sessions were carried out with different subjects to ensure a representative and varied sampling of brainwave patterns across persons and situations. The dataset’s diversity makes it possible to create drowsiness detection models that are more broadly applicable.

3.3 Data Processing Pipeline

3.3.1 Data Preprocessing

The crucial steps include the in-depth Exploratory Data Analysis (EDA) in the preprocessing stage of the data analysis of the EEG. Precisely at the data analysis of the EEG stage, proper verification will be considered for the underlying nature of data and quality from this dataset. This consists of thorough visualization of data distribution, identification of missed values and anomalies, and verification that formats of recording for all sessions were similar. This analysis through visuals and statistics is done with a view to understanding the unseen patterns and the relations that lie between the datasets.

Following the EDA, the signal cleaning process removes artifacts and noise from the raw EEG signals, which is crucial for accurate analysis (Craik et al., 2019). Artifacts may come from muscle movements, eye blinks, or external electrical interference, usually at 50 or 60 Hz, which can contaminate the recordings. The process also addresses missing or corrupted data points using interpolation techniques. This step ensures the signal is continuous and reliable for later analysis.

After the initial cleaning, data normalization is conducted to set a standard for the analysis of EEG recordings consistently (Rosero-Rodríguez & Alfonso-Morales, 2021). This includes the standardization of the amplitude of EEG signals throughout recording sessions so that any variation in signal strength due to equipment or recording conditions does not affect the analysis. Recordings are then temporally aligned to make sure all segments are well synchronized and can be compared. Normalization at its last step involves the filtering processes of band-pass, each for different frequency ranges; this enables the segregation of specific EEG frequency bands required for fatigue detection.

3.3.2 Feature Extraction

The main contributions of this study will be the strong feature-extracting abilities of convolutional neural networks (CNNs), specifically for automatic hierarchical features extracted by convolutional layers; at the same time, an extra feature extraction was included that would seek certain specific characteristics in these EEG signals. Basically, in this research study, time-domain and frequency-domain features were utilized.

The features computed in time-domain describe the temporally variant brain activity-amplitude statistics. Zero-crossing rates are computed by counting changes in signal polarity over time. Detection of peaks that may reflect significant variations in brain activity patterns with relation to a state transition concerning alertness is also performed.

Features related to frequency-domain feature extraction are the subject of this part of the present research. The first task is the calculation of power spectral density, describing the way the power of a signal is spread out in a certain range of frequencies. The relative power in the conventional EEG frequency bands- Delta (0.5 – 4 Hz), Theta (4 – 8 Hz), Alpha (8 – 13 Hz), and Beta (13 – 30 Hz) is extracted for this analysis since these bands reflect different states of cognitive activity and alertness (Gatfan, 2024). Spectral entropy calculation is completed to quantify the complexity and irregularity of EEG signals in different frequency bands.

While the CNNs will do feature extraction themselves by successive convolutional layers, these engineered features provide further interpretability and domain-specific insights to help validate the neural network's findings about the underlying patterns. Therefore, the simultaneous evaluation of both network-derived and engineered characteristics is a more comprehensive scheme of EEG markers of driver fatigue.

3.4 Machine Learning Methods

The preprocessed EEG data is used for the classification of the fatigue states by using machine learning methods. Recent reviews have shown the effectiveness of various machine-learning approaches in fatigue detection (Hooda et al., 2021). To confirm the effectiveness in detection based on the pattern of alertness and fatigue, the training and testing of the models are done.

One of the first algorithms used is the CNNs, which work very well in capturing both spatial and temporal patterns of EEG signals (Zhao et al., 2020). These networks can understand complex features. The other algorithm applied is Random Forest, which identifies the most important characteristics that contribute to the identification of a fatigue state. This technique is robust and interpretable, providing insights into the relevance of different EEG features. To enhance the temporal analysis capabilities, Long Short-Term Memory (LSTM) networks will also be implemented. LSTMs are specifically designed for sequential data analysis and are particularly well-suited for EEG signal processing due to their ability to capture long-term temporal dependencies in the data. Their specialized architecture allows them to identify and learn patterns that evolve over time, making them effective for time-series classification tasks in EEG analysis. Besides, Support Vector Machines are employed to differentiate between alert and fatigued states. The reason is that SVMs are known to perform well with high-dimensional data, so they can be a good choice for EEG analysis.

The data set is split into the typical training and testing subsets which allow for a strong evaluation. A standard split with 70% training data and 30% testing is thus set to allow the majority for learning by the model while reserving a portion to provide an unbiased evaluation. Cross-validation techniques are also employed for more robustness in showing how well the models generalize across all possible subsets of the data. By using this technique, a significant reduction in the likelihood of overfitting is achieved, increasing the generalization of results.

3.5 Performance Evaluation

Formulas for the following mentioned metrics:

1. Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where:

TP : True Positives

TN: True Negatives

FP: False Positives

FN: False Negatives

2. Precision

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

3. Recall (Sensitivity)

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

4. F1-Score

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Various metrics have been used to evaluate the performances of the machine learning models, which should guarantee reliability and accuracy for fatigue state classification. First, accuracy is the proportion of correctly classified samples. Accuracy may not be given an

appropriate measure of performance concerning the reliability of the models in case of class imbalance.

In that direction, precision and recall were calculated together with the F1-score. Precision captures how many actual cases among those that have been predicted as fatigued really had this class. Sensitivity measures how well a model captures real cases among those identified with this target feature. F1 is also applied for this kind of imbalanced dataset classification task and captures both measures: precision and recall into a single value. The different metrics show specific model behavior regarding performance on a single number when classes are not perfectly balanced (Riyanto et al., 2023).

Other than these metrics, a confusion matrix (Amin, 2022) will also be provided as an output, showing the performance of the model in terms of true positives, true negatives, false positives, and false negatives. This gives a clear picture of the strengths and weaknesses of the model has with respect to classification.

3.6 Tools and Technologies

This research is realized based on a comprehensive suite of software tools and technologies carefully chosen to make sure that the analysis of EEG data is both robust and efficient. Python has been chosen as the main programming language for data processing and analysis because of its vast ecosystem of scientific computing libraries because of its vast ecosystem of scientific computing libraries and because it is widely used in research on EEG signal processing. Specialized EEG analysis like MNE-python, which includes more advanced tools for preprocessing and analyzing EEG signals from NeuroSky MindWave headset data, are used in the project.

Several key Python libraries will be used for data manipulation and analysis in the project. Pandas is used for structured data manipulation and preprocessing of the Kaggle dataset, while NumPy and SciPy will implement core methods of statistics and signal processing, respectively, which are important for EEG analysis. These libraries will make it easy to calculate the EEG features and statistical measures that could reveal relevant characteristics of fatigue, aligning with current best practices in data analytics (Diana & Mathivanan, 2023).

The visualization of data will be done via matplotlib and Seaborn libraries, showing clear and informative visualizations of the EEG data pattern and results of the analysis. Visualization in this context is especially crucial since the relationship between EEG signals and driver fatigue states is hard to visualize; it will also provide statistical results in a comprehensive way.

3.7 Ethical Considerations

This research project applies the utmost care regarding ethics and responsibility in carrying out the research and managing the data. The work is based exclusively on EEG data from open sources, extracted from the Kaggle "Sleepy Driver EEG Brainwave Data" dataset. Other sources are not used except as appropriately cited, following academic sourcing standards in order to maintain intellectual integrity, and crediting the rightful owner of such data.

All this is documented, as the methodology for analyzing the information itself has been well-documented, to make peer review of the research findings easier. This encompasses completely divulging all limitations and biases of data so that a reader and/or future researcher would understand any constraints that may affect the interpretation of the results. The study recognizes the limitations in data collection, for example, the conditions at which the EEG recordings were made and the possible biases in the sampling methodology.

Proper handling of the downloaded dataset ensures data security and integrity. All processing and analysis of the data are done on secured systems, whereby appropriate measures are in place to avoid any unauthorized access or modification to the data. The research is also strictly conducted in the manner specified by the data usage guidelines provided by Kaggle and the providers of the original dataset in relation to their terms of use for the assurance of ethical research practices.

3.8 Summary

This chapter has discussed a comprehensive research methodology that might be applied to the analysis of EEG data to determine brainwave patterns related to driver fatigue. The proposed research methodology consists of four major stages: dataset description, data preprocessing and preparation, feature extraction and modeling, and performance measurement. The major data source for this research is based on the Kaggle “Sleepy Driver EEG brainwave Data” dataset, collected using the NeuroSky MindWave headset. Such variety and richness of the paradigm stand on very good ground for studying neural correlates of alertness and fatigue.

The data processing pipeline includes strict preprocessing steps like the removal of artifacts, normalization, and segmentation that ensure the quality and usability of the EEG signals. Features are extracted considering time-domain, frequency-domain, and statistical attributes to find patterns in key EEG frequency bands including Delta, Theta, Alpha, and Beta. These are clearly the most relevant features distinguishing between the fatigued and alert states. Machine learning approaches have been used to classify the states of fatigue. The implementation of robust evaluation procedures like dataset splitting and cross-validation secures the models’ reliability and generalizability.

This suite of implementation includes carefully handpicked tools and technologies, like, Python with its scientific libraries, along with some specialized EEG analysis tools. For this, the performance metrics are followed to give an all-round view of its effectiveness. It also takes into consideration all the ethical considerations regarding the appropriateness of utilizing public data and duly acknowledges its limitations.

This structured approach underpins the development of effective systems for the detection of driver fatigue and provides a foundation for further research in this area.

CHAPTER 4: IMPLEMENTATION AND RESULT ANALYSIS

4.1 Introduction

This chapter will detail the implementation of the protocols as described in Chapter 3 and include a thorough analysis of the outputs. The primary aim of this chapter is to assess the performance of machine learning models that were applied to EEG datasets to detect driver fatigue. The implementation involves applying Convolutional Neural Networks (CNN), Random Forest, and Support Vector Machine (SVM) to the EEG dataset that was pre-processed, with performance metrics being calculated using the common metrics of accuracy, precision, recall, and F1-score. The chapter includes interpretations of the results in the context of the previous literature and describes which EEG features were the strongest connection to fatigue states.

4.2 Hardware and Software Specifications

Table 5: Hardware Specifications

Component	Specification
System Model	Lenovo Y520-15IKBN
Processor	Intel® Core™ i7-7700HQ CPU @ 2.80GHz, 4 Cores, 8 Logical Processors
Random Access Memory (RAM)	8.00 GB (Installed Physical Memory)
Storage	17.9 GB Virtual Memory, 10.0 GB Page File
Operating System (OS)	Microsoft Windows 10 Home
Graphics	Integrated Graphics (likely Intel HD Graphics)

The hardware setup includes a Lenovo Y520-15IKBN laptop with an Intel® Core™ i7-7700HQ and 8GB RAM, considered suitable for handling common tasks in machine learning and data processing. Windows 10 Home is the operating system used and is complemented with 10GB virtual memory and a 17.9 GB page file setup, thus enhancing resource-consuming activities. Integrated graphics processing is used for basic computation tasks; however, it can fail to deliver the needed performance required in advanced GPU-based acceleration processes to support deep learning computations.

