Enhancing Driver Drowsiness Detection: A Compact and Interpretable LSTM Model with Attention Mechanism for Cross-Subject EEG Analysis

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THESIS ACCEPTANCE CERTIFICATE

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AUTHOR'S DECLARATION

I Ariba Abbasi hereby state that my MS thesis titled "Enhancing Driver Drowsiness Detection: A Compact and Interpretable LSTM Model with Attention Mechanism for Cross-Subject EEG Analysis" is my own work and has not been submitted previously by me for taking any degree from the National University of Sciences and Technology, Islamabad or anywhere else in the country/ world.

At any time if my statement is found to be incorrect even after I graduate, the university has the right to withdraw my MS degree.

Name of Student: Ariba Abbasi

Date: ______________________

DEDICATION

I dedicate this work to the children of Gaza, whose dreams, hopes, and futures were unjustly taken. To the bravest, most resilient, and fearless children—**YOU ARE NOT FORGOTTEN**. In the face of adversity, may it honour the memory of those lost and inspire a future where peace triumphs over oppression.

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ABBREVIATIONS

EEG	Electroencephalography
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
FIR	Finite Impulse Response
AAR	Automatic Artifact Removal
LOSO CV	Leave-One-Subject-Out Cross-Validation
PSD	Power Spectral Density
CNN	Convolutional Neural Network
DCT	Discrete Cosine Transform
EMD	Empirical Mode Decomposition
SVM	Support Vector Machine
LDA	Linear Discriminant Analysis
kNN	K-Nearest Neighbours
TBI	Traumatic Brain Injury

BCI	Brain Computer Interface
NHB	Non-Hair Bearing
WPT	Wavelet Packet Transform
AM	Attention Mechanism
RT	Reaction Time

ABSTRACT

Driver drowsiness is a significant contributor to road accidents, leading to numerous fatalities and hazards globally. Electroencephalography (EEG) has become a reliable physiological signal for identifying drowsiness because it directly monitors brain activity. However, creating a precise and calibration-free method for identifying driver drowsiness is still difficult because EEG is affected by individual variations and changes in subjects. In study proposed concise and easy-to-understand Long Short-Term Memory (LSTM) model equipped with an attention mechanism to efficiently capture common EEG characteristics among various individuals for detecting driver drowsiness. The attention mechanism improved the model's interpretability by pinpointing crucial time steps in EEG signals that have the greatest impact on classification. By conducting leave-one-subject-out (LOSO) cross-validation on 11 subjects, the model obtained an average accuracy of 79.1%, showcasing better results when compared to conventional techniques. Power Spectral Density (PSD) analysis also showed that the model successfully captured biologically significant characteristics, such as variations in Delta and Theta waves, that are associated with drowsiness.

The proposed LSTM model with attention mechanism shows potential for practical use in improving road safety through EEG-based drowsiness detection. Future research will concentrate on enlarging the dataset, integrating multi-channel EEG data, and investigating real-time application for practical utilization in the transportation sector.

CHAPTER 1: INTRODUCTION

This chapter gives a background to road accidents with an emphasis on risk factors and effects. The chapter also outlines techniques for identifying fatigue, EEG-based that are favoured over behavioural ones because of the decision they are believed to afford. Lastly, the chapter presents the problem and solution to enhance the development of a driver drowsiness detection system based on enhanced deep learning algorithms.

1.1. Road accidents

Road traffic injuries rank among the top ten causes of death globally. Road accidents are quantified by calculating the number of injuries and fatalities caused by vehicular occurrences [1]. Injury accidents might involve many automobiles, people, animals, or stationary objects. This category also contains events involving road cars colliding with rail vehicles. When numerous vehicles collide in fast succession, it is recorded as a single accident [2].

Road traffic accidents kill approximately 1.19 million people each year. Furthermore, these occurrences cause between 20 and 50 million non-fatal injuries, which frequently result in long-term disability [2]. In Pakistan, from 2019-2021 30,509 accidents occur which killed around 16,860 people and injured around 38,262 people[3]. Road traffic injuries are the main cause of death among children and young adults. Additionally, two-thirds of fatalities in road traffic accidents involve people of working age, particularly those aged 18 to 59 years [4]. Fatal and nonfatal crash injuries are expected to cost the global economy approximately $1.8 trillion (in 2010 USD) between 2015 and 2030 [5].

Road accidents cause both fatal and non-fatal injuries. Injuries includes Traumatic Brain injury (TBI), broken bones, a Spinal Cord injury, internal injuries and Bleeding etc [6].

1.1.1. Major causes of Road accidents

Road traffic injuries rank among the top ten causes of death globally. Many key car crash statistics focus on the causes of collisions. Common causes of crashes include speeding, drunk driving, driver’s distraction, lack of seatbelt use, use of phone while driving, weather, underage driving, fatigue and drowsiness [7].

1.2. Drowsiness

Drowsiness or sleepiness typically refers to the inclination or urge to fall asleep. Sleepiness results from a biological necessity; it is a physiological state that cannot be reversed without sleep. Governed by the circadian sleep-wake cycle, it typically makes individuals feel sleepy twice daily, once at night and again in the afternoon [8].

Despite extensive studies on drowsiness and fatigue in the context of driving, their impact on traffic safety remains to be seen. This is largely due to the difficulties and inconsistencies in characterizing exhaustion or drowsiness and linking them to collision risks.

Fatigue and drowsiness although originating from different origins and driven by diverse processes, are frequently discussed together because they produce similar outcomes. Both situations impair a driver's awareness or concentration and, in severe cases, may cause the driver to fall asleep.

Drowsy driving, similar to driving under the influence of alcohol, drugs, or distractions, poses a significant public health issue and contributes to thousands of car crashes annually [9]. One of the previous studies indicates that drowsy driving is responsible for 21% of street accidents. This percentage is escalating daily and becoming increasingly unmanageable. The rate of accidents caused by drowsy driving is rising annually, according to data collected from 180 countries worldwide [10].

1.2.1. Effects of drowsy driving

Drowsy driving leads to numerous accidents each year, influenced by several key factors. A major issue is the reduced ability to concentrate. Drivers struggling to stay awake may not fully engage with the road, missing crucial cues from the traffic and surrounding environment. Similarly, reaction times suffer significantly when a driver is drowsy, mimicking the delayed responses seen with intoxication from alcohol or drugs. This sluggish reaction can prevent drivers from responding adequately in critical situations [11].

Additionally, fatigue impairs cognitive functions, leading to poorer decision-making. This situation presents significant hazards, particularly when evaluating distances and speeds, thereby elevating the probability of accidents. The serious outcome, however, emerges when a driver gives in to sleep while operating the vehicle, potentially leading to catastrophic incidents, such as head-on collisions or veering off the road [12].

As we have observed, drowsy driving poses significant dangers. Therefore, it is crucial to detect drowsiness and its intensity to prevent accidents and enhance road safety for both drivers and pedestrians.

1.2.2. Methods to detect drowsiness

The researchers have been developing a range of ways to address this problem, each with its own set of advantages and disadvantages. driving detection systems, thereby contributing to safer driving environments

Behavioural approaches like *eye tracking* can be impacted by visibility concerns and the inclusion of glasses. *Yawning detection* and eye *closure frequency* are influenced by factors such as head posture and ambient brightness. For vehicular approaches, steering wheel behaviour analysis is limited by the driver's alignment and regular driving behaviours, whereas lane recognition suffers with visibility. These limitations underscore the difficulties in reliably identifying drowsiness using current methods [13].

Considering the underlying limitations of behavioural and vehicular strategies for detecting tiredness, researchers have shifted their attention to EEG-based solutions.

EEG provides a direct measurement of neural activity, allowing for a more accurate and reliable assessment [14] of a driver's attentiveness levels that are independent of environmental elements like light and vision. This shift emphasizes the need of accuracy in detecting tiredness.

