Predictive Analysis of Driver Drowsiness Progression: Multi-Level Drowsiness Classification Using Physiological Signals

Natchira Dachoponchai [1], Yodchanan Wongsawat [1], and Jetsada Arnin [1*]
[1] Department of Biomedical Engineering, Faculty of Engineering, Mahidol University, Nakhon Pathom, Thailand
E-mail: natchira.dac@student.mahidol.edu Tel: +66-892165777
E-mail: yodchanan.won@mahidol.ac.th Tel: +66-24414255
[*] E-mail: jetsada.arn@mahidol.ac.th Tel: +66-835666542

Abstract— **Drowsiness poses a significant challenge to cognitive and motor functions, compromising safety in critical tasks such as driving and increasing the risk of traffic accidents. Existing driver drowsiness detection systems inadequately address the gradual progression of drowsiness, focusing solely on binary classifications of drowsiness. This study aims to develop a neural network model that utilizes physiological signals, including Electroencephalogram (EEG) and Electrocardiogram (ECG), to detect multiple levels of a driver's current drowsiness (Alert, Moderately Drowsy, and Extremely Drowsy). EEG and ECG data were collected from ten participants during 1-hour simulated driving experiments, supplemented by video recordings for once-per-minute drowsiness assessments through Observer Rating of Drowsiness (ORD) by two observers, which served as the ground truth. The neural network trained on 2-channel prefrontal EEG frequency-domain features, heart-rate variability (HRV) features, and driving time achieved accuracies of 92%, 77%, and 77% for Alert, Moderately Drowsy, and Extremely Drowsy, respectively. This high performance, with reliance on minimal electrodes and simple architecture, supports its feasibility for real-time applications as an early warning system for critical drowsiness in order to promote driver safety.**

I. Introduction

Drowsiness is a transitional state to falling asleep, characterized by fluctuating levels of alertness and the onset of sleep, manifested as difficulty in maintaining wakefulness and attentiveness during activities. It is a major concern in many daily-life scenarios, especially in attention-demanding tasks such as driving. Monotonous driving lowers physiological arousal, sensorimotor functions, and information processing, thereby reducing the driver's capacity to react to sudden and critical situations on the road and making drivers prone to drowsiness [1, 2]. Cognitive and behavioral changes resulting from drowsiness can reduce task efficiency and compromise safety, potentially leading to life-threatening consequences [3].

In recent years, intensive research has been conducted into techniques for detecting driver drowsiness to create a more objective evaluation. The current limitation of most driver drowsiness detection systems lies in emphasizing the binary classification of human mental states as *alert* or *drowsy* and issuing alerts to drivers only upon reaching severe levels of drowsiness [4, 5]. Since drowsiness is a dynamic process, defining a threshold that separates mental states into only two extreme categories is too simplistic and impractical. Increasing the number of detection levels allows for a more comprehensive capture of the gradual progression of drowsiness, which is essential for timely and effective intervention. However, overly fine-grained classification may make it difficult for users to interpret the result and make prompt decisions. Therefore, this study focuses on a three-level classification of driver drowsiness to identify the intermediate state between extremely alert and drowsy, enabling drivers to be aware of their mental state and decide when to rest before reaching severe drowsiness.

Driver drowsiness detection systems can be classified into four main types: biological-based, image-based, vehicle-based, and hybrid-based methods [4-7]. Physiological measures achieve the highest accuracy among these categories, directly representing our functional state. EEG and ECG are two commonly used physiological signals in drowsiness detection, offering insights into the underlying neurological and cardiovascular systems. EEG, a brain electrical signal, is considered the gold standard to indicate drowsiness as it represents the central nervous system activity [8]. The frequency shift of EEG signals is found to correlate with drowsiness. The study by Zhao *et al.* shows the rise in low-frequency power caused by drowsiness after driving for 90 minutes [9]. Various feature extraction methods are developed to obtain significant parameters underlying the complex and non-stationary dynamics of the brain [10]. The change in alertness affects the central and autonomous nervous systems, which is linked to HRV that can be extracted from ECG [11]. During drowsiness, our body becomes restful, where parasympathetic activity increases and sympathetic activity decreases. This relaxing response lowers the heart rate and increases the intervals between heartbeats, allowing high-frequency HRV to occur [12]. The previous study suggests that combining EEG and ECG features enhances binary drowsiness detection model performance [13], making them the primary parameters for model development in this study.