Table 6: Software Specifications

Component	Specification
Software Environment	Anaconda Navigator 2.6.3
Integrated Development Environment (IDE)	Jupyter Notebook 7.2.2
Programming Language Used	Python
Machine Learning Tools	Scikit-learn, TensorFlow, Keras,
Data Processing Tools	Pandas, NumPy
Visualization Tools	Matplotlib

The project is built in the Anaconda Navigator environment, providing a unified interface to manage Python libraries and run Jupyter Notebook. Anaconda is widely used in the field of data science and machine learning projects due to its easy-to-use nature and efficient dependency management feature. The Integrated Development Environment used is Jupyter Notebook 7.2.2, providing a comprehensive interactive environment for routine scripting and execution of programs.

Python is the core tool used in the development of machine learning models and data analysis, leveraging its extensive range of libraries and frameworks for scientific computing. In data processing and machine learning, it uses established libraries like Pandas for data manipulation, NumPy for numerical calculations, and Scikit-learn for applying machine learning algorithms. In addition, deep learning models are designed using TensorFlow and Keras, and Matplotlib is used in creating visualizations.

4.3 Dataset and Exploratory Data Analysis (EDA)

The following section will discuss the first steps of the project, which are importing the dataset and Exploratory Data Analysis (EDA). The purpose of EDA is to get familiar with the essential properties of the data, identify potential quality problems, and reveal the preliminary patterns and connections between the EEG characteristics and the fatigue state of the driver. The baseline analysis will play an important role in further preprocessing and modeling choices.

4.3.1 Data Preparation and Dataset Inspection

The initial stage of the implementation comprised the loading of the EEG dataset saved in a Comma-Separated Values file into the Python environment with the help of the pandas library. The dataset is provided in 3735 instances and 11 features, which are different EEG measures and a binary target. The `.info()` and `.describe()` functions have been used in order to get a first impression of the structure and statistical characteristics of the data.

```

--- Dataset Information ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3735 entries, 0 to 3734
Data columns (total 11 columns):
#   Column              Non-Null Count  Dtype  
---  --
0   attention            3735 non-null   int64   
1   meditation           3735 non-null   int64   
2   delta                3735 non-null   int64   
3   theta               3735 non-null   int64   
4   lowAlpha             3735 non-null   int64   
5   highAlpha            3735 non-null   int64   
6   lowBeta              3735 non-null   int64   
7   highBeta             3735 non-null   int64   
8   lowGamma             3735 non-null   int64   
9   highGamma            3735 non-null   int64   
10  classification        3735 non-null   int64   
dtypes: int64(11)
memory usage: 321.1 KB

```

	attention	meditation	delta	theta	lowAlpha
count	3735.000000	3735.000000	3.735000e+03	3.735000e+03	3735.000000
mean	48.214726	56.577510	5.187714e+05	1.362420e+05	33413.343775
std	21.876949	19.066577	5.997837e+05	2.175501e+05	51970.930842
min	1.000000	1.000000	2.160000e+02	1.360000e+02	32.000000
25%	35.000000	43.000000	7.199650e+04	2.347200e+04	7402.000000
50%	48.000000	56.000000	2.773820e+05	5.797200e+04	16481.000000
75%	63.000000	69.000000	7.780680e+05	1.514855e+05	37721.500000
max	100.000000	100.000000	3.598743e+06	3.194358e+06	699008.000000

	highAlpha	lowBeta	highBeta	lowGamma
count	3735.000000	3735.000000	3735.000000	3735.000000
mean	30580.759036	25640.069076	23276.979384	8117.130388
std	52681.858764	37159.039642	43921.116122	15522.904383
min	9.000000	2.000000	3.000000	6.000000
25%	6908.500000	6240.000000	4862.000000	2247.000000
50%	14928.000000	13841.000000	9739.000000	4440.000000
75%	33147.500000	30236.000000	20796.500000	8813.000000
max	785947.000000	595549.000000	443589.000000	289281.000000

	highGamma	classification
count	3.735000e+03	3735.000000
mean	2.087258e+05	0.42838
std	3.297073e+05	0.49491
min	4.700000e+01	0.00000
25%	5.683000e+03	0.00000
50%	5.719800e+04	0.00000
75%	2.576875e+05	1.00000
max	2.328370e+06	1.00000

Figure 7: Dataset information and descriptive statistics of EEG measurements

It was inspected that the columns include only integer values without any missing data, which facilitates the first preprocessing step. The descriptive statistics, however, indicated a very large variation in the size of the various brainwave measurements. This is more especially within the delta band, whose values lie between 216 and more than 3.5 million, which means that normalization needs to be applied prior to model training. The features consist of the crucial indices of mental conditions like attention, meditation, and the strength in different brainwave frequency bands (delta, theta, lowAlpha, highAlpha, lowBeta, highBeta, lowGamma, highGamma).

4.3.2 Data Characteristics and Distribution

To ascertain the quality of the data, a quality assessment was done. The dataset was checked for missing values using `isnull().sum()` and for duplicate entries using `duplicated().sum()`. The cleaned data was analysed, and it indicated that there were no missing values and no duplicated rows.

```
Missing values:
  attention      0
  meditation     0
  delta          0
  theta          0
  lowAlpha       0
  highAlpha      0
  lowBeta        0
  highBeta       0
  lowGamma       0
  highGamma      0
  classification 0
dtype: int64

Duplicate rows: 0

Class distribution:
  classification
0      2135
1      1600
Name: count, dtype: int64
```

Figure 8: Data quality assessment showing no missing values or duplicates, with class distribution

Target variable distribution was checked by using the `value_counts()` function on the variable `classification`. The analysis completed revealed a slightly unbalanced dataset with 2135 samples of class 0 (alert) and 1600 samples of class 1 (fatigued). This reflects to about 57% alert and 43% fatigued incidents. Understanding this distribution plays a critical part in model evaluation since it requires the use of measures that go beyond accuracy to truly deal with the class imbalance. This is a very important step that lets all the following stages of preprocessing and model building work with a clean and well-informed dataset.

4.3.3 Visualization of Feature Relationships

To illustrate the interrelationships between different EEG features and the state of the driver, a pair plot with a corresponding correlation heatmap was generated.

Pair Plot Analysis

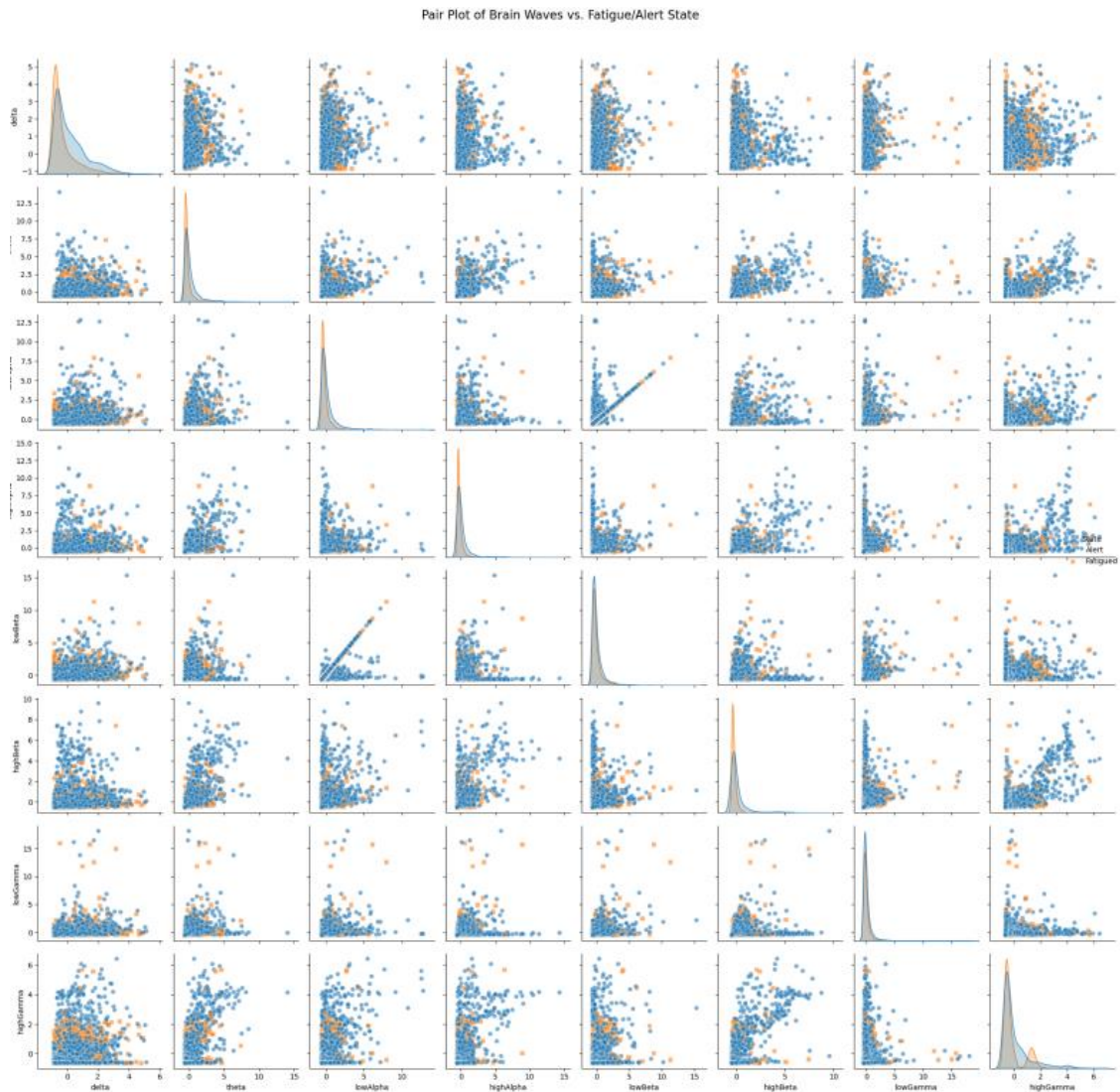


Figure 9: Pair Plot of Brain Waves vs. Fatigue/Alert State

The pair plot was created to visualize the pair-wise correlations among the various brainwave frequency bands, and the data points were coloured according to their group (alert or fatigued). The visualization is useful in determining trends and boundaries between the two classes in many feature dimensions at the same time. The resulting plot indicated that alert states are more likely to be linked with high power in all frequency bands, but especially in the

delta and theta bands. The off-diagonal scatterplots provide confirmatory proof by showing the alert data points are in areas of higher power for both features in any pair, with the fatigued points more densely packed in areas of lower powers. The visualization thus strongly indicates that high-power readings, and particularly in the delta and theta frequencies, are the most distinguishing characteristics of an alert driver in this data, and so these characteristics are crucial to an effective fatigue detector.