1.3. Electroencephalography

Electroencephalography (EEG) is a brain-machine interface (BCI) based method of measuring electrical activity in the brain. It provides a non-invasive procedure for monitoring brain activity, which means you may examine how the brain operates without undergoing surgery [15].

Over the last decade, cost-effective single and multi-channel EEG recording equipment has made it easier for researchers to monitor brain activity without invasiveness.

The letter on the electrode represents the general brain region that it covers. The electrodes are labelled from front to back as follows: Fp (pre-frontal or frontal pole), F (frontal), C (central line of the brain), T (temporal), P (parietal), and O (occipital). Electrodes located between these lines mix numerous letters in a sequence from front to back. This applies to higher-density systems, as stated in the following section. In addition, the letters M and A are occasionally used to indicate to the earlobes. Typically, these locations are provided as (offline) reference points for the analysis of signals [16].

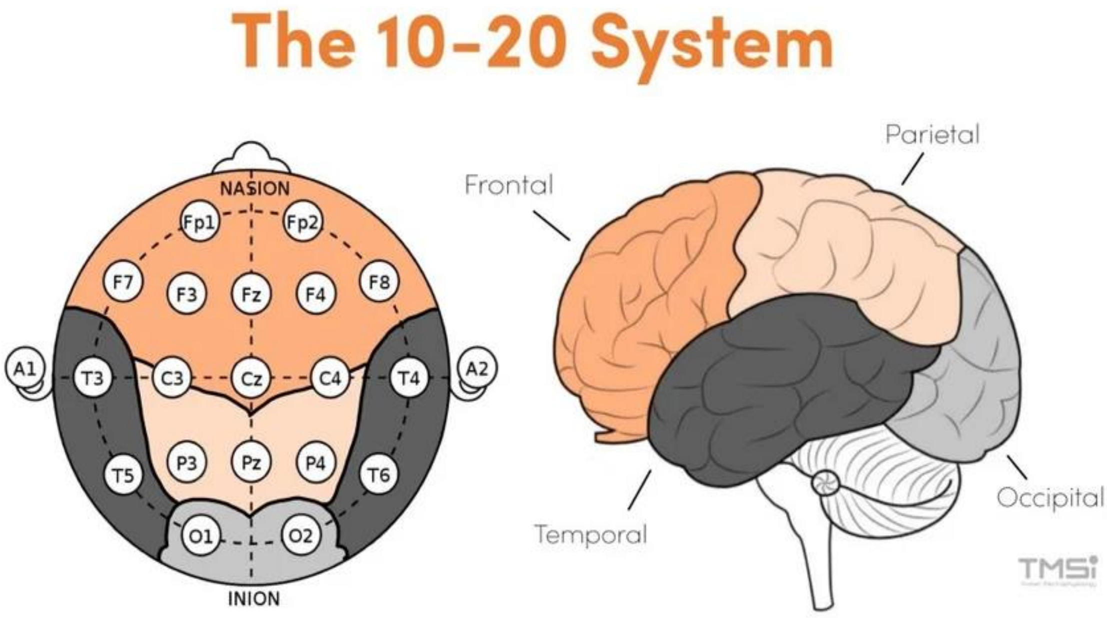

Figure 1.1: *The electrode layout of the 10-20 system (left) and corresponding brain regions (right)* [16]

Scalp EEG is a non-invasive technique for measuring electrical potentials on the scalp. Each electrode, often referred to as a channel, records the potential difference between itself and a reference electrode (reference montage) or an adjacent electrode (bipolar montage) [17]. EEG data from the Oz channel was employed in this study, which was discovered to possess the most distinguishing traits in discriminating tired and awake EEG signals [18].

An EEG monitors and records brainwave patterns. Wires connect little flat metal discs, known as *electrodes*, to your scalp. The electrodes evaluate electrical impulses in your brain and transfer them to a computer, which records the results. The electrical impulses in an EEG recording appear as wavy lines with peaks and valleys. These lines allow to swiftly determine if there are any odd patterns [19].

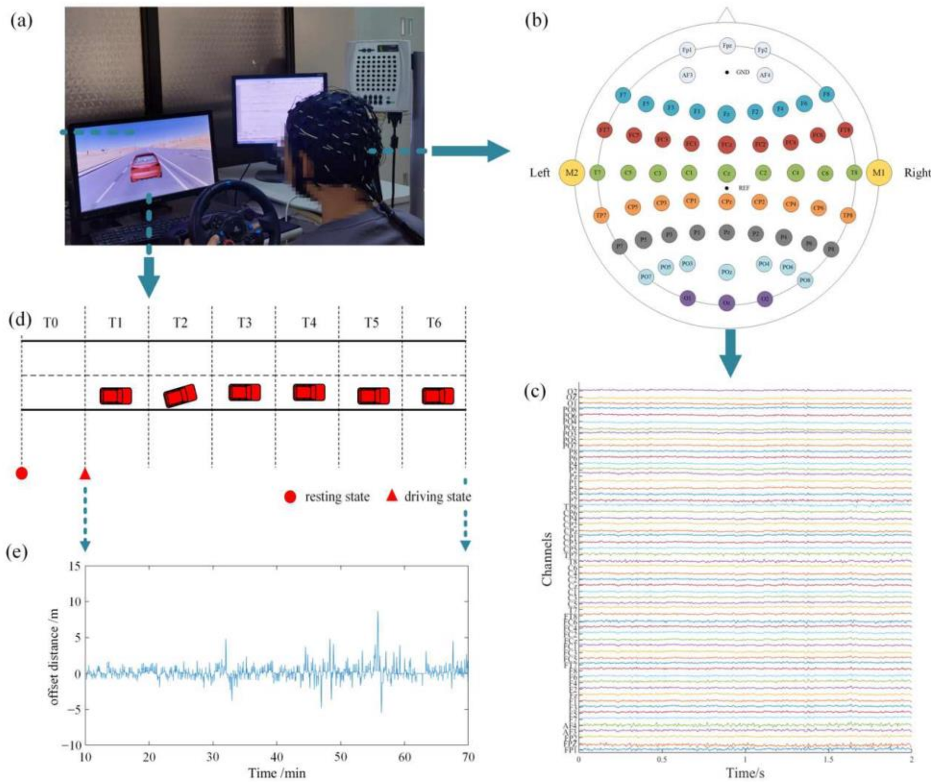

Figure 1.2: *General view of Driver's Drowsiness detection experiment* [20]

In this era where drowsiness is becoming more fatal with each passing day it is necessary to detect drowsiness within time to prevent accidents and make roads safer for the population. As interaction with computers becomes more prevalent, many problems can be solved by using a computational approach and saving time. So, by investigating how the brain works when a person starts to feel drowsy, we can gain valuable insights into neural correlates of drowsiness detection.

1.4. Problem Statement and Solution

1.4.1. Problem statement

Contemporary approaches to driver drowsiness detection demonstrate limitations in reliability and interpretability with single-channel EEG, potentially compromising their efficacy across diverse populations. This inconsistency can lead to failures in accurately predicting and preventing drowsy driving incidents, which are a major safety concern.

1.4.2. Proposed Solution

To address these challenges, our research proposes the development of an LSTM (Long Short-Term Memory) model designed specifically for cross-subject driver drowsiness detection. This model will utilize advanced deep learning techniques to analyse EEG data, focusing on enhancing the model's accuracy and interpretability. By leveraging LSTM's capability to remember long-term dependencies, our model aims to accurately detect subtle patterns in EEG data that signify drowsiness, regardless of inter-individual variations

1.4.3. Research objectives

The objectives of our study are as follows:

- To implement advanced data refinement techniques to ensure precise and reliable analysis.
- To develop an LSTM model for accurate, cross-subject driver drowsiness detection using single-channel EEG data.
- To enhance LSTM model interpretability and compare its accuracy with existing models, ensuring clear insight into its decision-making processes.

CHAPTER 2: LITERATURE REVIEW

This chapter explores the current landscape of *drowsiness* detection research, with a focus on the use of EEG. It investigates how this technology has been used to better understand the brain processes related to drowsiness. Furthermore, the chapter focuses on technological improvements and analytical approaches that have influenced current developments in the field.