Practicality is also important, apart from detection accuracy. This study aims to minimize the system's complexity to ensure feasibility for further real-world applications. We focus on reducing the electrode requirements to enhance the potential for developing wearable devices or gadgets and simplifying the detection model for real-time processing.

Thus, the main objective of this study is to develop the physiological-based multi-level driver drowsiness classification model using minimal EEG channels and individual ECG leads. Since NHTSA reports young adults aged 16-24 as a high-risk group for falling asleep while driving [14], young adult participants were chosen as representative EEG and ECG data acquisition groups in a controlled and safe simulated monotonous driving environment.

II. Materials and Methods

The development of a physiological-based machine learning model for multi-level driver drowsiness classification involves three phases: *Data Acquisition*, including driving simulator setup and data collection; *Data Preparation*, including data preprocessing, feature extraction and selection, and ground truth labeling; and *Model Development*, as shown in Fig. 1.

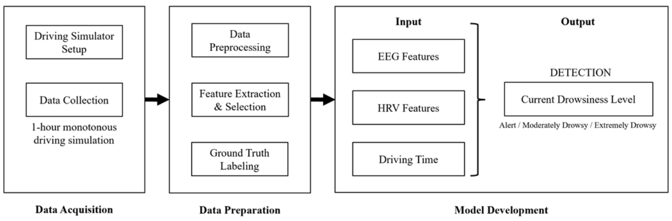

Fig. 1 Overview of Multi-Level Driver Drowsiness Classification Model Development

A. Driving Simulator Setup

Data Acquisition was performed using a 1-hour driving simulation in the Brain Computer Interface (BCI) Laboratory at Mahidol University with the 'City Car Driving' simulator and Logitech G27 USB Racing Wheel to mimic a monotonous driving environment. Physiological signals including EEG (12 channels - O1, O2, Fp1, Fp2, F3, F4, P3, P4, P7, P8, T7, T8) and ECG (lead II) were collected via a 16-channel g.USBamp RESEARCH device at a sampling rate of 512 Hz. Participant behaviors were monitored through video recordings using two cameras to capture overall body movements and facial expressions for drowsiness level labeling. Ethics approval for this experiment was granted by Mahidol University (MU-CIRB 2023/283.1209).

B. Data Collection

Data for model development was obtained from 10 healthy young adults aged 20-24 with valid driver's licenses and no known neurologic or cardiac conditions that could interfere with EEG and ECG signal interpretation. Individuals who took medications that may affect neurological or cardiac function, had a recent history of substance abuse in the past six months, consumed alcohol or caffeine within 8 hours before the study, or experienced recent traumatic events that might affect sleep patterns or mental state were excluded.

All participants were instructed to maintain a constant speed in a specified lane during a one-hour drive. To maintain a controlled environment and ensure the authenticity of participants' drowsiness progression, no more than three observers were present during the experiment, and their interaction with the subjects was minimized.