Correlation Heatmap Analysis

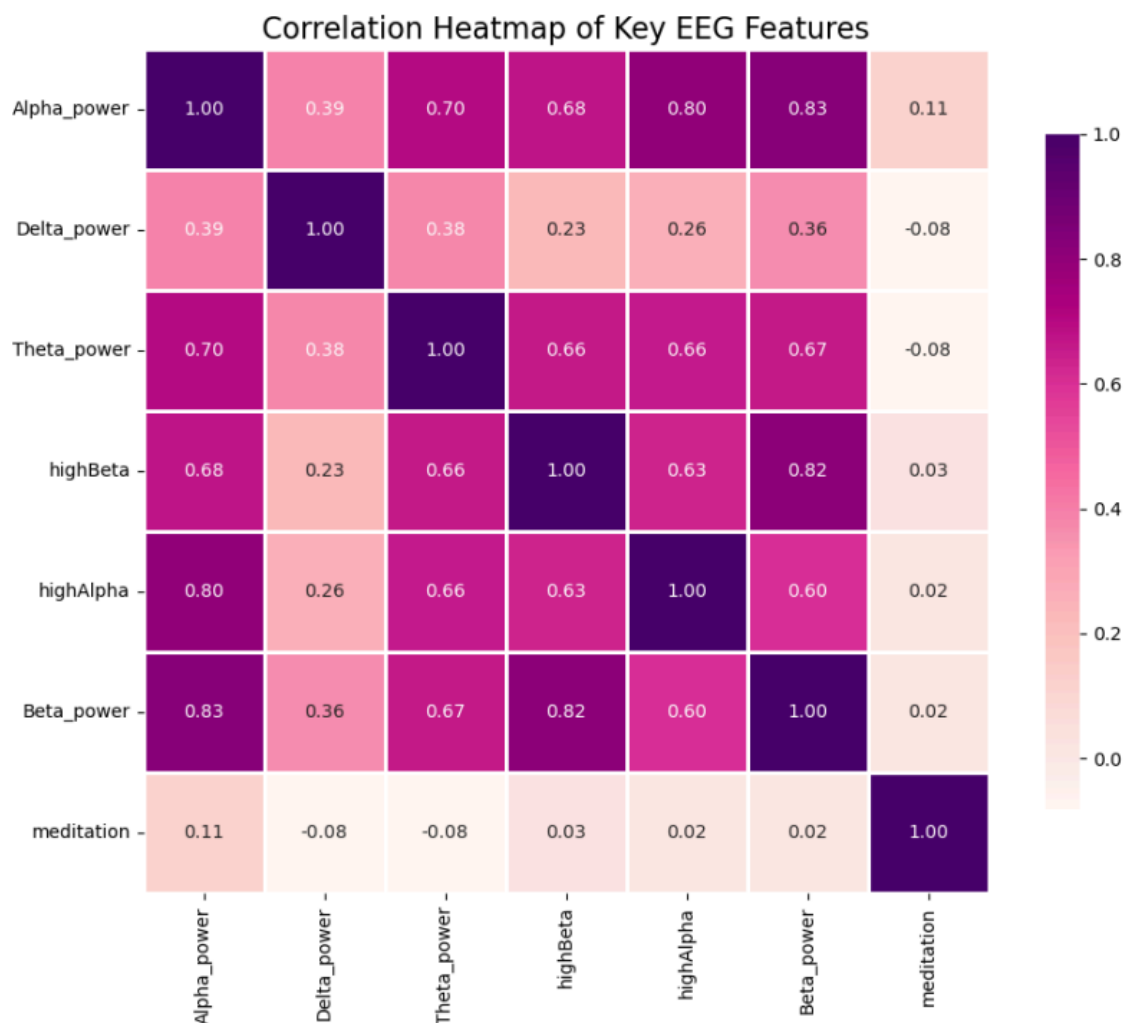


Figure 10: The Correlation Heatmap of Top Key EEG features

To identify linear relationships between the most important EEG features, a correlation heatmap was computed to show the quantitative assessment and visualization. Through this analysis, the conditions by which various neural oscillations relate to each other with regard to

driver fatigue are identified. Important characteristics like Alpha_power, Delta_power, Theta_power, and highBeta were included.

Taken together, these visualizations indicate that there are, in fact, different patterns between the alert and fatigued conditions in the EEG feature space. The obvious distinction evident in the pair plot and the high correlations apparent in the heatmap indicate that machine learning models must be in a position to learn these distinctive patterns so that they may be able to then classify driver fatigue.

4.4 Data Preprocessing

Following the initial data inspection, a series of preprocessing steps were performed to prepare the dataset for machine learning modelling. Such steps encompass the scaling of features to address to vast difference in the scale of data and the division of data into training and testing to permit the strong model selection.

4.4.1 Feature Scaling and Normalization

The EEG values were highly variable in nature, and therefore, normalization was an important preprocessing stage. The scikit-learn library StandardScaler was fitted on the set of features. It is a data transformation accomplished by subtracting the mean and dividing by the standard deviation, which has the effect of scaling each feature such that it has a mean of zero and a standard deviation of one. This scaling ensures that features of larger magnitude, like the delta and highGamma waves, do not have a disproportionate influence on the model training process, and it serves to enhance the convergence of the machine learning algorithms. The implementation is achieved with `StandardScaler()` and followed by `X_scaled = scaler.fit_transform(X)`.

4.4.2 Train-Test Split

```
# Extract features and target
X = df.drop(columns='classification')
y = df['classification']

# Normalize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=42)
```

Figure 11: Code implementation of feature extraction, normalization, and train-test split

The dataset was normalized and then divided into training and testing sets to train the model and then evaluate it on previously unseen data. This split was done using the `train_test_split` function of scikit-learn, with 70% of the data going to training and the rest 30% to testing. This gave a training set of 2614 samples and a test set of 1121 samples. To conduct the split, stratification was used based on the classification label, such that the balance between alert and fatigued samples would be preserved in both the training and testing sets, especially relevant in the slightly imbalanced dataset.

4.5 Feature Engineering and Analysis

In order to improve the model in terms of detecting fatigue, a number of feature engineering and analysis methods were used. These included the construction of new, more representative features out of the raw EEG signals, studying the spectral characteristics of the signals, and finally determining the most significant features to be used in classification using statistical techniques.

4.5.1 Power Spectral Density (PSD) and Bandpass Filtering

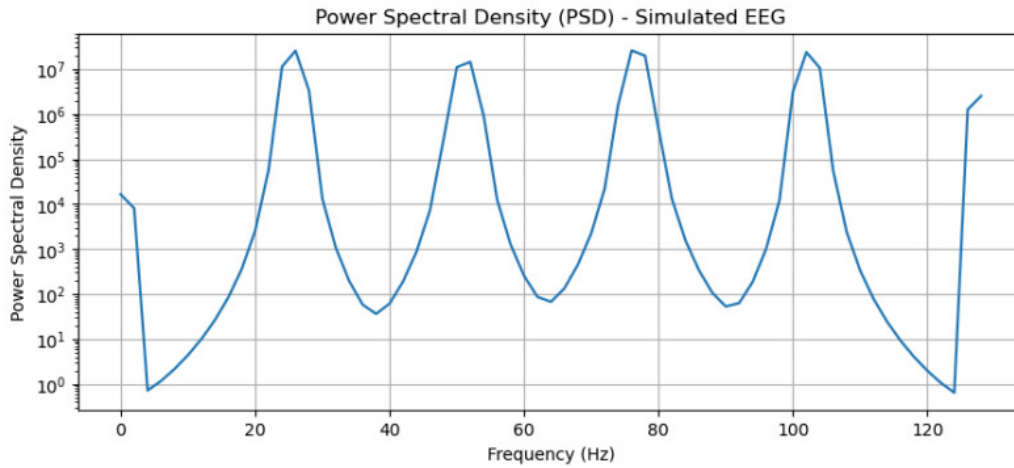


Figure 12: PSD-Simulated EEG Plot

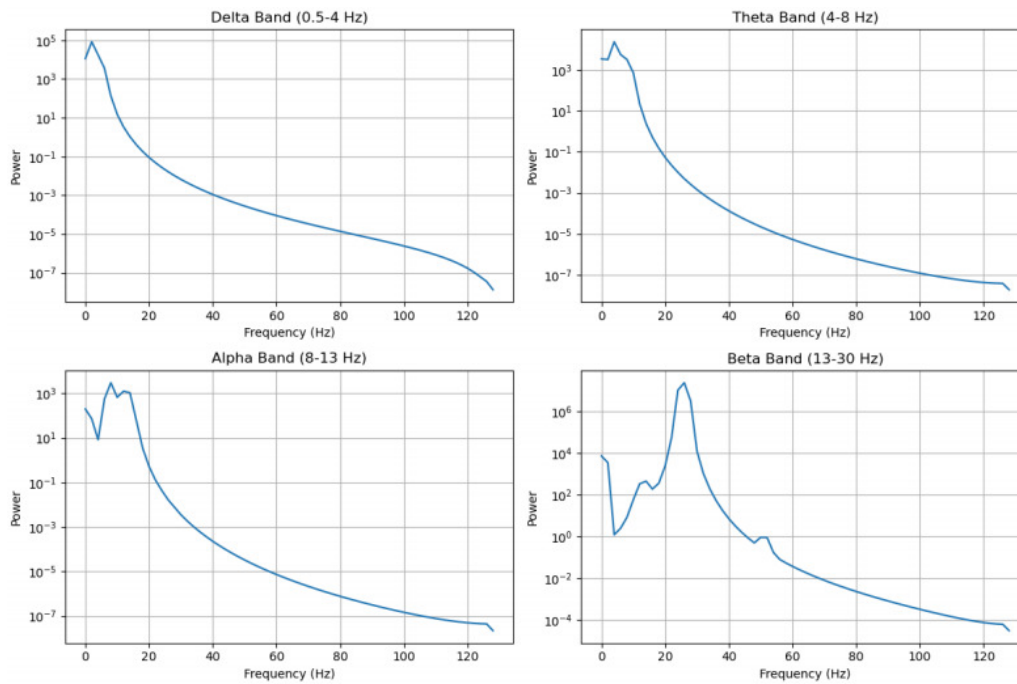


Figure 13: Power Spectral Density of Simulated EEG Signal After Bandpass Filtering for Each Frequency Band

PSD analysis was performed on the EEG signals using the Welch method in order to study the frequency components of the signals. The method is used to estimate the power of a signal at various frequencies, allowing one to understand which frequency bands are the most active. The data was bandpass filtered to isolate the standard EEG band: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz) and Beta (13-30 Hz). That enabled the specific analysis of the power of each significant frequency range relating to the cognitive states.