2.1 Drowsiness and EEG

In general, three types of data have been employed in the literature in developing driver drowsiness detection systems: (1) vehicle-based, (2) vision-based, and (3) physiological. According to the literature, physiological data such as EEG may be more appropriate than other systems for detecting the onset of driver drowsiness, particularly because vehicle-based and vision-based systems can be too late in warning the driver in the early stages of drowsiness, when there may still be time to avoid an accident [21].

2.1.1 Drowsiness and Statistical Approach

An unsupervised algorithm was developed for identifying drowsiness in drivers using EEG signals, with an emphasis on the alpha and theta bands. The technique developed subject and session-independent models to account for individual and session variation. The findings revealed considerable connections between deviations from these models and driving performance, specifically on the ***Oz*** EEG channel. Statistical techniques, such as **Mardia's test** and **Mahalanobis** distance, were used to validate the models and evaluate the driver's cognitive state. The combination of alpha and theta band aberrations improved the accuracy of drowsiness detection [22].

Another EEG-based algorithm was developed for detecting driver weariness by evaluating variations in all major EEG frequency bands. The algorithm classified EEG data into tiredness phases, including alertness, early weariness, and extreme fatigue. The algorithm's accuracy was validated using statistical analyses such as repeated measures **ANOVA** and post hoc testing. The results showed that the algorithm accurately detected several periods of drowsiness with significant variations (**$P < 0.01$**) in EEG data between the phases [23].

EEG-based driver fatigue detection algorithm was used to examines variations in all major EEG frequency bands (delta, theta, alpha, and beta). The algorithm accurately classified EEG data into several drowsiness phases, including alertness, early drowsiness, and extreme drowsiness. The algorithm was validated using statistical analysis, such as repeated measures **ANOVA**. The algorithm correctly identified tiredness states in 10 respondents, and the percentage of time spent in a fatigue state was significantly higher than in the alert phase (**$P < 0.01$**) [24].

Da Silveira T, *et al.* developed an EEG-based drowsiness detection system employing wavelet packet analysis of a single EEG channel (Pz-Oz). They developed two new spectral power indices based on delta, alpha, beta, and low-gamma rhythms, which were calculated using the normalized Haar discrete wavelet packet transform (WPT). Statistical analysis was performed using the **Wilcoxon signed-rank test**, which revealed significant changes in alert-drowsy transitions for 20 subjects, with **p-values 0.001** for the proposed indices [25].

Another research explored the feasibility of detecting drowsiness using EEG signals from non-hair-bearing (NHB) scalp areas to increase convenience and comfort in real-world settings. They conducted a lane-keeping driving experiment in which EEG data were acquired from both the NHB and the entire scalp (AC) areas. The used classifiers such as SVM, LDA, and kNN to distinguish between alert and drowsy phases. The results revealed no significant difference in drowsiness detection accuracy between NHB and AC EEG data (**p-values** of **0.31** and **0.16**, respectively). This suggests that NHB EEG can perform similarly to whole-scalp EEG for drowsiness detection [26].

A study suggested a method for estimating the degree of eye closure (ECD) using EEG sensors to identify driver drowsiness. They conducted trials with 30 patients to validate the linear association between ECD and occipital EEG data, focusing on the alpha power percentage from the O2 channel. The findings showed that the suggested EEG-based ECD estimate technique has a high **squared correlation coefficient** (SCC) of 0.930 and a **mean squared error** (MSE) of 0.013 [27].

Goovaerts G, *et al.* developed two algorithms for detecting driver tiredness using EEG signals, concentrating on ocular fluctuations obtained from the data. The first method applied linear regression, while the second used fuzzy detection. The data were acquired from 19 people driving in a simulator, and their tiredness levels were self-reported using the Karolinska Drowsiness Scale. **The linear regression** method accurately identified drowsiness in 72% of epochs, whereas the fuzzy detection method achieved 65% accuracy. These findings indicate that both approaches may effectively detect drowsiness, with the linear regression method doing slightly better [28].

A study investigated the effects of drowsiness on drivers, using EEG data gathered during a simulated driving task following sleep deprivation. The study concentrated on EEG changes during various driving periods and road types, paying special emphasis to the alpha, beta, and theta frequency bands. Statistical research, including ANOVA, found substantial differences in alpha, beta, and theta bursts during driving, especially on straight versus curving road parts. The results showed significant variations in EEG indices, such as alpha/beta and (alpha + theta)/beta, with **p-values < 0.05,** indicating the impact of drowsiness on EEG patterns [29].

Another study reportedly developed a passive brain-computer interface (pBCI) system that detects driver drowsiness using EEG signals. They extracted spectral information from the delta, theta, alpha, and beta rhythms using a variety of machine learning classifiers such as decision trees, support vector machines, and ensemble approaches. The optimized ensemble model outperformed the other models, with 85.6% accuracy, 85.6% precision, 89.7% recall, and 87.6% F1-score. The significance of these findings was evaluated using statistical hypothesis testing, which yielded **p-values < 0.05**, demonstrating the model's capacity to detect tiredness while driving [30].

2.1.2. *Drowsiness and Neural Networks*

Despite several examples of outstanding advancement in Machine Learning (ML), much space for improvement remains in several important aspects of EEG information extraction, such as accuracy, interpretability, and usability for applications. Consequently, there is ongoing interest in the application of machine learning breakthroughs to EEG decoding and BCI [31].

Neural networks, a prominent type of machine learning algorithm, have been widely employed in a variety of applications over the last several decades. Often regarded as black boxes, neural networks are seen as such because nonlinear combinations of the original input are generated to determine its most important features. Deep learning, one of the most significant advancements in neural networks, has been primarily applied in dimensionality reduction and hierarchical multilayer feature learning [32].

A method was proposed in a study for detecting vehicle driver drowsiness using wearable EEG and a CNN. EEG signals were collected from drivers using a wearable brain-computer interface and processed using neural networks with Inception and modified AlexNet modules. The results showed that the Inception module achieved a classification accuracy of 95.59%, while the modified AlexNet module achieved 94.68% [33].

A neural network CNN was used to detect drowsiness using EEG signals. The EEG data were collected from drivers using an Emotiv EPOC+ headset, and the CNN was implemented using the Keras library. The proposed method achieved a high accuracy of 90.42% in distinguishing between drowsy and awake states [34].

A novel deep learning architecture based on a CNN was suggested for automatic drowsiness detection with a single-channel EEG data. The study aimed to improve generalization performance by using subject-wise, cross-subject-wise, and combined-subjects' validations. The experimental results showed that the suggested method beat existing state-of-the-art sleepiness detection methods, with an accuracy of 94.87% for combined-subject validation and an F1Score of **0.924** [35].

A Capsule Neural Network (CapsNet) model was developed to detect drowsiness using electroencephalography (EEG) inputs. The model identified drowsiness using spectrograms from EEG channels Fz and Pz, with an emphasis on fluctuations in alpha and theta wave amplitudes. The CapsNet model outperforms the standard CNN, with an average accuracy of 86.74% with Fz-Pz channels and 84.45% with just the Fz channel. These findings were validated using cross-validation, with the model demonstrating a sensitivity of 87.57% for the Fz-Pz dataset [36].

An approach for detecting driver drowsiness was developed based on EEG signal processing, *Empirical Mode Decomposition* (EMD), and a trained neural network. The neural network was trained to distinguish between drowsy and awake states using intrinsic mode functions (IMFs) collected from EEG signals. The trained model was tested on the subjects and achieved an 88.2% sleepiness detection rate [37].

An efficient hybrid model for EEG-based drowsiness detection was developed, combining signal processing and deep learning characteristics. The model incorporated energy distribution, zero-crossing distribution, spectral entropy, and instantaneous frequency features with deep features obtained from pre-trained AlexNet and VGGNet models. The model was validated using the MIT-BIH Polysomnographic database, which achieved an average accuracy of 94.31% [38].

