ISSN 1846-6168 (Print), ISSN 1848-5588 (Online)
https://doi.org/10.31803/tg-20250326030355

Original scientific paper
Received: 2025-03-26, Accepted: 2025-09-02

Development of Drowsy Driving Detection System Using EEG

Ssang-Hee Seo

Abstract: Drowsy driving is a major contributor to serious traffic accidents, highlighting the urgent need for effective real-time detection systems. This study proposes a real-time drowsiness detection system based on electroencephalogram (EEG) signals and a lightweight convolutional neural network (CNN). The system comprises five main components: EEG signal acquisition, preprocessing, feature extraction, CNN-based classification, and user feedback delivery via an Android application. The experiment involved four healthy adult male participants with an average age of 24.5 years. EEG data were collected using the DSI-24 device, and the relative power in the alpha band from the prefrontal (Fp1, Fp2) and occipital (O1, O2) regions was identified as the primary feature for distinguishing drowsiness. The proposed CNN model, trained on these features, achieved a classification accuracy of 91.56%, comparable to the 92.66% accuracy of the more complex AlexNet model, while being significantly more lightweight and suitable for real-time deployment on embedded systems. The Android application provides real-time feedback on the user's drowsiness level and recommends nearby rest areas to help mitigate the risk of drowsy driving. This study presents a practical and efficient EEG-based driver monitoring solution. Future work will focus on large-scale data collection under actual driving conditions to further validate and improve the system's performance.

Keywords: Android application; Brain-computer interface (BCI); Convolution neural network (CNN); Drowsiness detection; Electroencephalogram (EEG); OpenViBE

1 INTRODUCTION

Vehicles are among the most common means of transportation in daily life, and drowsy driving is one of the leading causes of traffic accidents. According to the 2024 traffic accident statistics published by the Korean National Police Agency, a total of 10,767 accidents caused by drowsy driving occurred over the five-year period from 2019 to 2023, averaging 5.9 incidents per day. During the same period, drowsy driving resulted in 316 fatalities—equivalent to approximately 2.9 deaths per 100 accidents—which is nearly twice the fatality rate of drunk driving-related accidents during the same timeframe. Notably, vehicles used for business purposes on highways have been found to be especially vulnerable to drowsy driving. Despite efforts such as expanding safety facilities, broadcasting public service announcements, and conducting awareness campaigns, little measurable improvement has been observed in preventing drowsy driving accidents [1].

Drowsiness represents a transitional state between wakefulness and sleep. In this state, drivers experience reduced attention, significantly delayed reaction times, and impaired judgment, making it difficult to maintain proper head posture and orientation [2, 3]. Common signs of drowsiness include frequent eye closures and repeated yawning. These observable behaviors can be used to deliver early warnings to drivers and help prevent potential accidents. In recent years, driver drowsiness detection technologies have received increasing research attention [4-9]. These studies can be broadly classified into four categories: (1) image-based approaches that use cameras to analyze facial expressions and driver behavior; (2) biosignal-based approaches that rely on physiological signals measured via wearable sensors; (3) vehicle-based approaches that monitor driving patterns and vehicle behavior; and (4) hybrid approaches that combine multiple modalities. Among these, biosignal-based methods have demonstrated superior performance in drowsiness detection compared to image-based methods [10].

In this context, a variety of biosignals—including EEG, ECG, EMG, and EOG—have been utilized for drowsiness detection [11-13], with EEG-based techniques being especially prominent due to their high temporal resolution [14, 15]. In recent years, the analysis of biosignals has gained substantial interest in the fields of driver monitoring and human-computer interaction. As the complexity and volume of physiological data continue to grow, deep learning models have emerged as effective tools for robust feature extraction and signal classification. Architectures such as Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), Autoencoders (AE), and Convolutional Neural Networks (CNN) have shown strong performance in noise filtering, time-series signal processing, and biomedical signal classification tasks [16, 17].

Among these models, CNNs have been particularly successful in anomaly detection due to their ability to achieve high classification accuracy and automatically learn discriminative features from raw data [18]. Recent studies applying CNNs to EEG-based drowsiness detection have reported encouraging outcomes [19, 20]. Given that EEG signals are time-series data that are often high-dimensional and noisy, traditional feature engineering techniques are frequently inadequate. CNNs, in contrast, are well-suited for handling such unstructured signals, as they excel at extracting local spatial and frequency-domain features. Moreover, CNNs eliminate the need for manual feature design by automatically learning relevant patterns from the data. Based on these strengths, we propose a lightweight CNN model designed for real-time classification of drowsiness and wakefulness states using EEG signals collected with the DSI-24 device. The proposed model is optimized for computational efficiency, making it well-suited for real-time deployment in embedded systems, such as in-vehicle driver monitoring applications.

The primary objective of this study is to implement a system capable of detecting the driver's drowsiness state in real time and providing immediate feedback to the user, thereby aiming to prevent traffic accidents caused by drowsiness. To achieve this, we propose a lightweight CNN model that classifies drowsiness by extracting relevant features from EEG signals. In addition, the system offers real-time feedback to the user by issuing auditory warnings and displaying nearby rest areas, making it applicable to actual driving environments. The remainder of this paper is organized as follows. Section 2 describes the data collection process, EEG signal preprocessing, feature extraction methods, and the architecture of the Android application used for user interaction. Section 3 presents the performance evaluation of the proposed model along with experimental results. Finally, Section 4 concludes the study with a summary of the findings and outlines directions for future research.