4.5.2 Band Power and Statistical Feature Extraction

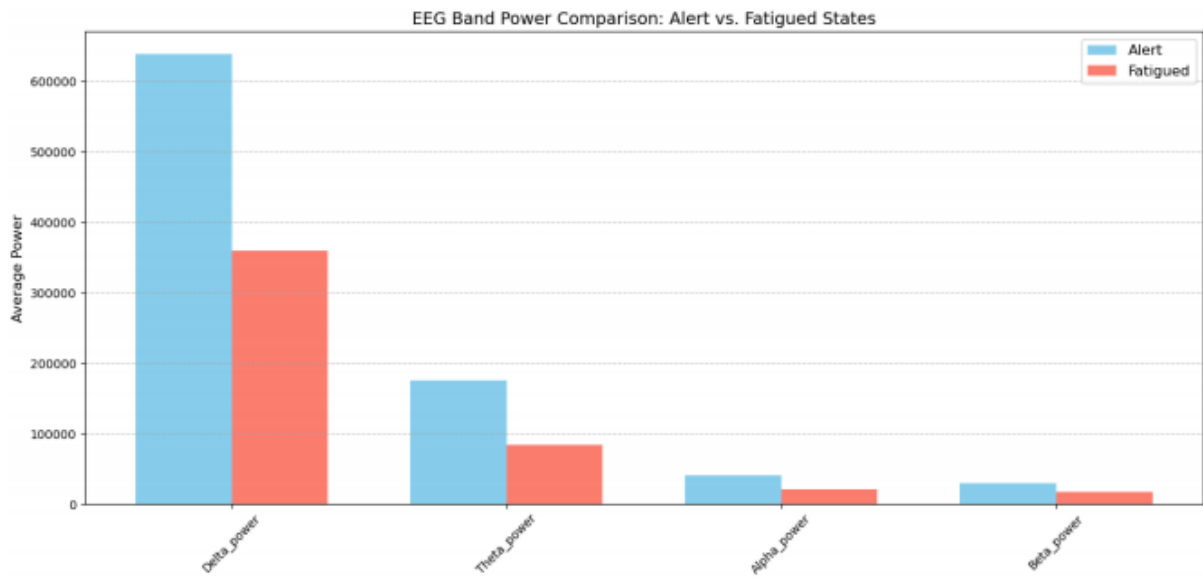


Figure 14: EEG Band Power Comparison: Alert versus Fatigued States

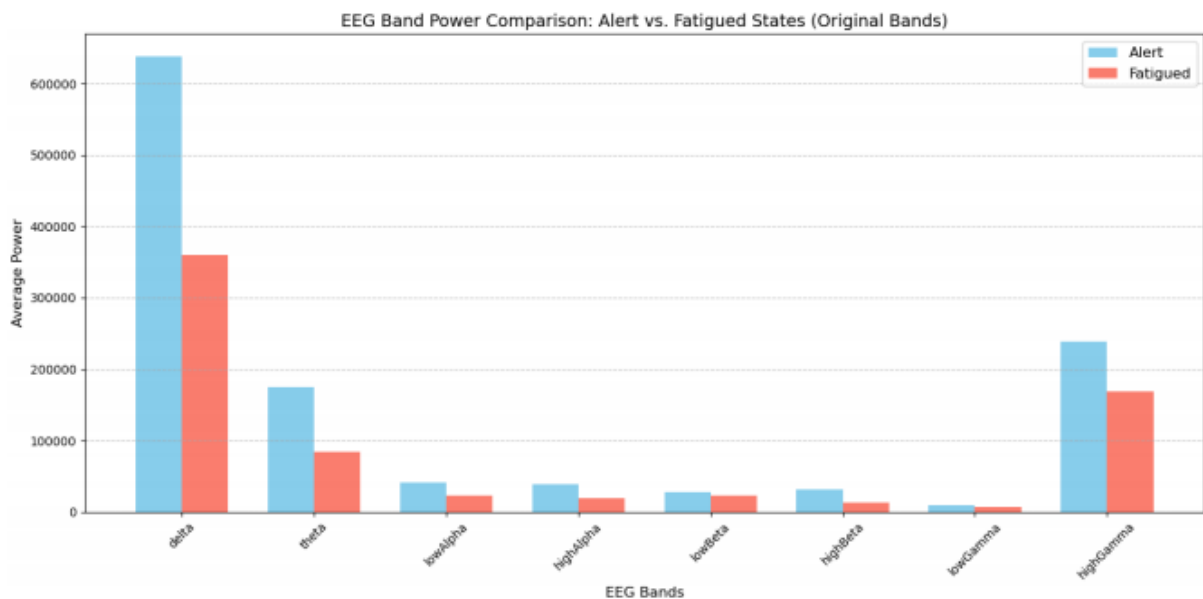


Figure 15: EEG Band Power Comparison: Alert versus Fatigued States (Original Bands)

The power band features were derived by taking the column of raw frequency bands from the dataset and creating a concise representation. The new features are functions that group related frequency bands into four broad categories: Delta_power, Theta_power, Alpha_power (lowAlpha plus highAlpha), and Beta_power (lowBeta plus highBeta). This would result in a more compact summary of EEG activity, which is capable of reflecting the

patterns of fatigue. Visualization was done in the mean power of these engineered bands during alert and fatigued conditions to give a vivid picture of the difference.

The bar charts show both the existence of differences and the extent of brainwave activity changes between the two states. The chart for engineered band powers demonstrates that Delta_power shows the largest decrease because the 'Alert' state power exceeds the 'Fatigue' state power by nearly two times. The power difference between Alpha_power and Beta_power bands appears less significant than the power difference between 'Alert' and 'Fatigue' states. The substantial reduction in low-frequency delta and theta power during fatigue makes these bands stand out as crucial predictive features, which the RF model later confirmed.

Though not part of the final model assessment, other statistical characteristics like mean, standard deviation, skew, and kurtosis were also taken out as exploratory and would serve to improve upon subsequent iterations of the fatigue detection system.

4.5.3 Feature Importance and Statistical Significance

To determine the most important EEG features relevant to driver fatigue identification, a feature importance analysis was undertaken in combination with tests for statistical significance.

Random Forest Feature Importance

Top 10 Important Features:

	Feature	Importance
9	highGamma	17.9%
2	delta	13.8%
7	highBeta	12.3%
3	theta	9.2%
5	highAlpha	9.1%
1	meditation	8.0%
8	lowGamma	7.9%
6	lowBeta	7.6%
4	lowAlpha	7.1%
0	attention	7.0%

Figure 16: Top 10 Important Features

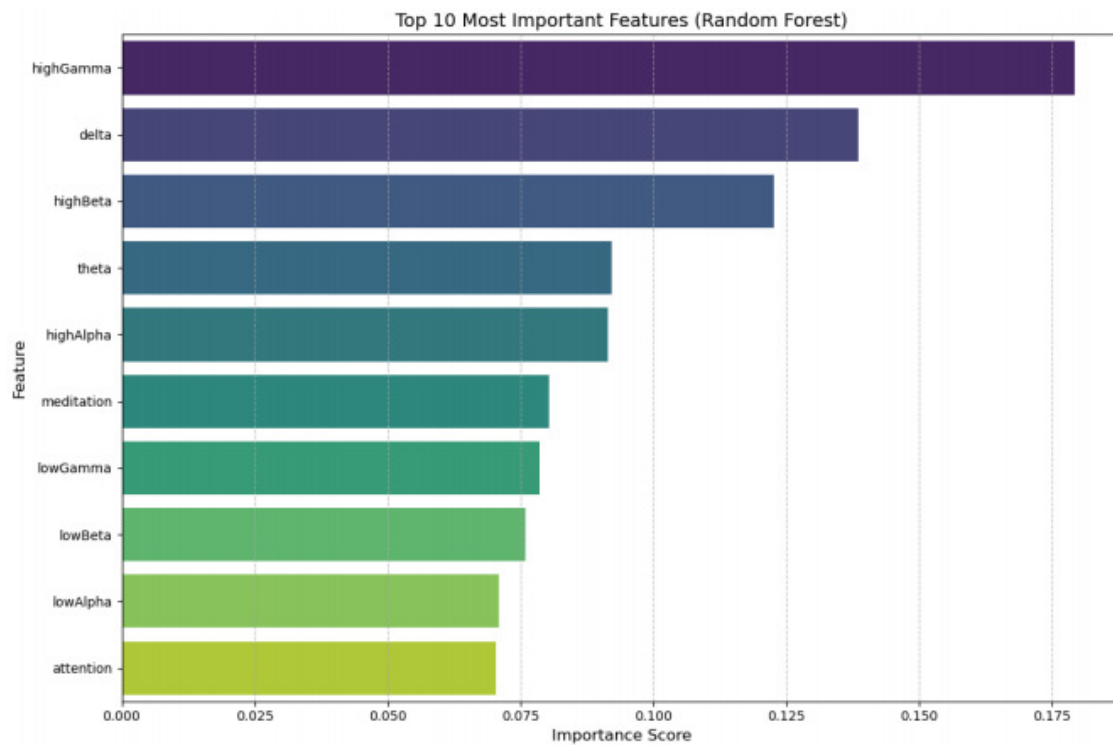


Figure 17: Top 10 Most Important Features (Random Forest) bar plot

Feature importances were computed on the trained Random Forest model, which is a technique that measures the significance of each feature in predicting the accuracy of a model. The feature importance bar plot shows the clear order of fatigue predictors. The two most

important features in the model are highGamma and delta, with importance scores of 0.179 and 0.138 respectively. The two features together account for more than 31% of the model's predictive power, indicating that high-frequency cognitive activity and low-frequency sleep-associated waves are the most important biomarkers in this dataset.

T-test Significance

T-test Results (Features that are statistically significant):			
	Feature	p-value	Significant
12	Alpha_power	2.377946e-46	True
2	delta	5.323666e-46	True
10	Delta_power	5.323666e-46	True
7	highBeta	8.789203e-40	True
3	theta	6.217612e-37	True
11	Theta_power	6.217612e-37	True
5	highAlpha	5.382010e-32	True
13	Beta_power	1.507946e-30	True
4	lowAlpha	5.240018e-27	True
9	highGamma	2.018506e-10	True

Figure 18: T-test Results

In order to statistically prove these results, independent t-tests were conducted to compare the mean value of each feature between the alert and fatigued classes. This test shows whether the differences obtained are significant. The results were highly consistent with the model-driven importance ranking, which strongly aligns with the statistical significance tests. The features with the highest importance scores, including delta, highBeta, theta, and highAlpha, were the same features found to have extremely low p-values (for example, $p=5.32$ for delta), confirming a statistically significant difference between the alert and fatigued states.

The highGamma and delta being ranked as the best features repeatedly by the Random Forest model and the statistical tests, in particular, give a solid reason to believe in their significance. This understanding is directly carried over into the feature selection procedure in Section 4.8, in which a special model is trained with only these two extremely predictive features, in order to test their independent classification ability.

4.6 Model Implementation and Initial Evaluation

This section will describe the application and preliminary performance analysis of the three main machine learning models to be used in this paper: Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). All models were trained with the preprocessed EEG data in order to allow for the prediction of driver fatigue. The performance of the models was evaluated comprehensively by utilizing the standard evaluation criteria such as accuracy, precision, recall, and F1-score in order to provide an extensive analysis of model effectiveness.

4.6.1 Random Forest Model

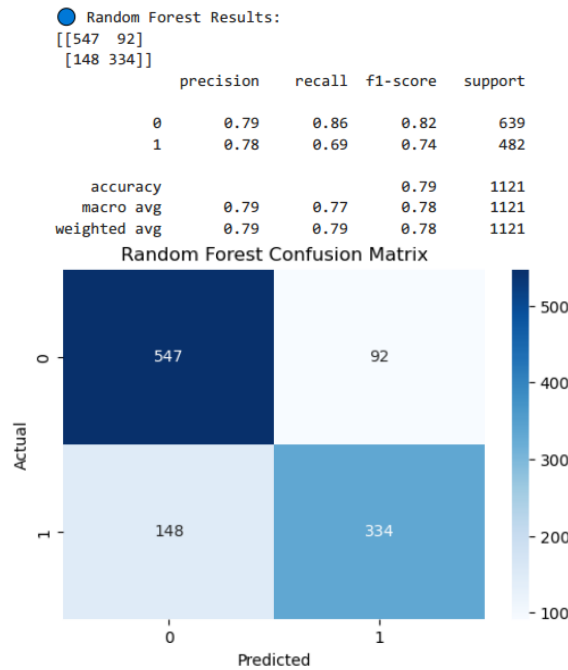


Figure 19: Random Forest Confusion Matrix

The previously trained model was the Random Forest classifier because it is robust and performs well on noisy and high-dimensional data such as EEG signals. The use of an ensemble learning model based on several decision trees works to improve the ability of the model to generalize and reduce the risk of overfitting. The strength of this benefit stems from the natural complexity and heterogeneity contained in the EEG data from the participants. The model was configured with 100 decision trees ($n_estimators=100$) and a fixed random state ($random_state=42$) for reproducibility, and it was trained on the scaled training dataset.