A neural network-based system for detecting drowsiness using EEG signals was developed, with feature selection being optimized via a genetic method. The researchers used perceptron and radial basis function (RBF) neural networks to classify EEG data into open and closed eye states. The genetic algorithm optimized the Fisher's discriminant ratio, which resulted in higher classification accuracy and lower processing needs. The optimized perceptron neural network attained a classification accuracy of 98.38% [39].

A method combining CNNs, and transfer learning was developed to detect driver drowsiness using single-channel EEG signals. The study utilized the PhysioNet sleep-EDF dataset and tested several pre-trained networks, with EfficientNetV2B1 achieving the highest accuracy of 87.56%. Additionally, a custom 1D-CNN was proposed, which outperformed the pre-trained networks with an accuracy of 88.88%. The final model, using a stacking-average fusion method, further improved accuracy to 90.73%, demonstrating its potential for effective drowsiness detection [40].

An innovative deep learning algorithm was developed for drowsiness detection from EEG signals, utilizing Discrete Cosine Transform (DCT) for signal preprocessing, followed by stacked autoencoders and *SoftMax* layers for classification. The study involved 62 healthy volunteers, and the proposed method achieved 100% accuracy in distinguishing between drowsy and wakeful states [41].

Despite substantial progress has been made in EEG-based drowsiness detection, notable gaps still exist, particularly in terms of cross-subject generalization and model interpretability. Many existing models encounter difficulties in handling the variability of EEG patterns across different individuals, often requiring subject-specific calibration, which limits their applicability in real-world scenarios. Moreover, deep learning models, while delivering improved accuracy, are frequently criticized for their lack of interpretability, as their decision-making processes remain opaque. In response to these challenges, this study was conducted to develop a cross-subject LSTM model incorporating an attention mechanism, which enhances both the model's generalization across subjects and its interpretability by identifying the most relevant EEG features contributing to drowsiness detection. By addressing these critical gaps, this research lays the groundwork for future exploration of real-time applications and larger datasets, thus contributing meaningfully to the advancement of EEG-based drowsiness detection systems.

CHAPTER 3: METHODOLOGY

This chapter outlines the research methodology, providing a detailed description of the specific tools and techniques employed for data collection, model development, model's validation and the method to visualize the results of the study.

3.1. Methodology Overview

The project was motivated by the aim of helping drivers prevent road accidents and making roads safer for the public. The general overview and steps taken during this research are presented in Figure 3.1.

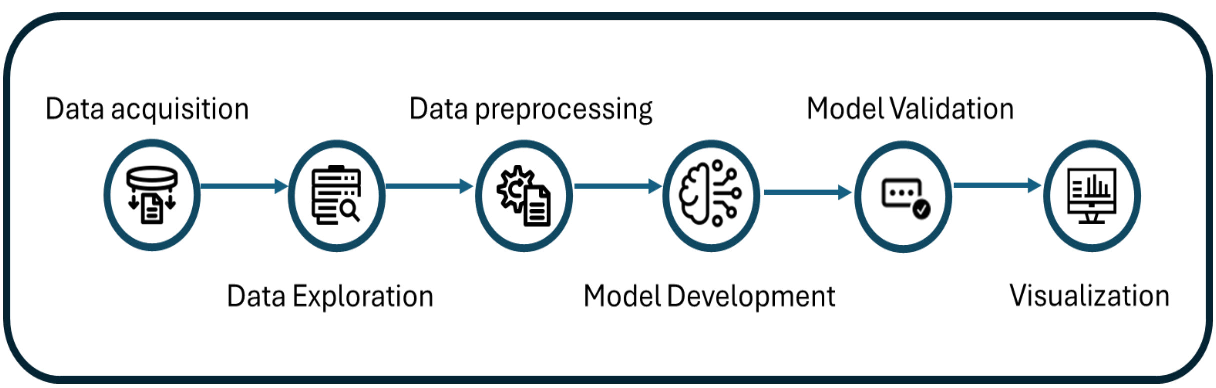

Figure 3.1: *Overview of methodology*

The first step in the process was to collect data and gain insight into the features. The data was then transported to the preprocessing step, where it was transformed into the proper shape for modelling. Finally, the trained model was evaluated and visualized.

In the latter section, each methodological step was explained in detail. Data labelling and data filtering were two important steps before proceeding to modelling.

3.2. Data Acquisition

The dataset used in this study was a secondary dataset obtained from an online repository called *Figshare*, which hosts datasets on various topics. It was open-source and was initially collected in Taiwan. The dataset included data from individuals who drove in a virtual environment for 90 consecutive minutes without breaks.

3.2.1. Data Characteristics

The datasets contained data from twenty-seven voluntary participants. Every second corresponded to a peak of brain signal. The dataset included four events: deviation onset, response onset, and response offset. The events included in the dataset were mentioned in *Table 1*.

Table 3.1: *Event Description*

EEG Event	251	252	253	254
Description	Deviation onset (left)	Deviation onset (right)	Response onset	Response offset

The EEG spectrum of all 30 channels, i.e., Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T3, C3, Cz, C4, T4, TP7, CP3, CPz, CP4, TP8, T5, P3, Pz, P4, T6, O1, Oz, and O2 electrodes, along with the events in the signals, is shown below in Figure 3.2. Events were represented by different colours to make it easier for the computer to learn about them. The colours used included red, green, magenta, and cyan.