2 MATERIALS AND METHODS

We implemented a real-time drowsiness detection system based on EEG signals that provides immediate feedback to the user. The system is broadly divided into two main components: the user system and the server system. The user system comprises (1) an EEG device that collects brainwave signals from the user and (2) an Android application that provides real-time notifications of the user's drowsiness state. The server system includes (1) a preprocessing module that filters and processes the collected EEG signals in real time to extract relevant features and (2) a CNN model that classifies the user's drowsiness state based on these features. Fig. 1 illustrates the overall architecture of the proposed drowsy driving detection system.

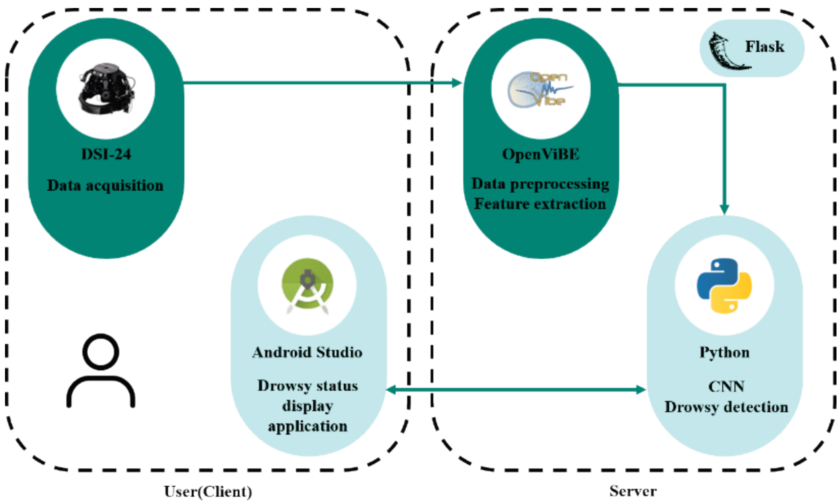

Figure 1 Structure of the proposed drowsy detection system

2.1 Data Acquisition

In this study, EEG data were collected using the DSI-24 device from Wearable Sensing. The DSI-24 is a wireless dry-electrode EEG headset designed for the rapid deployment of 21 sensors positioned according to the international 10–20 system. It includes 19 electrodes covering the scalp, 2 ear clip sensors, and 3 auxiliary inputs for the acquisition of up to three additional biosignals. The device supports Bluetooth wireless transmission and samples signals at a rate of 300 Hz. Fig. 2 illustrates the international standard 10–20 electrode placement system. The experiment involved four healthy adult male participants with an average age of 24.5 years. Prior to participation, all subjects were informed of the experimental procedures and precautions and provided written consent. EEG data were collected in a room isolated from light and noise to ensure a comfortable environment for the participants. Additionally, a camera was installed to record facial expression changes associated with drowsy during the session. The experimental procedure was as follows: (1) The participant wore the EEG device and was seated in a stationary position. (2) The participant viewed a pre-recorded video of highway driving. During this time, EEG signals were recorded simultaneously with video footage of the participant's facial expressions. The driving video lasted approximately 20 minutes. (3) Based on the recorded EEG data and facial footage, specific segments of EEG signals were classified into drowsy and wakeful states.

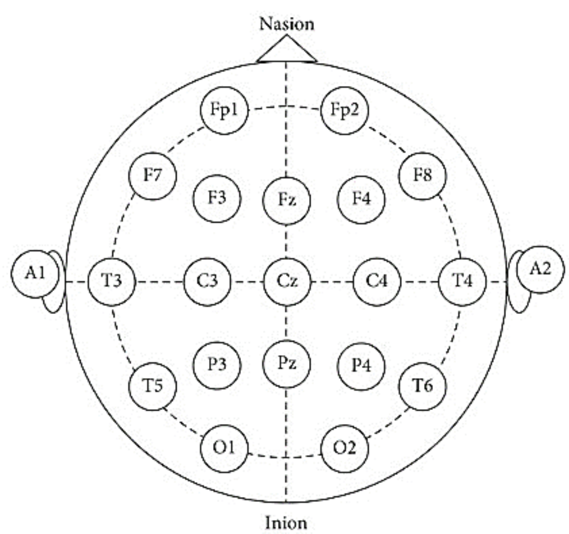

Figure 2 International 10-20 electrode system

2.2 EEG Signal Processing

During the EEG data collection, various types of noise—such as muscle movements, eye blinks, and electrical interference—can contaminate the signals. Given the low amplitude of EEG signals, such noise can significantly degrade signal quality. Therefore, a preprocessing step to remove noise from the recorded EEG data is essential. In this study, a band-pass filter was applied to retain only the frequencies within the 0–50 Hz range. Additionally, Independent Component Analysis (ICA), a widely used method for EEG denoising [21, 22], was employed to remove artifacts. Following preprocessing, the EEG signals were transformed from the time domain to the frequency domain using the Fast Fourier Transform (FFT). As shown in Tab. 1, the processed signals were then segmented into five spectral frequency bands. EEG activity is typically divided into Delta, Theta, Alpha, Beta, and Gamma bands, each associated with different cognitive and physiological states [23].