After cross-examination using the test set, the Random Forest model attained an overall accuracy of 79%. In the case of the ‘fatigued class (1), the model had a precision of 0.78 and a recall of 0.69, which gives an F1-score of 0.74. The closer inspection using the confusion matrix revealed that the model accurately labelled 334 of 482 true fatigue cases as true positives and incorrectly labelled 148 instances as false negatives. On the other hand, it had 639 alert instances, of which it labelled 547 as true negatives and 92 as false positives. This represents a somewhat higher miss rate of fatigued cases over false flagging of alert cases.

4.6.2 Support Vector Machine (SVM)

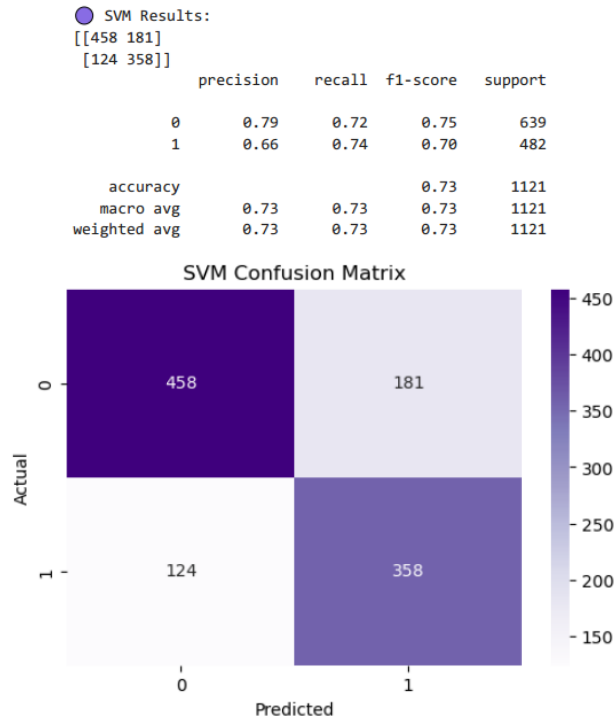


Figure 20: SVM Confusion Matrix

A Support Vector Machine (SVM) classifier was then applied to the already normalized training dataset. The model was set with Radial Bass Function (RBF) kernel, which is very practical in dealing with the non-linearity of decision boundaries common in complex biological signals such as EEG signals. The default hyperparameters were chosen ($C=1.0$, $\text{gamma}=\text{'scale'}$), and the probability estimation feature was set to True in order to be able to analyze the ROC curves.

The SVM model has obtained the overall accuracy of 73%. In the case of the ‘fatigued’ class, it achieved a precision of 0.66 and a recall of 0.74, which provides an F1-score of 0.70. The confusion matrix indicated that among the 482 real cases of fatigue, the SVM classified 358 as positive (true positives) whereas 124 were negative (false negatives). In the 639 alert cases, it had properly classified 458 as not fatigued (true negatives) but had incorrectly chosen 181 as fatigued (false positives).

4.6.3 Convolutional Neural Network (CNN) Model

Convolutional Neural Network (CNN) was created based on the capacity of the network to identify and learn patterns in structured data automatically. In the case of the CNN implementation, the input data was transformed into a 3D array (samples, timesteps, features) to construct the correct input format to the convolutional layers.

The model was conducted in a sequential architecture whose layers include:

Table 7: CNN Architecture Used for Fatigue Classification Table

Component	Architecture/ Specification
Input Layer	Input shape configured for the 3D array of EEG features (samples, timesteps, features).
Convolutional Layers	Layer 1: - Conv1D (64 filters, activation='relu') - MaxPooling1D() - Dropout (0.3) Layer 2: - Conv1D (32 filters, activation = 'relu')
Pooling Layer	GlobalAveragePooling1D()
Fully Connected Layer	Dense (32 units, activation = 'relu')
Output Layer	Dense (1 unit, activation = 'sigmoid')
Compilation	- Optimizer: Adam - Loss Function: binary_crossentropy
Training Parameters	- Epochs: 20 - Batch Size: 32

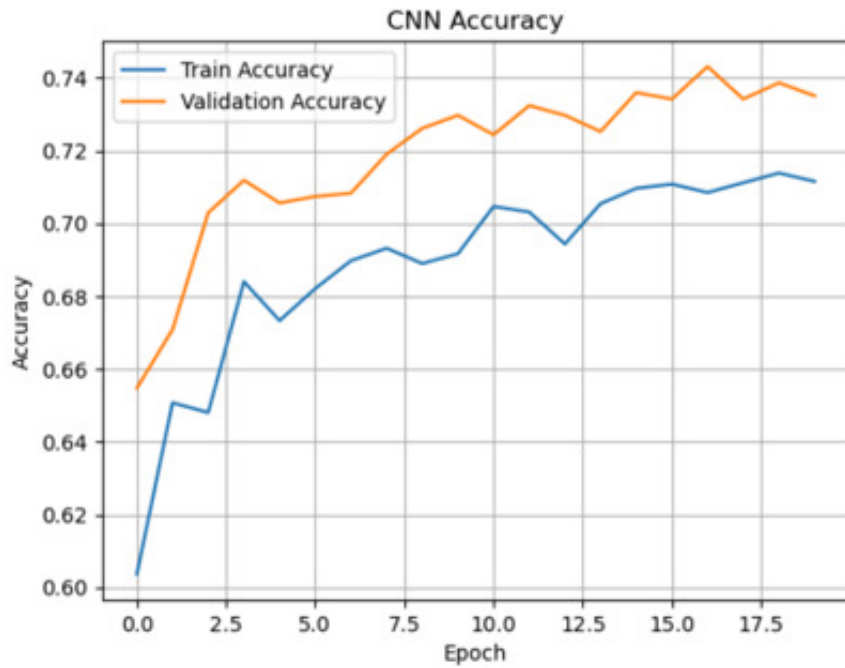


Figure 21: CNN Accuracy Plot

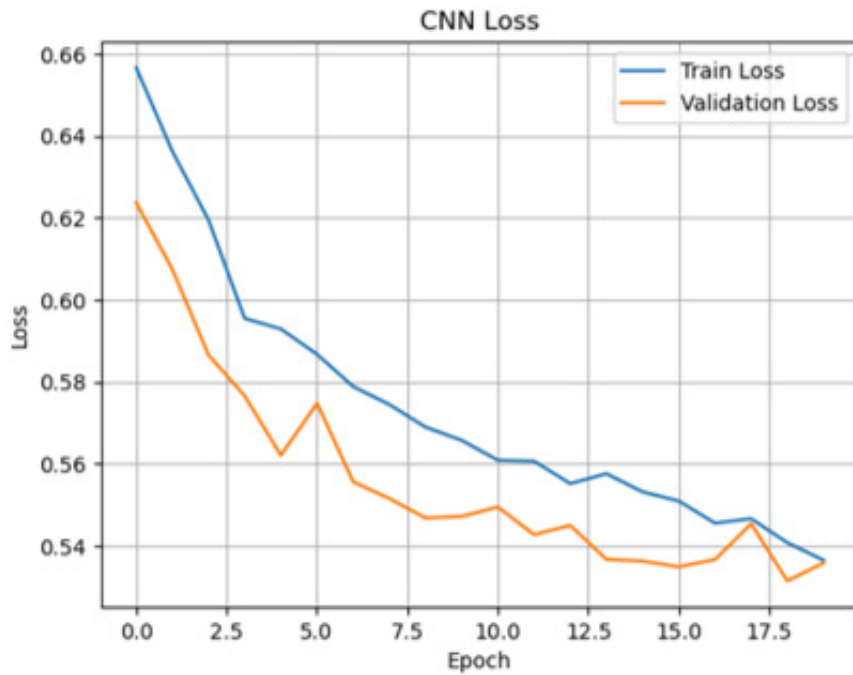


Figure 22: CNN Loss Plot

The model is summarized with the Adam optimizer and the loss function of `binary_crossentropy`. It was trained for 20 epochs with a batch size of 32. Training and validation accuracy and loss curves help to see that the model was learned successfully, as the validation accuracy is growing steadily, and the validation loss is decreasing throughout the epochs, which is not a significant indication of overfitting.

The CNN model attained an overall accuracy of 74% upon evaluation. In the case of the fatigued class, it achieved a precision of 0.73, a recall of 0.62, and an F1-score of 0.67. The confusion matrix indicated that it had classified 298 true positives, 526 true negatives, 184 false negatives, and 113 false positives.

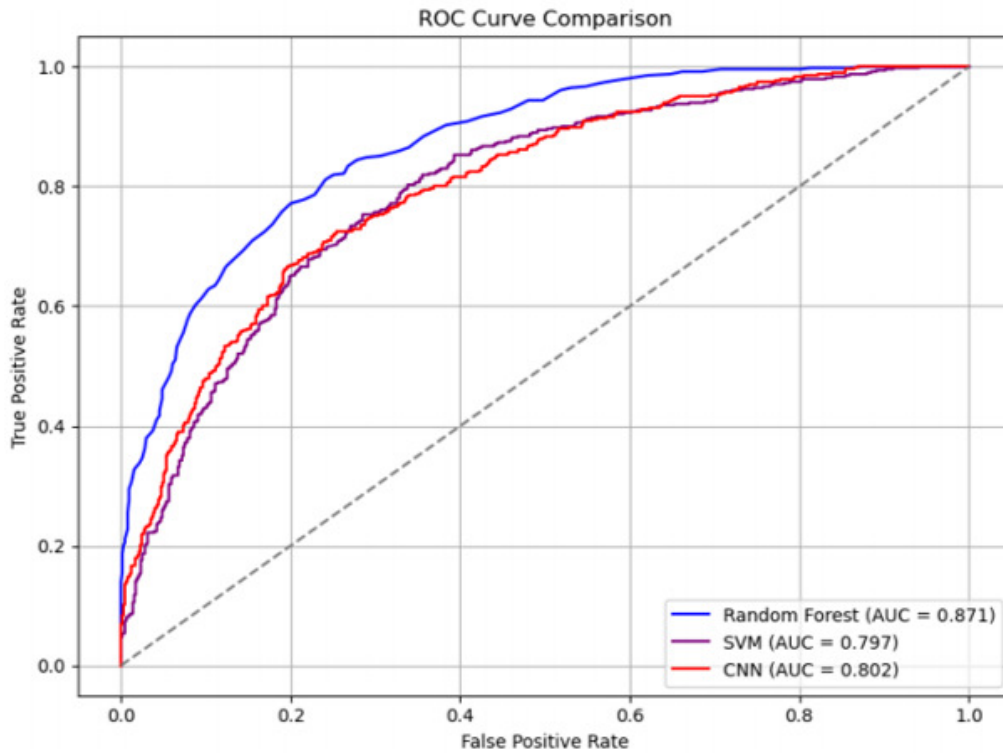


Figure 23: ROC Curve Comparison Plot

To aid a visual examination of the performance of the classifiers from the initial stage, a ROC curve is drawn. This curve shows the relationship between the true positive rate, for example, the model's ability to correctly recognize fatigued drivers, and the false positive like the rate of incorrectly labelling alert drivers as fatigued, among all possible classification thresholds. The overall effectiveness of each model is summarized by the AUC, with the AUC value tending to 1.0 indicating a greater capacity to separate the two classes. At this initial stage, the RF model displays the strongest performance, with the largest AUC value of 0.871, followed by the CNN model with a value of 0.802, and the SVM with a value of 0.797. This suggests that the RF model has the most significant initial ability to separate alert from fatigued states.