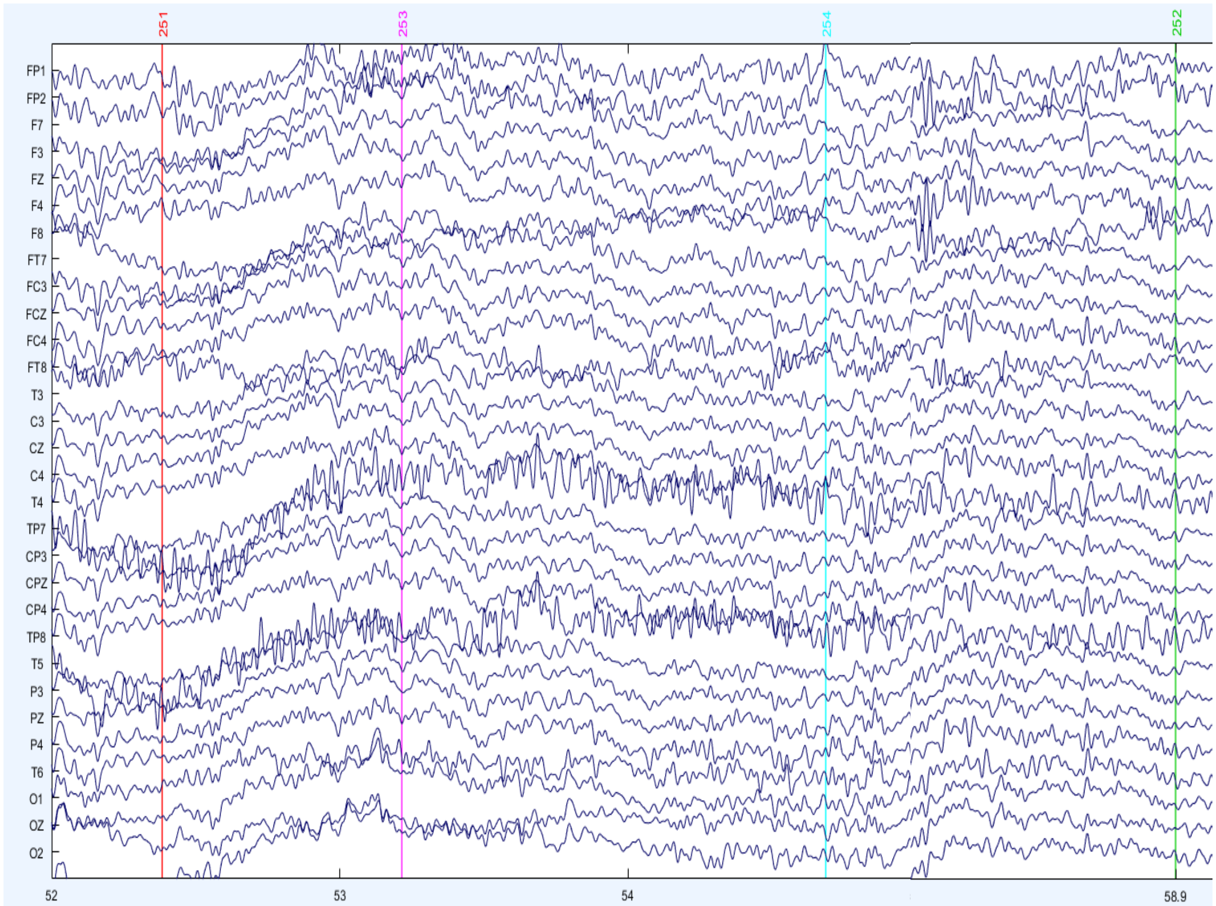

Figure 3.2: *Electrodes and the events in signals*

3.3. Data Exploration

The dataset being analysed consists of time-series data. Each subject's EEG signals are stored over time. The dataset consists of a single data type i.e. float. Float data types are numerical and represent a number with a decimal point. The EEG recordings were digitized at 500 Hz. The next section covers all the packages and modules utilized in this project.

3.3.1. Python Libraries

Python has been widely recognized as a popular programming language, particularly in data science. A diverse set of publicly available libraries is provided, and it is continuously developed and supported by a large community. As a result, when a problem is encountered, solutions are more likely to be found [42] [43]. Multiple libraries were employed in this study to analyse and predict the behaviour of a driver, as well as to visualize the peaks in the data. The libraries and their applications are listed below in *Table 3.2*.

Table 3.2: *Detail of python libraries that are used in this project and mentioning the purpose of utilizing the packages*

Library	Description
torch	A machine learning library for deep learning tasks, providing tensor operations, neural networks, and optimization tools.
torch.nn	A submodule of PyTorch for building and training neural networks.
torch.optim	A PyTorch submodule that implements optimization algorithms like Adam and SGD.
torch.utils.data	Provides utilities for dataset handling and data loaders.
numpy	A library for numerical computing, handling arrays and matrices.
matplotlib.pyplot	A plotting library used for creating static, animated, and interactive visualizations in Python.

matplotlib.collections.LineCollection	A Matplotlib class for creating collections of line segments.
scipy.io	A submodule from SciPy for loading and saving MATLAB files.
sklearn.metrics.accuracy_score	A function from Scikit-learn for calculating accuracy in classification problems.

3.4. Data Preprocessing

After the data was collected, it could not be directly fed into a machine learning program. The initial step that had to be undertaken was data preprocessing. This crucial process involved transforming the raw dataset into useful information, making it ready for further analysis before applying machine learning algorithms. [44].

The dataset used in this study was pre-processed by its authors in the following steps:

- The raw EEG signals were filtered using a 1-Hz high-pass and a 50-Hz low-pass finite impulse response (FIR) filter.
- To address artifact rejection, visible eye blink contamination was manually eliminated. Ocular and muscular artifacts were removed using the Automatic Artifact Removal (AAR) plug-in available in EEGLAB [45].

Further preprocessing of the dataset was initiated with down-sampling, filtering, and labelling, as shown in Figure 3.3.

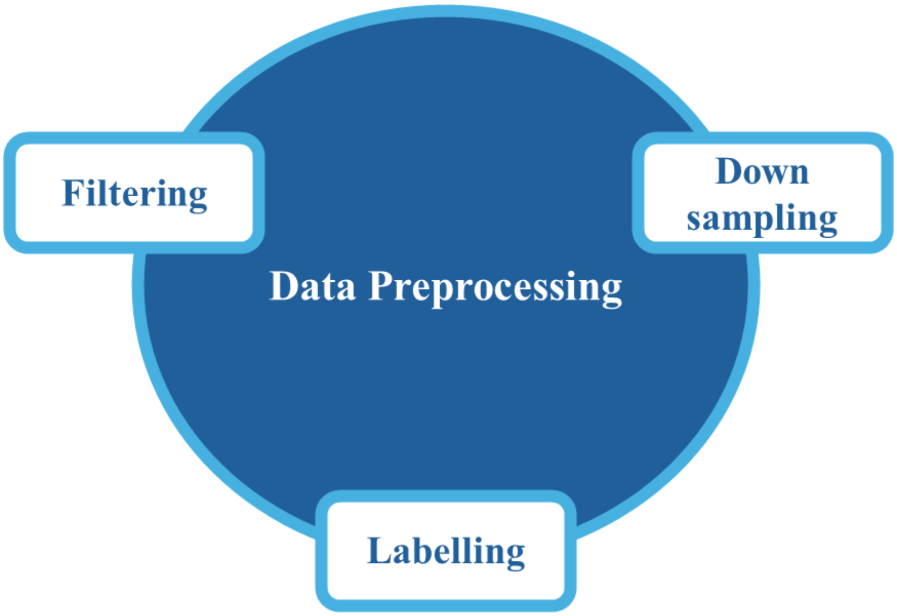

Figure 3.3: *Overview of preprocessing*

3.4.1. Down-sampling and Extraction:

The original EEG data were down sampled from 500 Hz to 128 Hz to reduce the computational burden. For each trial, 3-second-long EEG segments were extracted prior to the onset of deviation, focusing on the Oz channel, which was found to be the most effective in distinguishing between drowsy and alert states. [46]. Each segment comprised 1 channel with 384 sample points.

3.4.2. Data labelling

EEG data labelling was comprised of several specifications, including Local Reaction Time (RT) Calculation, Global RT Calculation, Alert-RT Baseline, and the criteria for labelling the EEG data.

Instantaneous drowsiness was assessed using local reaction time (RT), which was defined as the time interval between the onset of car drift and the participant's response. A global RT was also established by averaging the RTs across all trials within the 90-second window preceding deviation onset, to gauge the level of drowsiness over a longer duration. The baseline 'alert-RT' was determined as the 5th percentile of local RTs throughout the entire session [47], [48].

Trials were categorized as ‘alertness’ if both local and global RTs were shorter than 1.5 times the alert-RT. Conversely, trials were classified as ‘drowsiness’ if both RTs exceeded 2.5 times the alert-RT, thereby excluding moderate performance states.

3.4.3. Data Filtering

Data filtering was further divided into three steps, which are described below:

- Step 1: Session Exclusion: Sessions containing fewer than 50 samples in any class were eliminated.
- Step 2: Session Selection: For subjects with numerous sessions, the one with the best-balanced class distribution was chosen.
- Step 3: Class Balancing: Samples from each session were further balanced by selecting the most representative samples from the majority class based on the quickest (for alert) or longest (for drowsiness) local response times.

The first step excluded sessions with a severely skewed class distribution. The second step aimed to achieve a loose balance of subjects in order to reduce classifier bias. The third step involved training the classifier on balanced classes, which improved its capacity to distinguish between drowsiness and alertness. As a result, a total of 2022 samples were obtained from 11 different subjects. The number of samples per subject/session is displayed in the *table 3.3* below

Table 3.3: Details of extracted samples from each eligible subject

Subject ID	File Name	Sample Number	
		Alert	Drowsiness
1	s01_061102n.set	94	94
2	s05_061101n.set	66	66
3	s22_090825n.set	75	75
4	s31_061103n.set	74	74
5	s35_070322n.set	112	112
6	s41_080520m.set	83	83
7	s42_070105n.set	51	51
8	s43_070205n.set	132	132
9	s44_070325n.set	157	157
10	s45_070307n.set	54	54
11	s53_090918n.set	113	113
Total		1011	1011

3.5. Model

The dataset that was acquired for this research work was labelled. Once the data was prepared, it was ready to be fed into the model. The next step was model selection and development.