Table 1 Characteristics of EEG frequency bands

Brainwaves	Description	Frequency Interval
Delta	Refers to consciousness and sleep states	0.5 to 4 Hz
Theta	Refers to the half-sleep	4 to 7 Hz
Alpha	Refers to waking state	8 to 13 Hz
Beta	Refers to alert state	13 to 30 Hz
Gamma	Refers to hyper-vigilance state	30 to 50 Hz

Absolute and relative power spectrum analyses were conducted on the Theta and Alpha frequency bands, which are known to be closely associated with drowsiness. The power of each frequency component was calculated as the square of the magnitude of the complex-valued signal obtained via the Fourier Transform. Eq. (1) represents the Fast Fourier Transform (FFT), Eq. (2) denotes the Inverse Fast Fourier Transform (IFFT), and Eq. (3) defines the computation of total power.

$$H(f_n) = \sum_{k=0}^{N-1} h_k \mathrm{e}^{\frac{-j2\pi kn}{N}} = H_n, \tag{1}$$

$$h_k = \frac{1}{N}\sum_{n=0}^{N-1} H_n \mathrm{e}^{\frac{-2\pi kn}{N}}, \tag{2}$$

$$Total\ Power = \sum_{k=0}^{N-1} \left|h_k\right|^2 = \frac{1}{N}\sum_{n=0}^{N-1} \left|H_n\right|^2. \tag{3}$$

Here, h_k denotes a discrete signal sequence with a sample size of N. Absolute band power refers to the power value of the power spectrum within a specific frequency band for each channel. In contrast, relative band power represents the proportion of power within a specific frequency band relative to the total power across the entire frequency range in each channel.

In this study, a Python-based program was developed to extract relevant features. The process involved preprocessing the raw EEG data—including noise removal—followed by applying the Fast Fourier Transform (FFT). The resulting frequency-domain data served as input, and the program outputted the relative power differences between drowsy and wakefulness states for each EEG channel, identifying those with the most significant variations.

2.3 EEG Analysis Tool

In this study, OpenViBE was utilized as a real-time EEG signal analysis platform. OpenViBE is a software framework designed for building and testing brain–computer interface (BCI) systems, enabling real-time acquisition, filtering, processing, classification, and visualization of brain signals. The OpenViBE platform operated on the server side and was responsible for EEG signal processing and data transmission. The OpenViBE Acquisition Server was employed to receive EEG data from the DSI-24 device via Bluetooth communication. Additionally, the OpenViBE Designer was configured to perform preprocessing and feature extraction on the incoming EEG signals. After preprocessing and feature extraction, the Lab Streaming Layer (LSL) protocol was used to transmit the extracted EEG features to a Flask-based server. The Flask server then forwarded the incoming feature data to the deep learning classification module.

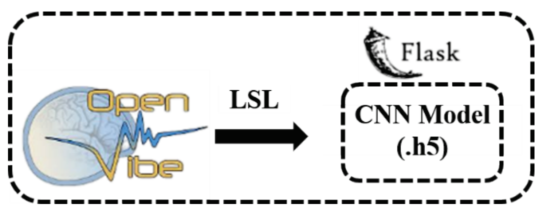

Figure 3 Structure of flask server

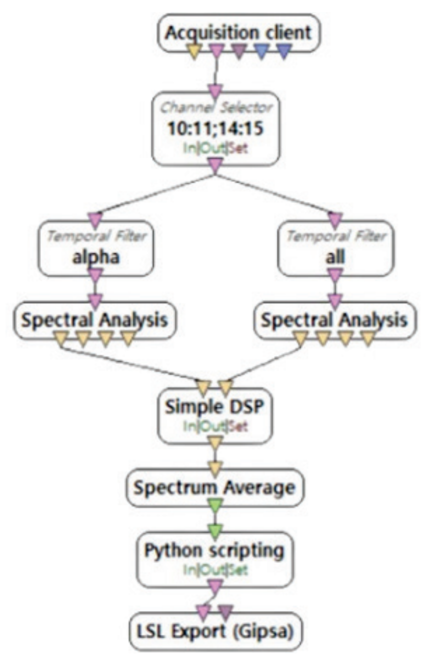

Figure 4 Proposed OpenViBE designer

Fig. 3 illustrates the architecture of the Flask server, and Fig. 4 presents the structure of the OpenViBE Designer workflow for EEG feature extraction. In the Channel Selector stage, channels 10, 11, 14, and 15—corresponding to Fp1, Fp2, O1, and O2—were selected based on their known relevance to drowsiness detection. In the Spectrum Analysis stage, the relative power of both the full frequency band and the Alpha band was calculated. In the Python Scripting stage, matrix-type data from the previous step was converted into a signal format suitable for transmission. Finally, the processed signals were sent to the server using LSL communication.