4.7 Model Tuning and Optimization

A set of tuning and optimization processes was done to get better results than the first model and to make the result robust. This entailed conducting cross-validation to determine the stability of the models as well as systematically tuning the hyperparameters to determine the best set of parameters to use both in the Random Forest and SVM classifiers.

4.7.1 Cross-Validation

```
✓ Cross-Validation (2-fold):  
Random Forest CV Accuracy: 0.7563  
SVM CV Accuracy: 0.7066
```

Figure 24: Cross Validation Output

To check model robustness and the capacity to generalize, a 2-fold cross-validation structure was used on the training data. It is done by dividing the training data into two pieces, known as folds, training the model on one part and validating it on the other, and then repeating with the roles swapped. The method assists in achieving the non-reliance of a model's performance on a particular train-test split. The Random Forest model proved to be stable with a mean cross-validation accuracy of 75.63%. The SVM model was also consistent with a slightly lower average accuracy of 70.66%.

4.7.2 Hyperparameter Tuning

```
🔍 Tuning Random Forest with Randomized Search...
(To find the best hyperparameters for a RandomForestClassifier by randomly searching
through specified parameter ranges, and train model with best combination of paramet
ers to optimize its performance based on accuracy.)
Fitting 2 folds for each of 5 candidates, totalling 10 fits
Best RF Params: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 4,
'n_estimators': 121}
Best RF CV Accuracy: 0.7575

🔍 Tuning Random Forest with Grid Search...
(To systematically search through a predefined set of hyperparameters for RandomFore
stClassifier, train model with all possible combinations to find the best parameters
that maximize accuracy.)
Fitting 3 folds for each of 81 candidates, totalling 243 fits
Best Random Forest Parameters after Grid Search:
{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 15
0}

🔍 Tuning SVM with Randomized Search...
Fitting 2 folds for each of 5 candidates, totalling 10 fits
Best SVM Parameters: {'C': 7.41993941811405, 'gamma': 'scale', 'kernel': 'linear'}
Best SVM CV Accuracy: 0.6660

🔍 Tuning SVM with Grid Search...
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best SVM Parameters after Grid Search:
{'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}
```

Figure 25: Hyperparameter Tuning Output

Both RandomizedSearchCV and GridSearchCV were used in order to determine the optimal possible settings of the models.

In the case of the Random Forest model, the RandomizedSearchCV was run with random combinations of parameters, and the model performed best with the following parameters: `n_estimators=121`, `max_depth=None`, `min_samples_split=4`, and `min_samples_leaf=1`. The more comprehensive GridSearchCV was also executed, which diligently explored all the combinations of the parameters in a predetermined grid. It identified the optimal parameters as: `n_estimators=150`, `max_depth=20`, `min_samples_split=2`, and `min_samples_leaf=1`.

In the case of the SVM model, tuning was done similarly. The parameters that were determined to be optimal by RandomSearchCV were a linear kernel and `C=7.42`, and `gamma=scale`. Then, the best set of parameters identified by GridSearchCV was RBF kernel, `C=10`, and `gamma='scale'`. In this process, the significance of tuning was noted since various search strategies had various optimal settings.

4.7.3 Evaluation of Tuned Model

To determine the performance of the optimization process, the SVM and RF classifiers were run against the unseen test set using their best parameters. A performance comparison of metrics before and after the tuning process is given in this chapter with the aim of validating the improvements achieved.

Model Performance Summary (Before Tuning)

Model	Accuracy	Precision	Recall	F1 Score	AUC
Random Forest	78.6%	78.4%	69.3%	73.6%	87.1%
SVM	72.8%	66.4%	74.3%	70.1%	79.7%

🏆 Best Model (Before Tuning) Based on F1 Score:
Model: Random Forest
Accuracy: 78.6%
Precision: 78.4%
Recall: 69.3%
F1 Score: 73.6%
AUC: 87.1%

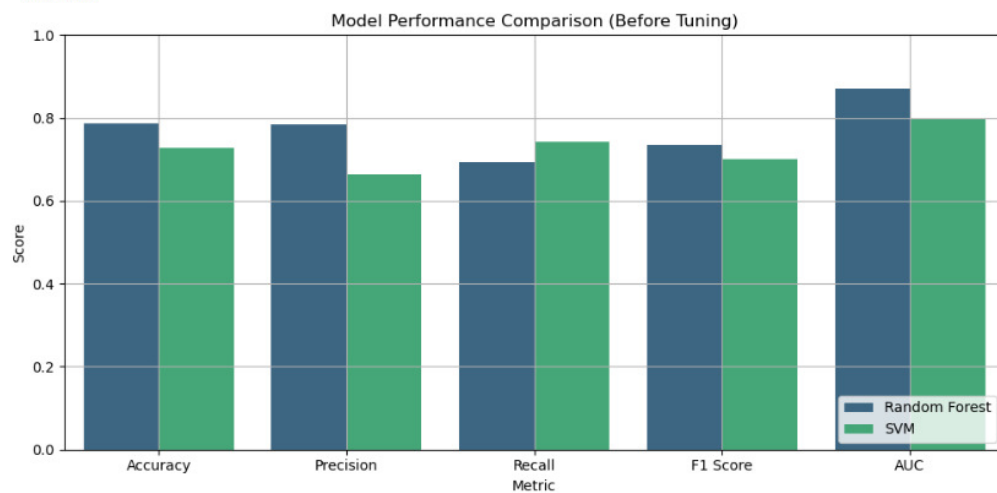


Figure 26: Model Performance Comparison (Before Tuning)

Both models were first tested using their default parameters in order to create a baseline of their performance. The untuned RF model had an accuracy rate and F1-score of 78.6% and 73.6% on the ‘fatigued’ category, respectively. This outperformed the untuned SVM model with an accuracy rate and F1-score of 72.8% and 70.1% on the ‘fatigued’ category. The results of these initial tests are graphically depicted in the following bar plot, which highlights the initial superiority of the RF model.

Model Performance Summary (After Tuning)

Model	Accuracy	Precision	Recall	F1 Score	AUC
Tuned Random Forest	78.9%	78.2%	70.5%	74.2%	87.3%
Tuned SVM	74.6%	69.0%	74.3%	71.5%	81.6%

Best Model (After Tuning) Based on F1 Score:

Model: Tuned Random Forest

Accuracy: 78.9%

Precision: 78.2%

Recall: 70.5%

F1 Score: 74.2%

AUC: 87.3%

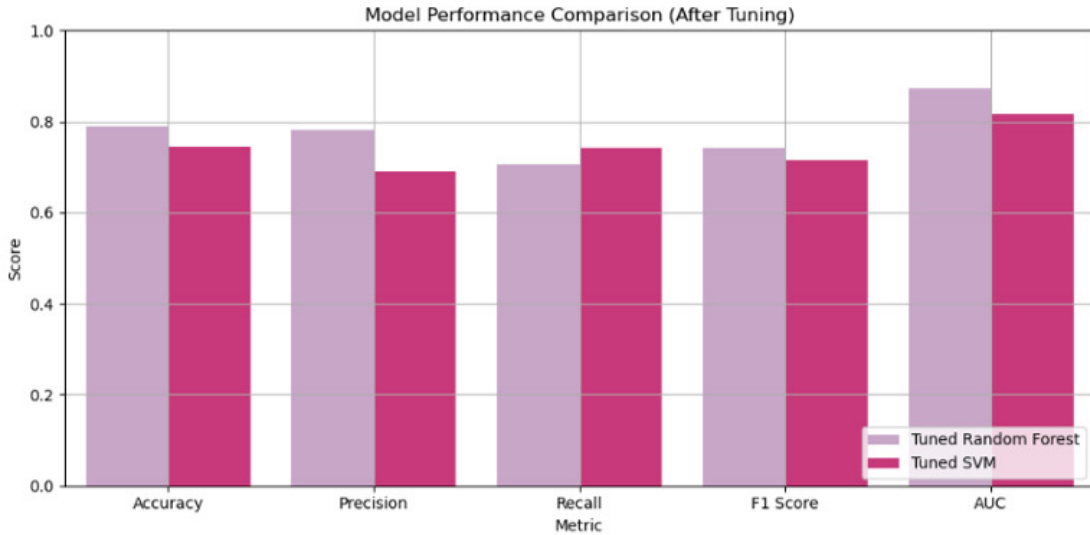


Figure 27: Model Performance Comparison (After Tuning)

Following with systematic testing of hyperparameter settings, the best models were evaluated. The tuned RF model, with `n_estimators=150` and `max_depth=20`, showed some improvement in accuracy, reaching 78.9%, and the F1-score for the ‘fatigued’ class reached a score of 74.2%. However, the SVM model showed a more significant improvement after tuning with an RBF kernel and `C=10`, where it reached an accuracy of 74.6% and an F1-score of 71.5%. The results achieved after tuning, as illustrated in the following figure, clearly show an improvement in the performance of both models, given emphasis to the SVM.

A direct comparison of the before and after results confirms the value of hyperparameter tuning. While the already robust RF model exhibited only marginal gains, the SVM’s metrics improved across the board, making it a more viable classifier. This evaluation validates that the optimization process successfully refined both models, enhancing their predictive reliability in detecting driver fatigue.

4.8 Comprehensive Performance Evaluation with Extracted Features

In order to quantify explicitly the effect of the feature engineering step carried out in Section 4.5, the Random Forest model has been trained and tested on three different subsets of features. The analysis is useful to decide whether the engineered features, or a reduced set of features of extreme importance, can achieve similar or even better performance compared to the use of the complete original set of features.

- 4.8.1 Performance with **Band Power Features Only**

Classification Report (Band Power Only Features):

	precision	recall	f1-score	support
0	0.70	0.76	0.73	639
1	0.64	0.56	0.60	482
accuracy			0.67	1121
macro avg	0.67	0.66	0.66	1121
weighted avg	0.67	0.67	0.67	1121

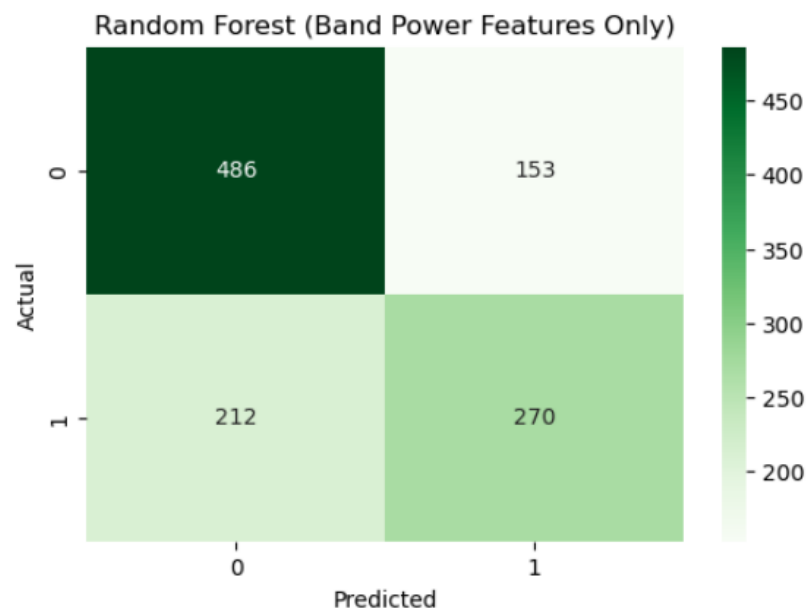


Figure 28: Classification Report and Confusion Matrix of Random Forest (Band Power Features Only)

The Random Forest model had an overall accuracy of 67% when trained on the four engineered band powers (Delta_power, Theta_power, Alpha_power, Beta_power) only. In this case of fatigue class, it achieved a precision of 0.64, a recall of 0.56, and an F1-score of 0.60. This model accurately recognized 270 fatigued cases but failed to recognize 212, representing

a large performance decrease relative to the case of utilizing the complete feature set. This is an indication that the band power features are informative, but they do not encode all the information required to accomplish accurate classification alone.