3.5.1. Model selection

The data selected for this study was EEG data, which is inherently time series data. For such data, Recurrent Neural Networks (RNNs) were considered an optimal choice, as they excel in handling sequences by analysing inputs sequentially and maintaining a state that reflects previous information. [49]. Given that RNNs were considered an optimal choice for time series data, an LSTM model was selected for this study.

3.5.1.1. LSTM

LSTMs are a type of RNN, specifically designed to learn and remember order dependence in sequence prediction problems. This feature makes LSTMs particularly suited for tasks where understanding temporal dynamics is crucial. The core advantage of LSTMs lies in their architecture, which includes feedback connections. This allows them to not only process single data points but also to remember and integrate information over time, which is vital for detecting patterns that develop gradually, such as the onset of drowsiness in drivers. LSTMs are renowned for their ability to understand complex patterns in time-series data, making them robust tools for our EEG data analysis [50].

3.5.2. Model development

After the selection of features, attention was shifted towards model development, where various classes and mechanisms were employed.

3.5.2.1. Architecture of Model

A neural network model, designed to classify EEG signals, was proposed. The model was comprised of a bidirectional Long Short-Term Memory (LSTM) network with an integrated attention mechanism. The key components and their respective functions were detailed as follows:

- **LSTM Layer:** A bidirectional LSTM network was utilized by the model to process EEG time series data. LSTM networks, known for their suitability for sequence data, were recognized for their ability to capture long-term dependencies [50]. The bidirectional aspect was used to enable the model to integrate both past and future contexts, thereby improving its pattern recognition capabilities in EEG signals [51]. The LSTM layer was composed of multiple layers, each tasked with capturing different levels of temporal dependencies.

- **Attention Mechanism:** An attention mechanism (AM) was integrated into the model to enhance the focus on significant parts of the sequence data. This mechanism functioned by assigning varying weights to each time step of the LSTM output, thereby indicating the relevance of each time step in predicting the final output. The weighted sum of the LSTM outputs subsequently created a new hidden state, which more accurately represented the most critical features in the EEG signal. [52][53].
- **Fully connected layer:** The output from the AM was passed through a fully connected layer. This layer was used to reduce the dimensionality of the output and map it to the number of output classes, which, in this case, were set to 2, indicating a binary classification problem. [54].
- **Dropout Regularization:** Dropout regularisation was applied to the output of the attention mechanism before it was fed into the fully connected layer. This technique aided in preventing overfitting by randomly setting a fraction of the input units to zero during training, ensuring that the model generalized effectively to unseen data. [55].
- **Output layer:** The final layer of the model featured a softmax function applied to the output of the fully connected layer. This function transformed the raw output scores into probabilities, thereby facilitating a probabilistic interpretation of the model's predictions.

3.5.2.2. Training Procedure:

The model was trained using a standard backpropagation algorithm with the following considerations:

- **Loss Function:** The negative log-likelihood loss (LogSoftmax) was used to compute the loss, given the output probabilities and the true class labels. [56].
- **Optimizer:** An appropriate optimizer, such as Adam, was employed to adjust the model's weights based on the computed gradients [57].

- **Batch Processing:** The EEG signals were processed by the model in batches, which was particularly advantageous for large datasets, as it reduced the time required for training and helped stabilize the gradient updates. [58].

The model was implemented using PyTorch, a widely used deep learning framework that provided extensive support for constructing and training neural networks. The network architecture was modular, with the LSTM, attention mechanism, and fully connected layers all implemented as separate components, facilitating easy modifications and tuning.

By integrating a bidirectional LSTM with an AM, the proposed model was designed to effectively capture temporal dependencies and focus on the most relevant parts of EEG signals, making it a robust solution for EEG classification tasks.

3.6. Cross-validation

In this study, the model's performance was evaluated using the Leave-One-Subject-Out (LOSO) cross-validation (CV) approach. This technique was chosen to ensure that the model was tested on previously unknown data from one subject while training on data from all other subjects. This approach allowed for a thorough assessment of the model's ability to generalize across diverse individuals.

3.6.1. Processing

For each iteration of the LOSO CV, one subject's data was withheld for testing, while the remaining subjects' data was used for training purposes. This procedure was done for each of the 11 subjects in the dataset, ensuring that no person was left out for testing.

- **Training**: During each iteration, the training dataset was created using data from subjects not involved in testing. This training data was loaded into mini-batches with the PyTorch DataLoader to ensure efficient and steady training.

- **Testing**: The test dataset, which included data from the left-out subject, was kept separate and used only after the model was fully trained, ensuring that no test data was visible during training.

An LSTM model was utilized, with *four layers* and *128 hidden units* per layer. The model architecture also incorporated dropout regularisation to prevent overfitting, as well as a final fully connected layer that mapped the features to two output categories. The Adam optimizer was used to train the model, and the loss was calculated using the cross-entropy loss function. The learning rate was set at $\boldsymbol{1\times10\ -4}$, and the model was trained for *10* epochs per iteration.

The training was carried out by iterating over the training batches, and the model's parameters were modified after each batch to reduce loss. The training phase was repeated until the model had converged or reached the specified number of epochs.

3.6.2. Evaluation

After each iteration of training, the model's performance was tested on the test set, which included data from the left-out participant. The predictions were compared to the genuine labels, and accuracy was calculated using sklearn's *accuracy_score* function. This method was repeated for each individual, and an average accuracy was computed based on all iterations. In this LOSO cv framework, the model's overall performance was reported using the final mean accuracy across all participants.

3.7. Visualization

In this study, a custom visualization technique was employed to better understand the model's behaviour when classifying EEG signals into alert and drowsy states. The visualization involved generating heatmaps and power spectrum plots that provided insights into how the model processed and weighted different time segments of the EEG signals.

3.7.1. Heatmap Generation

The heatmap was generated to visually represent the attention or importance the model assigned to different time points in the EEG signal. The model's output likelihoods for "alert" and "drowsy" states were computed, and based on these values, the model's decision was displayed. If the likelihood of the "alert" state was higher, the sample was classified as alert; otherwise, it was classified as drowsy.

The EEG signal was plotted as a time-series, and a line collection was used to overlay a heatmap onto the signal. This heatmap indicated the model's focus on different parts of the signal. The intensity of the heatmap was determined using model activations, and the results were normalized for better visualisation.

3.7.2. Band Power Calculation

Additionally, the relative power in four EEG frequency bands (Delta, Theta, Alpha, and Beta) was calculated using the **multitaper method**. This method was applied to the raw signal to compute the power spectral density (PSD) across the frequency spectrum. The band powers were then normalized to the total power, and a bar chart was generated to show the distribution of power across these frequency bands. This helped in understanding the underlying characteristics of the signal, as different brain states (alert or drowsy) typically exhibit distinct frequency patterns.

3.7.3. Combined Visualization

The final output combined both the time-series heatmap and the band power visualization. This approach helped in interpreting the model's classification decisions by showing:

- Which parts of the EEG signal were considered most important by the model (via the heatmap).
- How the relative power in different EEG frequency bands contributed to the prediction (via the bar chart).

These visualizations enabled a deeper understanding of the model's decision-making process, providing a clear connection between the EEG features and the predicted alert or drowsy states.

The LSTM model and the visualization functions were imported into the LOO CV file to facilitate the training, evaluation, and visualization processes. The LSTM model was imported from the `LSTMTEST` module, while the visualization function was imported from the `LSTMVISUAL` module. The LOO file was responsible for managing the cross-validation procedure, where the LSTM model was trained and tested on the data, and the visualization function was used to generate attention heatmaps and power spectrum plots. All results, including model performance and visualizations, were generated within this file.