2.4 Proposed CNN Model

Recently, Convolutional Neural Network (CNN) models have demonstrated outstanding performance the fields of computer vision and natural language processing, which has led to their application in EEG signal classification. Notably, Chaabene [19] and Zhu [20] applied CNNs to EEG-based drowsiness detection and reported promising results. Building on these advances, this study proposes a lightweight yet high-performance CNN model for real-time drowsiness detection. The collected EEG signals were labeled with 1 for drowsy and 0 for wakeful states, and a total of 36,987 labeled samples were compiled in CSV format to form the dataset. This dataset was divided into training (80%) and testing (20%) subsets for model development and evaluation. The trained CNN model was saved in H5 format and is invoked by the Flask server during runtime for real-time inference. The proposed CNN architecture consists of three convolutional layers followed by two fully connected layers. The model was trained using a dropout rate of 0.5, a batch size of 64, and 50 training epochs. The overall architecture of the proposed CNN model is illustrated in Fig. 5, and the detailed layer-wise structure is summarized in Tab. 2.

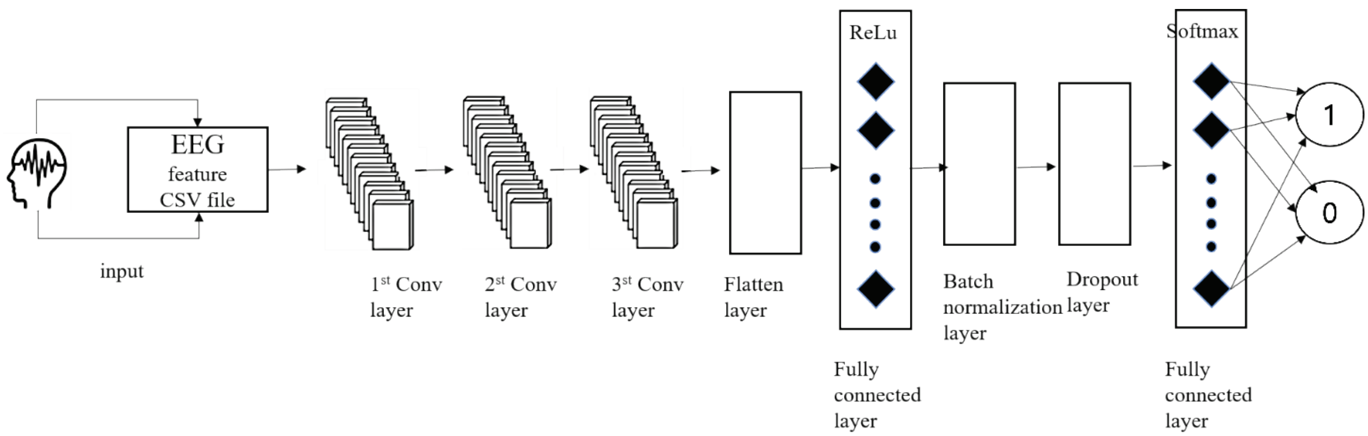

Figure 5 Proposed CNN model structure

Table 2 Summary of proposed CNN model structure

Layer Type	Parameters	Activation function	Notes
Conv2D #1	32 filters, 3×3 Kernel	ReLu	Input layer
MaxPooling2D #1	2×2 pool size	-	Dimension reduction
Conv2D #2	64 filters, 3×3 Kernel	ReLu	Mid-level feature extraction
MaxPooling2D #2	2×2 pool size	-	
Conv2D #3	128 filters, 3×3 Kernel	ReLu	High-level feature learning
Flatten	-	-	Converts 2D to 1D
Dense #1	128 units	ReLu	Dropout 0.5
BatchNorm	-	-	Normalization
Dense #2	64 units	ReLu	Dropout 0.5
Output	2 units	Softmax	Binary classification output

2.5 Drowsy Detection Application

The Android application developed in this study is designed to help prevent drowsy driving by providing real-time feedback to users regarding their drowsiness or wakefulness status, based on EEG data. Fig. 6 presents the overall architecture of the Android application. The app communicates with the server via HTTP, transmitting EEG data once per second. When the user is in a wakeful state, the application displays a real-time EEG graph along with a message indicating wakefulness. The background color of the interface is green, and a smiling emoticon is shown to convey a sense of safety and wakefulness. Conversely, when drowsiness is detected, the application presents the EEG graph along with a warning message indicating the drowsy state. The background color changes to red, and an audible alarm is triggered for three seconds to help awaken the driver.

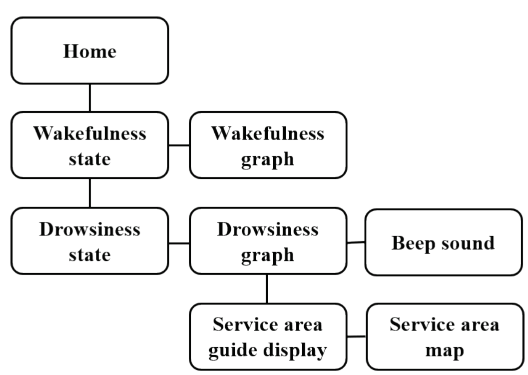

Figure 6 Structure of the drowsiness prevention app

Additionally, the application includes a user-interactive feature: by clicking a designated button, users can access Google Maps to view a list of nearby rest areas based on their current GPS location. Fig. 7 displays the interface in the wakefulness state, while Fig. 8 shows the interface during a detected drowsy state.