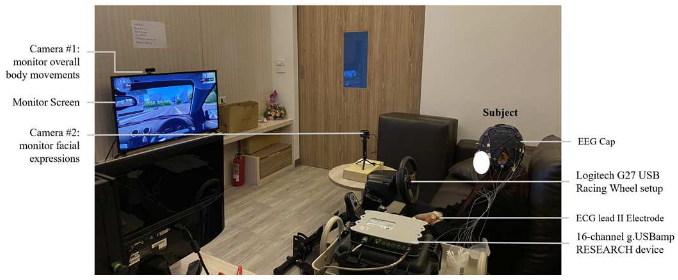

Fig. 2 Driving Simulator Setup at BCI Laboratory at Mahidol University

C. Data Preprocessing

Data preprocessing was executed using MATLAB's Signal Processing and EEGLAB Toolboxes. EEG preprocessing involves Butterworth band-pass filtering with a low-pass filter at 40 Hz (order 9) and a high-pass filter at 0.5 Hz (order 6), followed by Artifact Subspace Reconstruction (ASR) to remove artifacts. ECG preprocessing includes Butterworth band-pass filtering at 1-40 Hz (order 3) and QRS detection via the Pan & Tompkins Algorithm. Both EEG and ECG were then split into 1-minute segments with 50% overlap for further analysis. After preprocessing and excluding artifactual segments, a total of 1,132 segments each were generated from both EEG and ECG data.

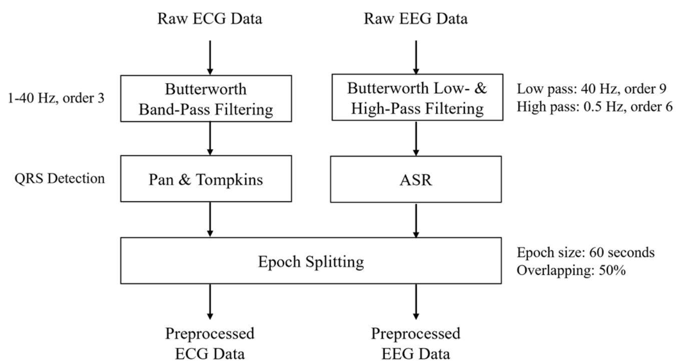

Fig. 3 Data Preprocessing Pipeline

D. *Feature Extraction and Selection*

This study focuses on the frequency domain features of both EEG and ECG signals. Features were extracted from each EEG and ECG data segment using MATLAB's Signal Processing and EEGLAB Toolboxes. The feature set includes:

EEG Features (from each channel): Relative Delta Power (0.5-4.0 Hz), Relative Theta Power (4.0-8.0 Hz), Relative Alpha Power (8.0-12.0 Hz), Relative Beta Power (12.0-30.0 Hz), Alpha/Beta Ratio, and (Theta+Alpha)/Beta Ratio

ECG Features: HRV features including Relative Low-Frequency (LF) Power (0.04-0.15 Hz), Relative High-Frequency (HF) Power (0.15-0.40 Hz), and LF/HF Ratio

Channels O1, O2, Fp1, and Fp2 were chosen as the primary EEG channels in this study due to their strong correlation with drowsiness, as indicated by previous research [13, 15] and their suitability for wearable device designs such as headbands. The feature sets from each channel were initially trained separately to determine the performance of single EEG channel usage. Subsequently, the combination of high-performing channels was examined to assess their integrated effects.

E. *Ground Truth Labeling*

ORD was applied for ground truth labeling, which involves assessing drowsiness levels by observing participants' behaviors and facial expressions from video recordings [16]. The 60-minute video data from the driving phase were divided into 60 segments, each one minute. For each video segment, two independent raters assigned a drowsiness level, categorized into five stages: Not Drowsy (scored as 1), Slightly Drowsy (2), Moderately Drowsy (3), Very Drowsy (4), and Extremely Drowsy (5). Then, the assessment scores from two raters were averaged, in order to minimize subjective bias. These labels for each minute of the sessions were aligned to the EEG and ECG segments at the same timestamps. In contrast, the segment that overlaps the labels was calculated by the mean of two consecutive labels that the segment overlaps. The average scores were used to categorize drowsiness into three simplified levels: Alert (average score ≤ 2), Moderately Drowsy ($2 <$ average score ≤ 3), and Extremely Drowsy (average score > 3). A score below two was classified as Alert, as the label 'Slightly Drowsy' is considered sufficiently alert for driving [17]. The cut-point of 3 for Extremely Drowsy was chosen because any segment with an average score above three must be labeled as 'Very Drowsy' or 'Extremely Drowsy' by at least one rater, which is critically harmful to driving. While not ideal for safe driving, the Moderately Drowsy stage is an early warning phase before progressing to the critical Extremely Drowsy stage.