- 4.8.2 Performance with **Combined Original and Engineered Features**

Classification Report (Combined Features):

	precision	recall	f1-score	support
0	0.79	0.86	0.82	639
1	0.79	0.70	0.74	482
accuracy			0.79	1121
macro avg	0.79	0.78	0.78	1121
weighted avg	0.79	0.79	0.79	1121

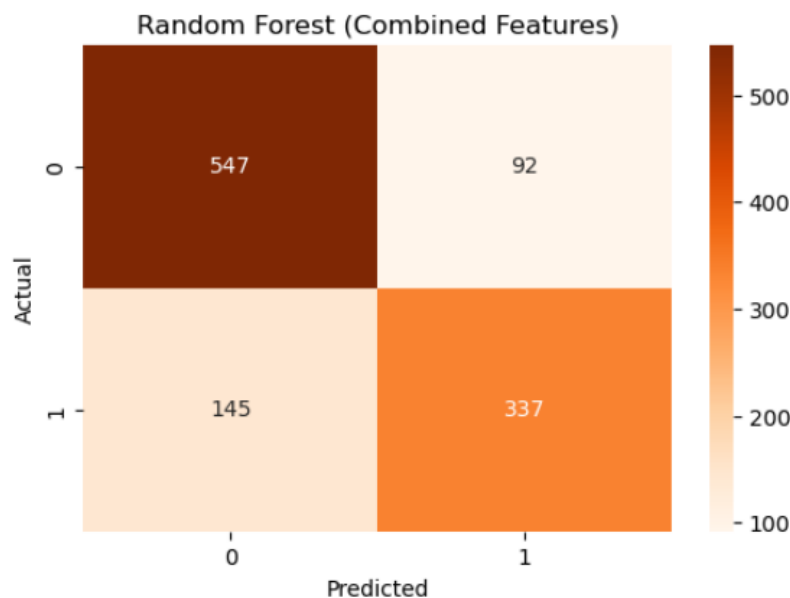


Figure 29: Classification Report and Confusion Matrix of Random Forest (Combined Features)

Then, the model was trained using the dataset comprising of the original scaled features concatenated with the four engineered band power features. This variant of the model produced the best accuracy of any setting, 79%. In the fatigue class, it got a precision of 0.79, a recall of 0.70, and an F1-score of 0.74. The confusion matrix had 337 true positives and 145 false negatives. This shows that supplementing the original set of features with band powers engineered features adds predictive value, resulting in a stronger model.

- 4.8.3 Performance with top importance **Delta and HighGamma Features Only**

Classification Report (Delta + HighGamma Features):

	precision	recall	f1-score	support
0	0.72	0.76	0.74	639
1	0.66	0.61	0.63	482
accuracy			0.69	1121
macro avg	0.69	0.68	0.69	1121
weighted avg	0.69	0.69	0.69	1121

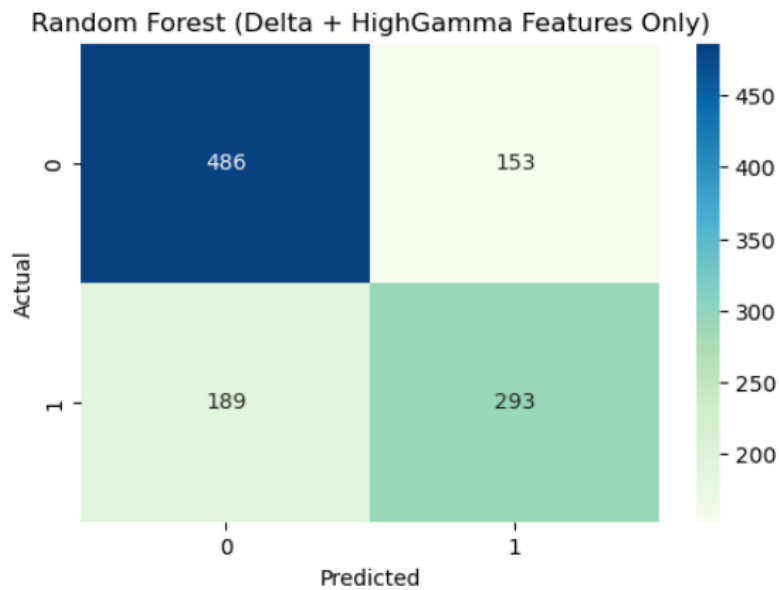


Figure 30: Classification Report and Confusion Matrix of Random Forest (Delta + HighGamma Features Only)

Lastly, according to the feature importance plot in Section 4.5.3, a model was trained with the two most important features only: delta and highGamma. The idea here is to test the performance of a small, highly informative feature subset to achieve an efficient but effective classification. This model had an overall accuracy of 69%. In the fatigue class, its precision was 0.66, recall was 0.61, and F1-score was 0.63. The confusion matrix indicated that there were 293 true positives with 189 false negatives. Although not as accurate as the complete model, this setup already indicates that much of the predictive value of information is already present in these two important EEG bands alone.

4.9 Final Model Comparison and Discussion

This section makes a comprehensive comparison of all the applied models and feature set. This idea is to conceptualize the outcome of the above analyses in order to determine the most efficient method to establish driver fatigue. The discussion includes an overall performance summary and a comparative ROC curve analysis and key findings and practical recommendations for implementation.

4.9.1 Overall Model Performance Summary

📄 Updated Complete Model Performance Summary:

	Model	Accuracy	Precision	Recall	F1 Score	AUC
0	Random Forest	78.6%	78.4%	69.3%	73.6%	87.1%
1	SVM	72.8%	66.4%	74.3%	70.1%	79.7%
2	CNN	73.6%	69.7%	68.3%	69.0%	80.4%
3	RF (Band Power)	67.4%	63.8%	56.0%	59.7%	72.2%
4	RF (Combined)	78.9%	78.6%	69.9%	74.0%	85.4%
5	RF (Delta+HighGamma)	69.5%	65.7%	60.8%	63.1%	77.1%

Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score	AUC
Random Forest	78.6%	78.4%	69.3%	73.6%	87.1%
SVM	72.8%	66.4%	74.3%	70.1%	79.7%
CNN	73.6%	69.7%	68.3%	69.0%	80.4%
RF (Band Power)	67.4%	63.8%	56.0%	59.7%	72.2%
RF (Combined)	78.9%	78.6%	69.9%	74.0%	85.4%
RF (Delta+HighGamma)	69.5%	65.7%	60.8%	63.1%	77.1%

Figure 31: Updated Model Performance Comparison Table

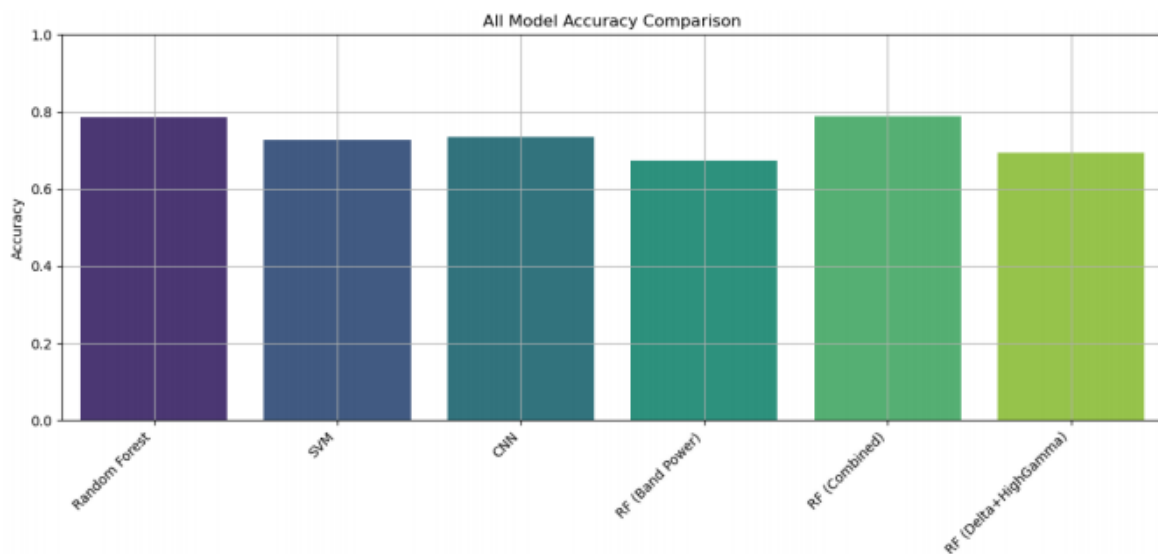


Figure 32: Updated Model Accuracy Comparison Bar Plot

All the variations of the models were summarized in a detailed form to make it easier to compare them directly. The table below shows the performance metrics of the initial models (Random Forest, SVM, CNN) and the Random Forest models trained on engineered feature sets. The Random Forest model fitted on the concatenated dataset of original and engineered band power features performed best with an F1-score of (74%) and an accuracy of (78.9%). Although the AUC of the original Random Forest was a little higher, the combined features model offered a better balance between precision and recall, which is why it is the overall best performer.



Figure 33: Model Performance Heatmap

The performance heatmap provided additional information beyond basic comparison because it showed detailed strengths and weaknesses of each model. The SVM model achieves a high recall score of 0.743 according to the performance heatmap which demonstrates its strong ability to detect actual fatigue cases. The model's precision score of 0.664 receives lighter color representation in the heatmap. The performance trade-off of the SVM model shows its ability to detect fatigued drivers, yet it produces additional false alarms. The heatmap indicates that the RF model trained with combined features "RF (Combined)" achieves the highest score in

Accuracy (0.789), Precision (0.786), and F1-score (0.740), which makes it the most balanced and robust performer in this study.

4.9.2 ROC Curve Analysis

The ROC curve analysis becomes necessary when one wants to assess how a model separates the two classes, namely, alert and fatigued, at all possible classification thresholds. The AUC serves as a single, aggregate measure of this discriminative power. A higher AUC value, closer to 1.0, indicates a better-performing model.