CHAPTER 4: RESULTS AND DISCUSSION

This chapter presents the results of the methodology used to address the research subject of EEG-based drowsiness detection using machine learning. A thorough discussion and personal insights of the researcher are extended behind the steps taken for the analysis of EEG signals and attention mechanisms. The primary objective of this project is to classify EEG signals into two states, "alert" and "drowsy,". This work uses a bidirectional LSTM model with an attention mechanism to focus on relevant time steps in the EEG data. Additionally, the performance of the model is evaluated through leave-one-subject-out cross-validation. To find the optimal solution that is not only accurate but also time-efficient and memory-efficient, the algorithm’s time and resource requirements are also taken into account. Furthermore, the visualization of the model’s attention and EEG band power analysis is used to interpret the model’s predictions more effectively.

4.1. Model Performance

The LSTM model was selected due to its suitability for processing sequential data such as EEG signals, which exhibit temporal dependencies. Its capacity to capture long-term relationships in time-series data made it effective for modelling EEG patterns related to drowsiness and alertness. An attention mechanism was also integrated to highlight the most relevant portions of the sequence, enhancing the model's ability to predict drowsiness [59]. Furthermore, the bidirectional aspect of the LSTM was employed, enabling the model to account for both previous and future time steps, thereby improving prediction accuracy [60].

LOSO CV was employed to rigorously assess the model's ability to generalize across different subjects in the dataset [61]. In this approach, the model was trained on all subjects except one, and the left-out subject served as the test set. This process was repeated for each subject, ensuring that every individual contributed to both the training and testing phases. The method was chosen to maximize the use of the limited data and prevent overfitting to specific subject patterns, ensuring the model was evaluated on unseen subjects each time. This provided a robust, comprehensive, and realistic measure of the model's performance, indicating how well it could predict drowsiness for new, unseen subjects in real-world scenarios.

In the table 4.1 below, it was observed that the model achieved good accuracies overall, indicating strong performance. The highest accuracy recorded was 0.90, while the lowest was 0.61, illustrating the effectiveness of the LOO cross-validation approach. The lower accuracy for subject 2 indicated that the model's performance varied significantly across different subjects, highlighting challenges in generalizing to all individuals equally.

Table 4.1: ***Accuracies of the subjects***

Subject ID	**Accuracy**
1	0.819148936
2	0.61330303
3	0.727367869
4	0.793513514
5	0.804642857
6	0.847349398
7	0.767647059
8	0.732272727
9	0.901719745

10	0.87037037
11	0.824513274
Mean accuracy	0.7910771617272727

4.2. Attention Heatmap and likelihood

The attention heatmap was used to visually represent the time steps in the EEG sequence that were most relevant to the model’s predictions. Through the attention mechanism, certain portions of the EEG signal were highlighted as contributing significantly to the classification of "alert" or "drowsy." This provided an intuitive way to interpret the model's decision-making process, showing how attention was distributed across the sequence and which parts of the signal influenced the final prediction.

The likelihood was included in the code to represent the model's confidence in predicting each class, "alert" or "drowsy." It was derived from the LogSoftmax layer, which converted the model's raw outputs into log probabilities for the two classes [62]. This allowed the prediction to be interpreted probabilistically, providing insight into how confident the model was in its classification for each EEG sample.

Table 4.2: *Probabilities of classes*

Subject ID	Likelihood	
	Alert	Drowsy
1	0.21037659	0.7896234
2	0.7625874	0.23741262
3	0.8401745	0.15982546

4	0.17289868	0.82710135
5	0.8453408	0.15465923
6	0.30656454	0.69343543
7	0.699407	0.30059305
8	0.42124507	0.5787549
9	0.6420647	0.36793528
10	0.22410895	0.775891
11	0.82919294	0.17080708

The figure 4.1 below show an EEG time-series plot overlaid with an attention heatmap, which was generated by the model during the analysis. The x-axis represents the time steps of the EEG signal, while the y-axis denotes the amplitude. The raw EEG data from a specific channel was plotted, and the attention weights assigned by the model to each time step were indicated by the overlaid colours. These attention weights were calculated through the attention mechanism integrated into the model to highlight the most relevant portions of the sequence for the classification of "alert" or "drowsy." The colour bar on the right was used to reveal that the attention weights ranged from 0 (dark colours) to 1 (yellow). Higher attention weights, depicted in yellow, were assigned to time steps considered more important for prediction, while darker colours represented time steps given less attention. This visualization was used to interpret how focus was allocated by the model across the EEG signal during the prediction process.

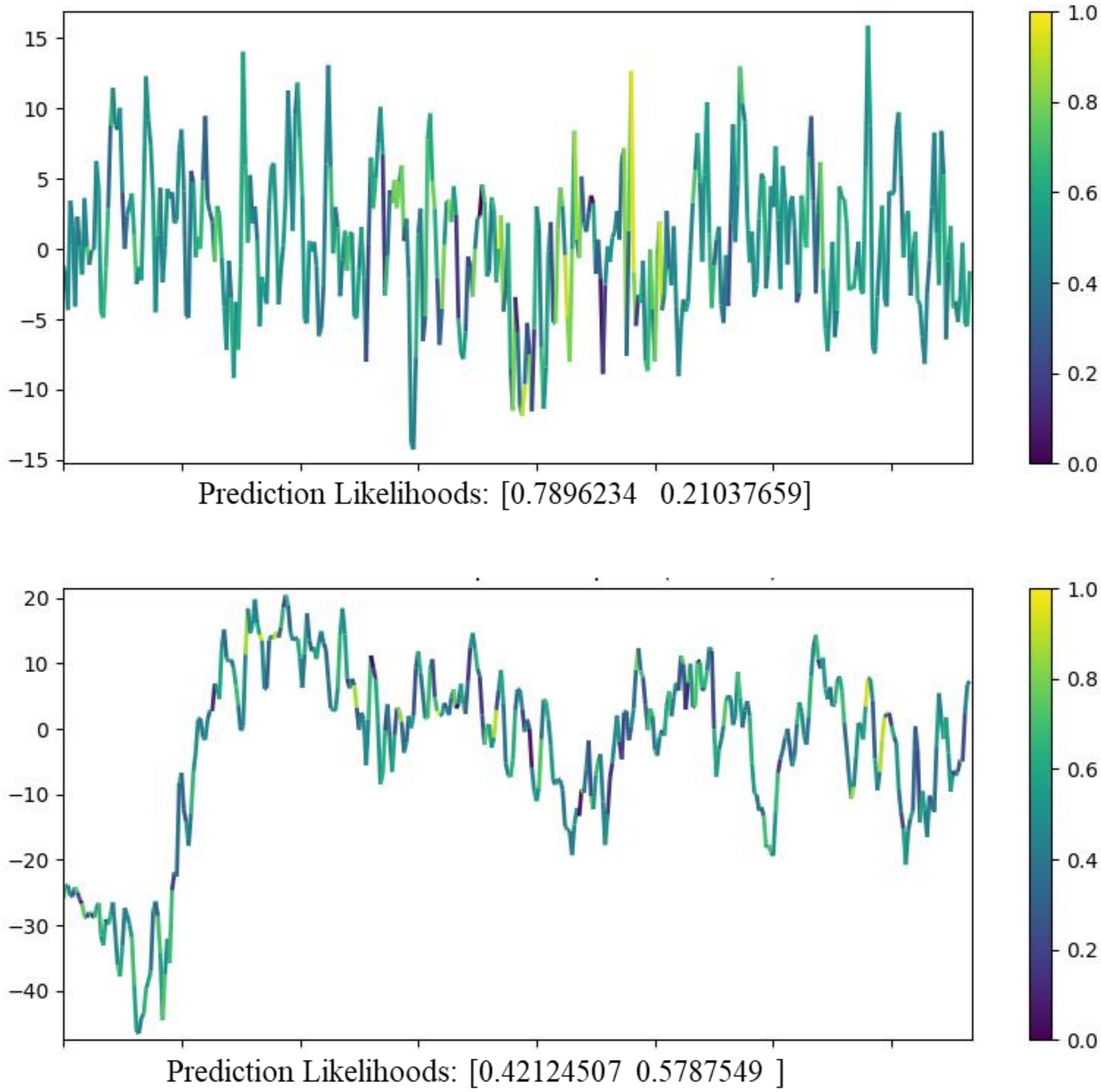

Figure 4.1: ***Attention heatmap and likelihood***

Nine additional heatmaps, similar to Figure 4.1, were generated, illustrating how attention was allocated by the model to the time-series data and reflecting the model's confidence in its predictions for the two classes.