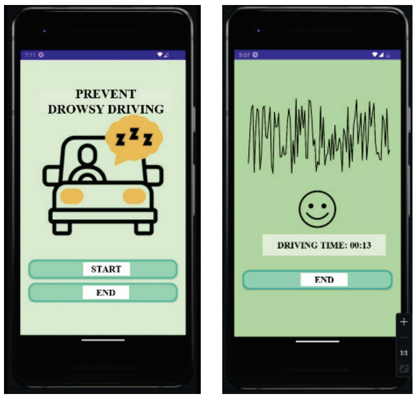

Figure 7 Wakefulness status screen

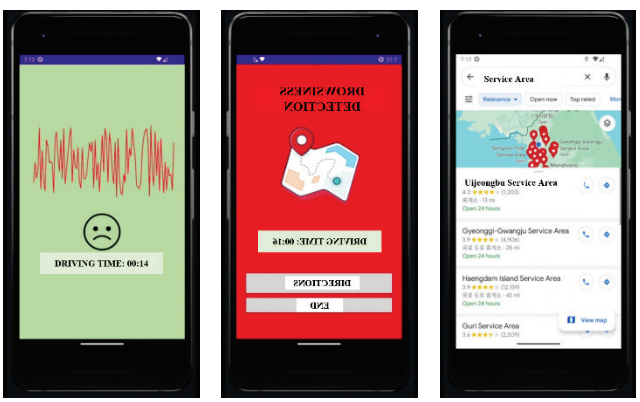

Figure 8 Drowsiness status screen

3 RESULTS AND DISCUSSION

3.1 EEG Feature Extraction Results

Timely detection of driver drowsiness is crucial, as even brief lapses can result in serious accidents. Extracting EEG-based features associated with drowsiness is a key factor in enhancing the system's processing speed and classification accuracy. In this study, feature extraction for real-time drowsiness detection was approached from two perspectives: (1) identifying the minimal and most effective EEG channel locations associated with drowsiness, and (2) determining the optimal frequency bands that reflect drowsiness-related brain activity. To achieve this, alpha relative power values were calculated from EEG signals recorded across 23 channels, referencing prior studies on EEG-based drowsiness detection [24]. Channels showing the greatest differences in alpha power between wakefulness and drowsy states were identified. Fig. 9 presents the relative alpha power distributions during wakeful and drowsy states across all channels. This analysis was conducted for four participants, and the figure illustrates the results for a representative subject. The y-axis displays relative power as a normalized ratio ranging from 0 to 1. Across all four participants, the most significant deviations in alpha relative power occurred in the prefrontal (Fp1, Fp2) and occipital (O1, O2) regions, indicating that these areas are highly correlated with drowsiness, particularly the prefrontal cortex. Subsequently, EEG data from these four channels (Fp1, Fp2, O1, O2) were further analyzed using both absolute and relative power spectrum analysis across three frequency bands associated with drowsiness: Theta (4–8 Hz), Alpha (8–13 Hz), and Theta-Alpha (5–9 Hz). The results of this analysis are summarized in Tab. 3. The table shows that both absolute and relative power values for the Theta, Alpha, and Theta-Alpha bands exhibited significant differences between wakeful and drowsy states. Since absolute power values can vary across individuals due to biological differences such as scalp and skull thickness, relative power was chosen as the more stable feature metric. Moreover, across all participants, the relative alpha power provided more consistent differentiation between wakefulness and drowsiness than the Theta-Alpha band. Based on these findings, this study selected the relative alpha power values at Fp1, Fp2, O1, and O2 as the primary features for EEG-based drowsiness detection.

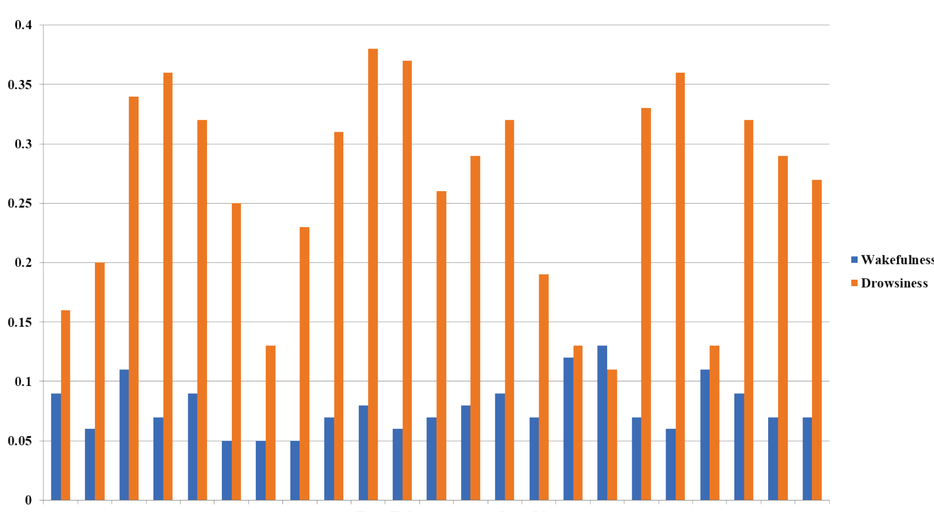

Figure 9 Comparison of alpha relative power values across all EEG channels during wakeful and drowsy states

Table 3 Absolute and relative power values in Theta, Alpha, and Theta-Alpha bands at Fp1, Fp2, O1, and O2 channels