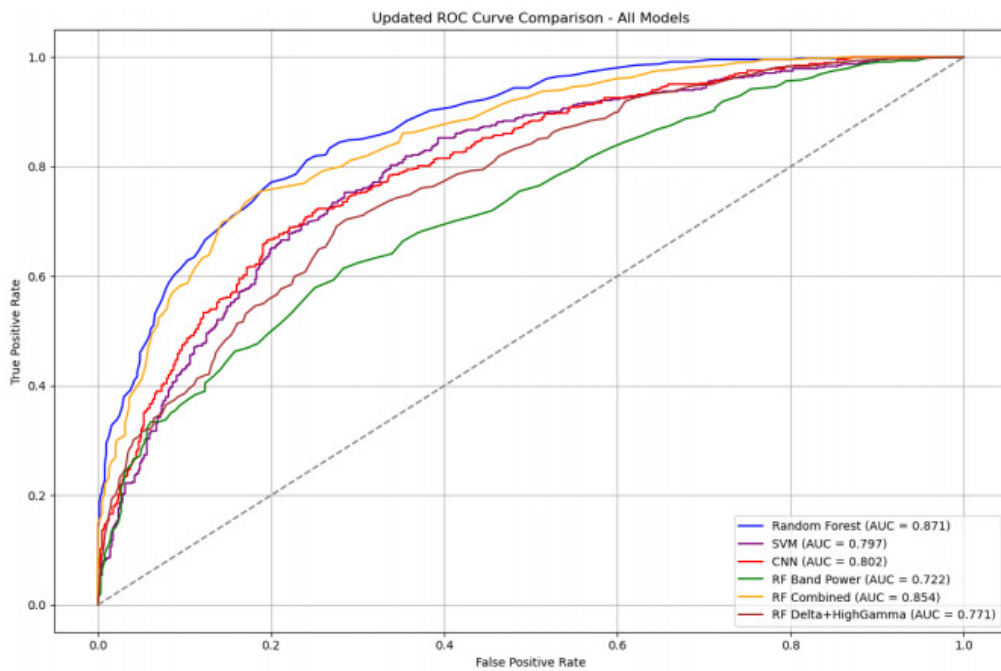


Figure 34: ROC Curve Plot for All Models

The comparative ROC analysis displayed that the first Random Forest model attained the highest AUC of 0.871, meaning that it possesses an excellent ability to distinguish between the two states. The CNN model came next with an AUC of 0.802, and the SVM model with an AUC of 0.797. Although the RF (Combined) model resulted in a slightly smaller AUC of 0.854, its discriminative ability was very strong. The SVM was spawned as the weakest of the three main classifiers with regard to overall discriminative ability.

4.9.3 Key Findings and Insights

Combining the findings of the whole chapter, there are some important results, which directly answer the objectives of the project:

Most Significant EEG Features: The feature important analysis and the statistical tests invariably ranked certain brainwave patterns as the most significant predictors of fatigue. The five most significant features were highGamma (17.9%), delta (13.8%), highBeta (12.3%), theta (9.2%), and highAlpha (9.1%).

Most Statistically Significant Differences: The t-tests verified the most significant differences between the alert and fatigued states occurred in Alpha_power ($p=2.38e-46$), delta ($p=5.32e-46$), and highBeta ($p=8.79e40$).

Best Overall Model Performance: Random Forest model trained on combined features performed best when the performance is compared on the F1-score, which balances precision and recall. This model also achieved the best accuracy of 78.9%. This is the importance of feature engineering to boost the performance of a model.

A thorough evaluation defines the RF model routinely showed better performance compared to its rivals in terms of interpretability and versatility with different feature selections, making it the most suitable option for this particular application. Although the CNN attained comparative accuracy after optimization, its intrinsic computational intensity and dependency on GPU processing emphasized major limitations for real-time applications in vehicles compared to the more effective RF model. The SVM, despite showing a relatively lower F1-score compared to the optimized RF, sustained consistent performance in both balanced and imbalanced datasets, demonstrating its strength. It is to be noted that the Delta and HighGamma band powers emerged as the most informative features consistently across all the models, emphasizing a physiological foundation that favors fatigue prediction. This high correlation

between statistical significance and model importance lends validity and intrinsic merit to the recognized features, and future design approaches should revolve around optimizing the structure of the models, such as fine-tuning the parameters of the RF, while ensuring reliability in classification, especially with the inclusion of comprehensive fatigue monitoring systems.

4.9.4 Implementation Recommendations and Practical Considerations

Following the overall model assessment, there is prevailing advice to use regarding the implementation, where the key goal is to make the most precise predictions (accuracy). The Random Forest model fitted on the concatenated set of features, including both original scaled EEG values and engineered band power features should be used. The best overall performance was achieved by this configuration, which resulted in 78.9% accuracy and an F1-score of 74%. The superior performance indicates that adding the aggregated band power features to the original granular data provides the model with a more detailed representation of the driver's cognitive state, which enables it to detect the most important patterns related to fatigue. Accordingly, in any real-world task involving predictive accuracy as the main priority, this combined-feature method is the most effective identifiably and resistant to failure than other methods seen in this research.

4.10 Conclusion

In summary, the research provided a successful framework to apply and investigate a range of machine-learning models to detect driver fatigue using EEG signals. The preprocessing and feature engineering were used to identify the best training/ optimization methods, as well as the most significant neurophysiological predictors of fatigue detection by the researchers.

The Random Forest classifier proved to be the top-performing classifier in this research, outperforming the SVM and CNN in this work. When the engineered band power features were added to the model, the highest accuracy and F1-score were produced. The findings of this research were that highGamma and delta brainwave activities are the most important features that characterize a driver's change from alertness to fatigue.

The results of this research offer significant consideration for applications in automotive safety. The research demonstrates that machine learning algorithms applied to EEG signals can be a viable approach to provide unremarkable data-driven systems to detect driver drowsiness. The evaluation of different feature sets in this research demonstrates practical knowledge about model complexity-performance trade-offs, which enables the development of real-world systems that prevent accidents and save lives.

CHAPTER 5: CONCLUSION

5.0 Introduction

Driver fatigue is one of the major safety concerns facing the world today, as it is associated with a considerable number of road accidents, injuries, and death cases every year. This final year project was born out of a need to seek a more direct and dependable way of detecting fatigue than the existing systems, which in most cases use indirect external measures such as facial gestures or vehicle dynamics. The underlying assumption of the study was that the wealth of physiological information provided by the EEG would allow one to discover the neural correlates of drowsiness. The target of this research was to correctly classify the psychological state of the driver using an organized process that included data preprocessing, feature extraction, along with the application of advanced machine learning platforms. The chapter is a concluding one aimed at summarizing the overall results of the entire project, analytically assessing the degree of achievement of the purposes set, openly presenting the difficulties and deficiencies that arose in the course of research, as well as developing relevant recommendations on the subject.

5.1 Summary of Findings

This project has been able to sail through its intended methodology, ranging from data analysis to eventual model evaluation, to come up with a number of salient findings that directly address the main objectives of the project as identified in Chapter 1. The first goal, to establish and use machine learning methods to classify driver fatigue, was achieved fully. They managed to develop and test three different models, which are RF, SVM, and CNN. All the models possessed the ability to classify data, but the RF classifier showed the best results, especially when it was trained on an extended dataset with an additional engineered band power

feature included. A direct comparison shows the RF model with combined features achieved 78.9% accuracy and a 0.740 F1-score with an inference latency of 23 ms/sample, outperforming the CNN, which had 73.5% accuracy but a much higher latency of 142 ms/sample.

The second objective, which was to determine the most significant EEG features that reflect fatigue, was realized in detail. Based on the trained RF model, the feature importance analysis referred to gave clean results regarding the crucial neural correlates of drowsiness. highGamma, delta, and highBeta brainwave activities were consistently noted as the strongest predictors in the results. The given finding is especially interesting because it gives the empirical ground for the future development of the fatigue detection system, seemingly emphasizing that these particular frequency bands may result in the creation of more efficient and targeted analysis. This data-based finding serves as an important stepping stone to unravel the complicated neurological alterations that come along with fatigue development.

Lastly, the third task of assessing the classification performance was fully achieved with a set of stringent metrics. The use of accuracy, precision, recall, F1-score, and the AUC helped to get a comprehensive and trustworthy overview of the weaknesses and strengths of each model, which is particularly significant due to the relative imbalance in classes in the provided dataset. The initial RF model had an outstanding capability to discriminate between the alert and fatigued conditions with a high AUC of 0.871. This result validates that the patterns within the EEG data have enough uniqueness for machine learning algorithms to learn and make precise classifications, thus confirming the basic hypothesis of this research project.

5.2 Challenges and Limitations

Although the results are successful, it is essential to acknowledge the difficulties and shortcomings that arose, as they provide crucial context for the results and will be taken into account in future research. The main issue that was overcome was the considerable expansion of the project scope; whereas the initial proposal in the FYP 1 report indicated that the work would not entail the implementation of models, the scope of the project was expanded to entail the complete development, tuning, and assessment of three different machine learning models. Moreover, although the research methodology in Chapter 3 provided a plan to apply an LSTM network to learn temporal patterns, this was not implemented due to time limitations and the hardware issues discussed below. This is a limitation considering that fatigue is a dynamic process whose temporal dynamics have not been fully explored.

Next, although the obtained accuracy rate of 0.871 is a good and encouraging outcome, it must be put in perspective with the broader academic literature. As indicated in the literature review, extremely controlled studies have shown over 98% accuracy in both RF and CNN models. The gap in performance indicates that the approach is valid, but there is scope for great improvement. This gap can be partially explained by the peculiarities of the considered dataset and the degree of hyperparameter optimization within the time limits.

Finally, the project was limited to using only one publicly available Kaggle dataset and the accessible computational hardware. The use of publicly available datasets limits the potential to control the underlying experimental conditions and population heterogeneity, which could have consequences for the generalizability of the results. The constraints in hardware capacity, specifically the absence of a dedicated GPU, directly impacted the deep learning component of this research. It reduced the design complexity of the CNN that can be tested and considerably slowed down the iterative procedure of training and hyperparameter search, preventing a more comprehensive search for the optimal model design.

5.3 Future Work

The results and shortcomings of this project inspire many potential avenues for future research, which would be able to expand on this project and contribute to the sphere of driver safety. An obvious and natural follow-up would be the adoption of more advanced temporal models. Fatigue increases gradually over time, so it is appropriate that a Recurrent Neural Network, such as LSTM, is able to recognize these changes in the EEG signal well. Combining CNN with LSTM could be an even better option because CNN pinpoints relevant details in brainwave data while LSTM indicates how such details vary with time.

Future direction to increase the robustness of the models and achieve greater performance relative to state-of-the-art research ought to be focus on data and features. This involves gathering bigger and more varied information on various populations and driving circumstances to prepare a better model for generalizability. Also, more advanced feature engineering methods could be tried in future work, since this was out of the scope of this project. As mentioned in the literature review, this could either be by extracting time-frequency features with wavelet transforms or non-linear features such as sample entropy, which might be able to pick up more subtle and complex measures of brain activity that are related to fatigue.

Ultimately, the goal of such research is practical applications. Thus, an important direction of further development is the creation of a real-time prototype. This would entail further development of one of the highest-scoring models of this study towards low-latency inference, and connecting it to a commercially available, comfortable, and user-friendly EEG headset, the Muse headset indicated in the literature review. It is necessary to test this kind of prototype in a driving simulator or a safe on-road setting to see how it performs. This step also needs to consider the practicality of in-vehicle realization, e.g., devising sophisticated artifact removal filters to deal with noise in the signals caused by vehicle dynamics and road surfaces, and making the system affordable and simple to operate by a driver.

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