F. *Model Development*

Multilayer Perceptron (MLP) was used to predict simplified drowsiness levels as Alert, Moderately Drowsy, and Extremely Drowsy from EEG and HRV features. Due to the progressive nature of drowsiness in a monotonous environment, driving time was included as one of the input features to enhance model accuracy. The dataset was split into an 80% Training set and a 20% Testing set, maintaining class proportions. The model architecture was simplified to ensure practicality for further real-time applications, consisting of an input layer, a batch normalization layer, two hidden layers with Rectified Linear Unit (ReLU) activation functions, each followed by a dropout layer and batch normalization layer, and a softmax layer for three-class prediction, as shown in Fig. 4. Hyperparameters were tuned using Random Search, varying the optimizer, learning rate, dropout rates, batch size, epochs, and units per layer as detailed in Table 1. 5-fold cross-validation was performed to minimize overfitting due to the limited sample size. Class weights were applied to handle class imbalance as some subjects might rarely experience extreme drowsiness under the simulated environment.

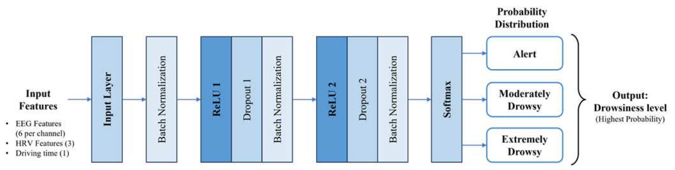

Fig. 4 Neural Network Architecture for Multi-level Drowsiness Classification

Table 1 Hyperparameter Search Space for Random Search

Hyperparameter	**Search Space**
Number of Units (2 hidden layers)	8, 16, 32
Dropout rates (2 dropout layers)	0.1 to 0.5
Optimizer	'adam', 'sgd', 'rmsprop'
Learning rate	0.001 to 0.1
Batch size	10, 20, 50
Epochs	50, 100, 150, 200

Several models were trained to compare performance across input feature sets to predict three drowsiness levels. EEG features were used in every model, with comparisons made based on different EEG channels (6 features from each channel) and the inclusion of HRV features (3 features). Additionally, the models with and without driving time as a feature were compared to investigate its impact on model performance. StandardScaler was used to rescale all features except driving time to preserve the consistent temporal properties, while vector concatenation was employed to integrate the input features.

III. RESULTS

A. *Comparison of Feature Sets*

Table 2 shows the class-wise accuracy and F1 scores for models trained on different feature sets. The results demonstrate that including driving time and HRV features improves the models' performance across all EEG channels (O1, O2, Fp1, Fp2).

Table 2 Class-wise Accuracy and F1-scores for Models Trained on Different Feature Sets

EEG Channel	**HRV features**	**Driving time**	**Class-wise Accuracy (%)** 1	2	3	**F1-score**
O1	No	No	48.96	48.68	70.59	0.537
		Yes	92.71	53.95	20.59	0.635
	Yes	No	48.96	59.21	73.53	0.579
		Yes	78.13	61.84	73.53	0.720
O2	No	No	33.05	51.32	50.00	0.445
		Yes	79.66	59.21	47.06	0.687
	Yes	No	46.61	52.63	73.53	0.545
		Yes	73.73	78.95	50.00	0.725
Fp1	No	No	55.08	53.95	64.71	0.578
		Yes	83.05	65.79	79.41	0.772
	Yes	No	61.86	51.32	73.53	0.609
		Yes	83.05	75.00	85.29	**0.813**
Fp2	No	No	64.60	52.86	81.82	0.650
		Yes	84.07	57.14	86.36	0.759
	Yes	No	69.03	57.14	72.73	0.670
		Yes	84.07	52.86	72.73	0.728