Frequency (Hz)	Power spectrum	Status	Fp1	Fp2	O1	O2
Theta (4-8 Hz)	Absolute power	Wakefulness	0.324871	0.390573	0.882764	0.218468
		Drowsiness	0.742031	0.793544	0.878072	0.494796
	Relative power	Wakefulness	0.006001	0.004885	0.014480	0.005602
		Drowsiness	0.009713	0.009572	0.011727	0.007571
Theta-Alpha (5-9 Hz)	Absolute power	Wakefulness	0.647676	0.784580	1.633170	0.421939
		Drowsiness	8.818757	9.216807	4.818486	2.443815
	Relative power	Wakefulness	0.011965	0.009812	0.026790	0.010819
		Drowsiness	0.115440	0.111174	0.064354	0.037393
Alpha (8-13 Hz)	Absolute power	Wakefulness	4.654174	5.297472	5.820197	2.817909
		Drowsiness	29.108761	31.083387	24.67349	12.845421
	Relative power	Wakefulness	0.085978	0.066253	0.095472	0.0722254
		Drowsiness	0.381043	0.374931	0.329530	0.196548

3.2 EEG Classification Results Based on CNN

A CNN model for drowsiness detection was designed using the Python-based Scikit-learn library, which is widely utilized for machine learning analysis. To evaluate the model's performance, both raw EEG data and feature-extracted data were used as input. The performance of the model was assessed using four common evaluation metrics: recall, precision, F1-score, and accuracy, each defined by Eqs. (4)-(7).

$$Recall = \frac{TP}{TP+FN}, \tag{4}$$

$$Precision = \frac{TP}{TP+FP}, \tag{5}$$

$$F1-score = \frac{2\times Precision \times Recall}{Precision + Recall}, \tag{6}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \tag{7}$$

TP: True Positive, *TN*: True Negative, *FP*: False Positive, *FN*: False Negative.

The classification_report function from the Scikit-learn metrics module was employed to compute these performance metrics. Tab. 4 presents the evaluation results of the proposed CNN model using the feature-extracted data, demonstrating a classification accuracy of approximately 91.56%. In Tab. 4, Support refers to the number of actual instances for each class; Weighted avg is the average weighted by the number of instances in each class; and Macro avg is the unweighted average, giving equal importance to each class. To further assess the classification capability of the proposed model, a confusion matrix was generated. As shown in Fig. 10, the confusion matrix revealed 455 true negatives and 1,048 true positives, confirming the model's robust performance with an overall accuracy of 91.56%. These results indicate that the proposed CNN model is both lightweight and accurate.

To validate its effectiveness of the proposed model, a comparative analysis was conducted against the well-established AlexNet architecture [25], using the same dataset. The proposed CNN model was specifically designed as a lightweight and efficient alternative to conventional deep learning models such as AlexNet, which was originally introduced in 2012 and achieved state-of-the-art performance in the ImageNet Large Scale Visual Recognition Challenge. While AlexNet consists of five convolutional layers with a high number of filters (up to 384), three fully connected layers with 4,096 units each, and more than 60 million trainable parameters, the proposed model significantly reduces computational complexity through a shallower and more compact structure. Specifically, the proposed model comprises three convolutional layers with 32, 64, and 128 filters, each using 3×3 kernels. These are followed by two fully connected layers with 128 and 64 units, respectively, and a final output layer with two neurons for binary classification. Dropout regularization (rate = 0.5) is applied to both dense layers to mitigate overfitting, and batch normalization is employed to stabilize the training process. Compared to AlexNet, the total number of parameters is drastically reduced, making the model suitable for training and deployment in resource-constrained environments such as mobile or embedded systems.

Table 4 Classification performance of proposed CNN model

	Precision	Recall	F1-score	Support
0	0.85	0.87	0.86	523
1	0.94	0.93	0.93	1127
Accuracy			0.91	1650
Macro avg	0.89	0.90	0.90	16540
Weighted avg	0.91	0.91	0.91	1650

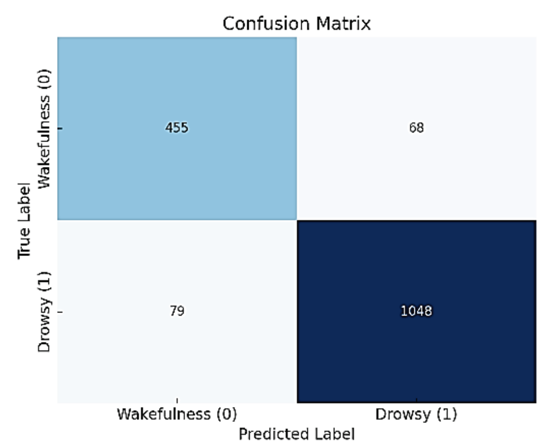

Figure 10 Confusion matrix of the proposed CNN model

Table 5 Classification performance between the proposed model and AlexNet

Model	Precision	Recall	F1-score	Accuracy
AlexNet	0.9379	0.9563	0.9466	0.9266
Ours	0.9476	0.9272	0.9373	0.9156

Tab. 5 presents the classification performance comparison between the two models. The proposed CNN model achieved an accuracy of 91.56%, while AlexNet achieved 92.66%. These results confirm that the proposed model maintains comparable classification performance while offering significantly lower computational overhead. Due to its relatively simple yet effective architecture, the model is highly suited for real-time EEG-based drowsiness detection, where inference speed and low resource usage are critical. To further verify the effectiveness of the extracted features, an additional comparison was performed using both raw EEG data and feature-extracted data as input to the proposed model.