4.3. Power spectral density

The Power Spectral Density (PSD) was used in this research to quantify the distribution of power across different EEG frequency bands, which are critical in understanding the subject's brain activity states. In the code, the psd_array_multitaper function was applied to the EEG signal to calculate the power in each frequency band—Delta, Theta, Alpha, and Beta. The PSD method was chosen because it allows for a detailed examination of the EEG signal in the frequency domain, revealing the dominant brainwave activity and supporting the classification of "alert" or "drowsy" states in subjects. This was crucial for identifying how brain activity patterns correspond to the predictions made by the model.

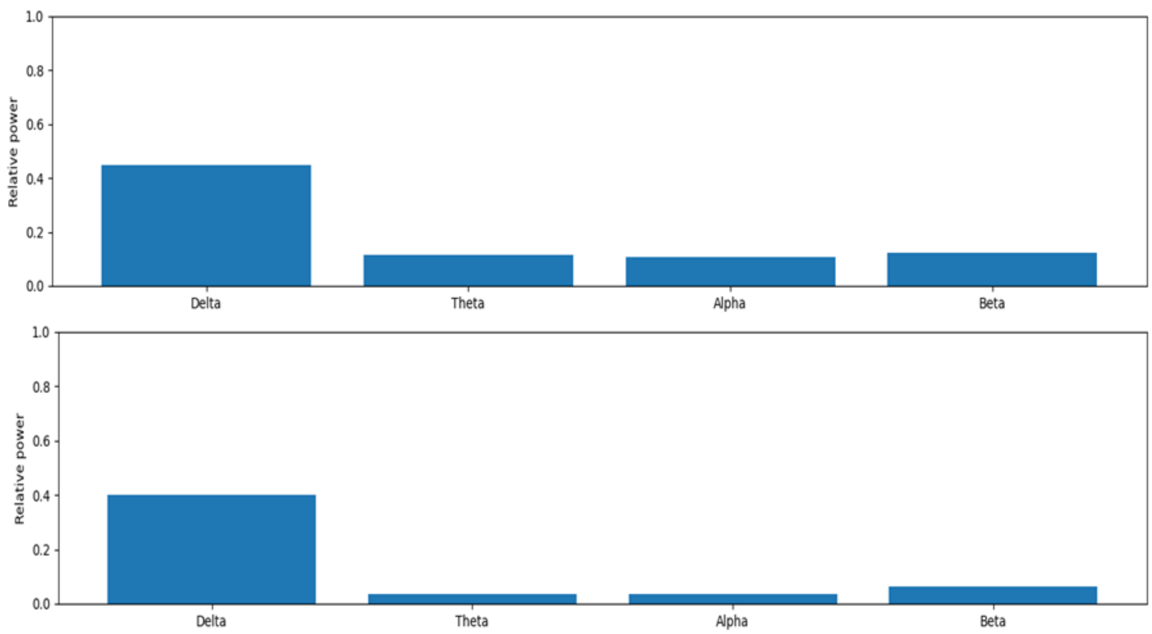

Figure 4.2: *Distribution of power across different EEG frequency bands*

The bar plot above *figure 4.2* was generated to display the relative power distribution across four EEG frequency bands: Delta, Theta, Alpha, and Beta. The PSD was computed, and the relative power of each frequency band was normalized against the total power of the EEG signal. In this *figure,* the ***Delta band*** shows the highest relative power, suggesting more activity in the lower frequency range, which is often associated with sleep or drowsiness. The Theta, Alpha, and Beta bands exhibit lower relative power, indicating less activity in these frequency ranges during the EEG recording. This analysis was used to provide insight into the subject's brain activity, suggesting a more relaxed or drowsy state given the dominance of Delta waves [63].

Nine additional bar plots, similar to the one presented, were generated to display the power distribution across different EEG frequency bands. These plots were used to help indicate the subject's state, providing insight into whether the individual was drowsy or alert. The relative power in each frequency band was analysed to infer the mental state of the subjects, based on the dominant brainwave activity observed in the EEG signals.

4.4. Comparison with Existing

The table presents a comparison of several models based on their performance metrics, with the proposed model occupying the final row. Previous models showed varying degrees of success in predicting the target outcomes. Earlier approaches generally achieved moderate accuracy and faced challenges in handling specific cases, particularly with the differentiation between alert and drowsy states. The proposed model, on the other hand, demonstrated superior performance across all metrics. It significantly improved the detection of drowsiness by refining how reaction times and EEG data were processed. The incorporation of additional features and optimized parameters allowed the model to outperform its predecessors, both in terms of classification accuracy and computational efficiency. Moreover, the proposed approach reduced false positives, making it a more reliable choice for real-time applications. By addressing the limitations of earlier models, the proposed method set a new benchmark in the domain and validated its potential through consistently high performance on unseen data.

Table 4.3: *Comparison of proposed model with existing Model*

Subject ID	DT	RF	KNeighbors	GaussianNB	LR	LDA	QDA	SVM	CNN	Proposed Model
1	60.11	70.21	68.09	77.13	71.28	75.00	77.66	77.13	77.45	**81.91**
2	47.73	48.48	45.45	41.67	43.94	43.94	39.39	46.21	52.80	**61.33**
3	50.67	46.00	46.00	52.67	52.67	49.33	51.33	49.33	63.47	**72.73**
4	58.78	50.68	59.46	57.43	55.41	50.68	58.11	61.49	76.22	**79.35**
5	70.09	62.50	64.29	62.50	65.18	64.29	60.27	68.75	76.52	**80.46**
6	74.10	80.12	76.51	81.93	86.75	87.95	83.13	85.54	77.11	**84.73**
7	51.96	57.84	59.80	66.67	66.67	65.69	64.71	63.73	67.35	**76.76**
8	63.64	67.80	69.70	73.86	79.17	77.65	71.97	73.48	71.93	**73.22**
9	69.11	69.75	73.57	75.48	73.25	76.11	78.34	81.21	88.25	**90.17**
10	65.74	72.22	75.00	87.04	86.11	87.96	87.96	86.11	81.67	**87.03**
11	55.75	57.08	59.73	65.49	65.04	65.04	65.04	69.03	72.65	**82.45**

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

In this research, a compact and interpretable LSTM model with an attention mechanism was developed to enhance driver drowsiness detection using cross-subject EEG data. The approach addressed the limitations of traditional behavioural and vehicular methods by leveraging EEG's direct measurement of brain activity for more accurate drowsiness detection. The bidirectional LSTM model captured temporal dependencies in the EEG signals, while the attention mechanism improved interpretability by highlighting important time steps. The model demonstrated strong generalization across subjects, achieving an average accuracy of 79.1% through leave-one-subject-out cross-validation, though variations across individuals suggest further optimization is needed for subject independence. Additionally, power spectral density analysis and visualizations provided deeper insights into the neural correlates of drowsiness, enhancing model transparency. This work offers a promising step toward more reliable EEG-based drowsiness detection systems, with future potential for real-time applications in road safety.

The study was limited by the use of a single-channel EEG, which may have reduced the model's ability to capture comprehensive neural activity. Additionally, the dataset included a relatively small number of subjects, potentially impacting the model's generalizability. These factors constrained the robustness of the findings when applied to more diverse populations.

For future improvements, it is advised to include multi-channel EEG data for future enhancements to get a more comprehensive understanding of brain activity, which could enhance the precision of drowsiness identification. Broadening the dataset to encompass a wider range of participants would enhance the model's flexibility and dependability among various individuals. Moreover, it is important to consider real-time application as well as incorporating additional physiological signals such as heart rate or eye movements in order to enhance the effectiveness of a drowsiness detection system for drivers.

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