Class 1: Alert, Class 2: Moderately Drowsy, Class 3: Extremely Drowsy

For all EEG channels, including driving time increases the class-wise accuracy across all classes, while adding HRV features results in less bias, more balanced class accuracies, and higher F1 scores. Among all EEG channels used, the Fp1 channel shows the most promising performance, with the model that includes HRV features and driving time achieving the highest overall F1-score of 0.813 and being the only one to reach an accuracy of at least 75% for all classes. When considering pairs of EEG channels, Fp1 and Fp2 generally provide higher accuracy than O1 and O2, representing a higher significant correlation with drowsiness classification. Thus, the combination of the former pair of EEG with both HRV features and driving time included is investigated.

B. Combination of Fp1 and Fp2 EEG channels

The final MLP is trained using an optimal combination of features, including EEG features from Fp1 and Fp2 channels, HRV features, and driving time. The optimized hyperparameters from the Random Search are 16 and 8 units in the first and second hidden layers, dropout rates of 0.12 and 0.46, the 'sgd' optimizer with a learning rate of 0.044, a batch size of 50, and 100 epochs. The predicted results, visualized in Fig. 5, indicate high true positive rates for Alert (92%), Moderately Drowsy (77%), and Extremely Drowsy (77%). The confusion matrix represents the model's high effectiveness in identifying the Alert state. For the Moderately Drowsy class, most errors are misclassified as a higher level of drowsiness, with a small proportion falsely classified as Alert. This is acceptable for a system designed to proactively and early detect higher levels of drowsiness rather than miss detections. Regarding the Extremely Drowsy class, 23% of samples are misclassified as Moderately Drowsy, indicating some confusion between these two classes. However, none of the actual Extremely Drowsy data points are detected as Alert, demonstrating the model's ability to distinguish between extreme classes and ensure safety in drowsiness detection during the extremely drowsy state.

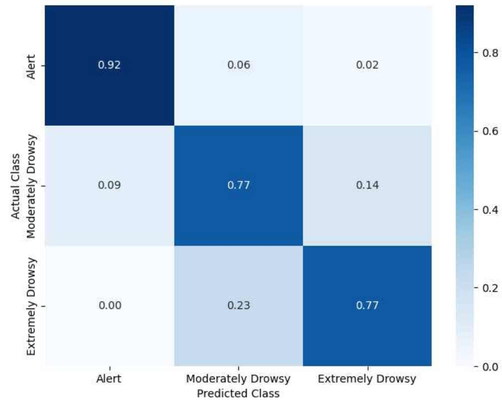

Fig. 5 Confusion Matrix for the Final Model Using Fp1 and Fp2 EEG Channels, HRV Features, and Driving Time

IV. Discussion

A. EEG channels

The Fp1 and Fp2 channels perform better in classifying drowsiness levels than O1 and O2 channels. This can be attributed to their placement over the prefrontal cortex, a brain region associated with executive functions and alertness. As drowsiness progresses, the frequency of EEG waves in this area tends to shift from higher frequencies, like beta waves, to lower frequencies, including alpha and delta waves, due to increased neuron synchronization [18]. Additionally, changes in blink rates, which affect EEG signals in Fp1 and Fp2, may also occur. These factors make frequency domain features from these complementary channels in the prefrontal cortex significant for neural networks to capture useful information from EEG and effectively classify drowsiness levels.

In contrast, the O1 and O2 channels are located over the occipital lobe and primarily process visual information. During relaxed states with eyes closed, sensory input reduction can lead to synchronous EEG and shifts to low-frequency ranges [19]. However, subjects must remain visually attentive during driving tasks despite cognitive declines. Therefore, Fp1 and Fp2 are more likely to reflect drowsiness-related changes during driving. Combining features from both channels can be more effective, especially when there is a loss of EEG signal or other issues.