Tab. 6 summarizes the classification accuracy for each input type: the model achieved 62.17% accuracy with raw EEG data, and 91.56% with feature-extracted data. These results highlight the effectiveness of the Alpha relative power values at Fp1, Fp2, O1, and O2 as meaningful features for drowsiness detection.

Table 6 Classification performance between the EEG raw data and feature extraction data

Data	Drop out	Epoch	Batch size	Accuracy
Raw data	0.5	10	64	0.6217
Feature extraction data	0.5	50	64	0.9156

The proposed CNN model achieved an overall classification accuracy of approximately 91%, with strong class-wise precision and recall. These results are in line with, or slightly exceed, those reported in recent EEG-based drowsiness detection studies. For instance, Chaabene [19] implemented a CNN model using Emotiv EPOC+ data and achieved 90.4% test accuracy, demonstrating the feasibility of deep learning in this domain. A more recent model, EEG_DMNet, which incorporates multi-scale spectral-temporal convolutional processing, reported 97.03% accuracy on the SEED VIG benchmark [26]. Additionally, hybrid models such as CNN-LSTM have achieved F1-scores up to 0.95 in binary classification tasks for drowsiness vs. wakefulness [27]. Multi-modal approaches that combine EEG with ECG and use RNN/CNN fusion have also demonstrated validation accuracies close to 97% [28]. While these advanced models offer slightly higher performance, they often come at the cost of increased model complexity, computational requirements, and dependency on additional signal modalities. In contrast, the proposed lightweight CNN model provides a well-balanced solution between performance, simplicity, and real-time applicability, making it ideal for embedded or mobile EEG-based driver monitoring systems.

Nevertheless, this study has several notable limitations. As a pilot study, it involved EEG data collection from only four adult male participants. Although the proposed CNN model demonstrated promising performance, the small sample size and limited dataset present significant constraints. First, the generalizability of the findings is limited. Models trained on data from such a small cohort are highly prone to overfitting and may capture individual-specific EEG characteristics, which hinders their applicability to broader populations with varying demographics such as age, gender, and health status. Second, the statistical reliability of deep learning model training is compromised. CNN-based models require a large volume of training data to effectively learn patterns and prevent overfitting. Although regularization techniques such as dropout, batch normalization, and hyperparameter tuning were applied to mitigate these issues, the current dataset is insufficient to ensure robust and reproducible outcomes. Third, statistical validation is inherently limited. With a small dataset, it becomes challenging to conduct meaningful comparisons between the drowsy and wakeful states. As a result, critical statistical indicators—such as effect sizes, confidence intervals, and p-values—cannot be reliably calculated or interpreted.

4 CONCLUSION

In this paper, we implemented a real-time drowsiness detection system based on EEG signals that alerts the user upon detecting signs of drowsiness. The system is composed of three main components: (1) a module that identifies brain regions and EEG features highly correlated with drowsiness, (2) a classification module that determines the drowsiness state based on these features, and (3) a user feedback module that delivers alerts and recommendations. Relative power in the alpha band from the prefrontal cortex (Fp1, Fp2) and occipital cortex (O1, O2) was identified as the primary feature for detecting drowsiness. The proposed lightweight CNN model achieved an accuracy of 91.56%, which is comparable to the 92.66% accuracy of the more complex AlexNet model. Despite its lower computational complexity, the proposed model demonstrated similar performance, making it suitable for real-time applications such as driver monitoring systems. To enhance user safety, the system is integrated with an Android application that not only notifies the user of their drowsiness state but also suggests nearby rest areas based on their current location. This real-time feedback mechanism is expected to help prevent drowsy driving and reduce traffic accident rates. It should be noted that this study represents a pilot investigation into real-time EEG-based drowsiness detection, and thus has certain limitations. The experimental dataset was collected from only four adult male participants, resulting in a limited sample size for model training and evaluation. To overcome these limitations, future work will involve data collection from a more diverse group of participants in terms of age, gender, and driving experience. Furthermore, EEG data will be gathered under actual driving conditions to enhance ecological validity. In addition, advanced validation techniques such as cross-validation and multi-center studies will be employed to improve the generalizability and statistical rigor of the model.

Acknowledgment

This work was supported by Kyungnam University Foundation Grant, 2023.