B. Combination of EEG and HRV Features

ECG signals provide valuable information about heart-rate variability, which reflects autonomic nervous system activity that changes as drowsiness progresses. Biological signals vary more distinctly between extreme states, such as being extremely alert and drowsy. The transition period, however, is challenging for the model to identify due to the gradual nature of drowsiness.

The study shows that integrating HRV features effectively enhances the model's ability to identify this intermediate state. This improvement is likely due to the more holistic view of physiological changes provided by ECG, enabling the model to detect subtle changes during the transition period between extreme states. Moreover, HRV features help mitigate some limitations of EEG signals, which are more susceptible to artifacts and noise that might obscure the neural patterns associated with drowsiness. Therefore, combining EEG and HRV features as a multimodal approach significantly enhances the drowsiness classification process by the neural network compared to using EEG features alone.

C. Driving Time

Adding driving time as a feature substantially impacts the model's performance. Drowsiness is a progressive condition, and including driving time helps the model understand the temporal context of the physiological signals. This temporal information allows the model to accurately capture the gradual transition between alertness and drowsiness and discern patterns and trends in the physiological data corresponding to different drowsiness stages. This is particularly important for detecting the Moderately Drowsy state, where transitions are more subtle and gradual. This finding also aligns with the previous study, which supports the positive impact of driving time on model performance [20].

Compared to HRV features, driving time has a greater influence on model accuracy, likely due to the similar pattern of drowsiness progression over time across individuals, while physiological responses can vary. Nevertheless, HRV remains a crucial complementary modality to EEG, as discussed earlier (see Discussion, *B. Combination of EEG and HRV Features*). The relative importance of HRV compared to driving time could be further investigated with greater consideration of circadian rhythms and other time-related factors that affect individual susceptibility to drowsiness [2].

D. Model Practicality

The practicality of the final model, trained using features from Fp1 and Fp2 EEG channels, frequency-domain HRV features, and driving time, is considered based on model performance and the feasibility of wearable technology.

In terms of model performance, the model effectively distinguishes between different levels of drowsiness, including the *Moderately Drowsy* state, with no instances of Extremely Drowsy being misclassified as Alert. This capability enables early warnings that allow users to be notified and aware of their declining mental readiness for driving before reaching a critical stage of drowsiness.

For application in wearable technology, the model's reliance on minimal electrodes, including two EEG channels in the prefrontal area, with HRV features, makes it feasible to design devices that capture those signals during driving. EEG monitoring devices can take the form of headbands for less intrusiveness and a more comfortable setup for continuous monitoring, while heart rate can be monitored via wristbands or smartwatches. Using minimal features and simple model architecture reduces the complexity, making real-time processing more feasible.

V. Conclusions

The study suggests that combining EEG and HRV features enhances the performance of 3-level drowsiness classification, particularly in identifying the intermediate state between alertness and critical drowsiness. Moreover, implementing driving time preserves the temporal pattern of drowsiness progression, leading to better overall accuracy. The final model based on 2-channel prefrontal EEG features, HRV features, and driving time yields high accuracy across all classes. Although there are some misclassifications, most errors in *Moderate Drowsy* detection are falsely predicted as *Extremely Drowsy,* which is acceptable for early warnings of critical drowsiness.

The model’s use of minimal electrodes and simple architecture supports its practicality for real-time applications, contributing to driver safety. Future developments could include expanding the variety of driving conditions and the participants’ age range to improve model generalization, developing wireless, real-time systems, and incorporating personalized participant data for improved accuracy. Additionally, pre-driving data could be applied to identify physiological markers correlating with drowsiness onset and progression, offering potential safety measures before driving.

VI. Acknowledgment

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