5 REFERENCES

[1] Traffic Accident Statistics of Korean. (2024, April 4). *Drowsy driving is more dangerous than drunk driving... Fatality rate is twice as high* [Internet]. Updated 2024 April 4; cited 2025 February 24. Available from: https://www.koroad.or.kr/main/board/6/302605/board_view.do?&cp=1&listType=list&bdOpenYn=Y&bdNoticeYn=N

[2] Gwak, J., Hirao, A., & Shino, M. (2020). An investigation of early detection of driver drowsiness using ensemble machine learning based on hybrid sensing. *Applied Sciences, 10*(8), 2890. https://doi.org/10.3390/app10082890

[3] Arakawa, T. (2021). Trends and future prospects of the drowsiness detection and estimation technology. *Sensors, 21*(23), 7921. https://doi.org/10.3390/s21237921

[4] Fuletra, J. D., & Bosamiya, D. (2013). A survey on driver's drowsiness detection techniques. *International Journal of Recent Innovations and Trends in Computing and Communication, 1*, 816–819. https://doi.org/10.17762/ijritcc.v1i11.2871

[5] Ramzan, M., Khan, H. U., Awan, S. M., Ismail, A., Ilyas, M., & Mahmood, A. (2019). A survey on state-of-the-art drowsiness detection techniques. *IEEE Access, 7*, 61904–61919. https://doi.org/10.1109/ACCESS.2019.2914373

[6] Sikander, G., & Anwar, S. (2018). Driver fatigue detection systems: A review. *IEEE Transactions on Intelligent Transportation Systems, 20*(6), 2339–2352. https://doi.org/10.1109/TITS.2018.2868499

[7] Dong, Y., Hu, Z., Uchimura, K., & Murayama, N. (2010). Driver inattention monitoring system for intelligent vehicles: A review. *IEEE Transactions on Intelligent Transportation Systems, 12*(2), 596–614. https://doi.org/10.1109/TITS.2010.2092770

[8] Nordbakke, S., & Sagberg, F. (2007). Sleepy at the wheel: Knowledge, symptoms and behavior among car drivers. *Transportation Research Part F: Traffic Psychology and Behaviour, 10*(1), 1–10. https://doi.org/10.1016/j.trf.2006.03.003

[9] Cho, S. J., Shin, S. U., Yoo, K. S., Min, K. T., & Jung, B. J. (2024). A study on real-time right-turn accident prevention model using YOLO object detection and transfer learning. *Journal of Innovation Industry Technology, 2*(4), 151–158. https://doi.org/10.60032/JIIT.2024.2.4.151

[10] Dinges, D. F. (1995). An overview of sleepiness and accidents. *Journal of Sleep Research, 4*(S2), 4–14. https://doi.org/10.1111/j.1365-2869.1995.tb00220.x

[11] Gromer, M., Salb, D., Walzer, T., Madrid, N., & Seepold, R. (2019). ECG sensor for detection of driver's drowsiness. *Procedia Computer Science, 159*, 1938–1946. https://doi.org/10.1016/j.procs.2019.09.366

[12] Choi, H. (2019). EMG feature extraction for the driver's drowsiness using RF wireless power transmission method. *International Journal of Engineering and Advanced Technology (IJEAT), 8*(3S), 494–497. Available from: https://www.ijeat.org/protfolio-item/c11040283s19

[13] Ahn, S., Nguyen, T., Jang, H., Kim, J., & Jun, S. (2016). Exploring neuro-physiological correlates of drivers' mental fatigue caused by sleep deprivation using simultaneous EEG, ECG, and fNIRS data. *Frontiers in Human Neuroscience, 10*, 219. https://doi.org/10.3389/fnjum.2016.00219

[14] Ma, Y., Chen, B., Li, R., Wang, C., Wang, J., She, Q., et al. (2019). Driving fatigue detection from EEG using a modified PCANet method. *Computational Intelligence and Neuroscience*, Article ID 47211863. https://doi.org/10.1155/2019/47211863

[15] Papadelis, C., Chen, Z., Papadeli, C. K., Bamidis, P., Chouvarda, I., Bekiaris, E., et al. (2007). Monitoring sleepiness with on-board electrophysiological recordings for preventing sleep-deprived traffic accidents. *Clinical Neurophysiology, 118*(9), 1906–1922. https://doi.org/10.1016/j.clinph.2007.04.031

[16] Jeong, J., Yu, B., Lee, D., & Lee, S. (2019). Classification of drowsiness levels based on a deep spatio-temporal convolutional bidirectional LSTM network using electroencephalography signals. *Brain Sciences, 9*(12), 348. https://doi.org/10.3390/brainsci9120348

[17] Vesselenyi, T., Moca, S., Rus, A., Mitran, T., & Tataru, B. (2017). Driver drowsiness detection using ANN image processing. *IOP Conference Series: Materials Science and Engineering, 252*, 012097. https://doi.org/10.1088/1757-899X/252/1/012097

[18] Alaskar, H. (2018). Convolutional neural network application in biomedical signals. *Journal of Computer Sciences and Information Technology, 6*(2), 45–59. https://doi.org/10.15640/jcsit.v6n2a5

[19] Chaabene, S., Bouaziz, B., Boudaya, A., Hökelmann, A., & Ammar, A., et al. (2021). Convolutional neural network for drowsiness detection using EEG signals. *Sensors, 21*(5), 1734. https://doi.org/10.3390/s21051734

[20] Zhu, M., Chen, J., Li, H., Liang, F., & Han, L., et al. (2021). Vehicle driver drowsiness detection method using wearable EEG based on convolution neural network. *Neural Computing and Applications, 33*, 13965–13980. https://doi.org/10.1007/s00521-021-06038-y

[21] Lin, C. T., Wu, R. C., Liang, S. F., Chao, W. H., Chen, Y. J., & Jung, T. P. (2005). EEG-based drowsiness estimation for safety driving using independent component analysis. *IEEE Transactions on Circuits and Systems I: Regular Papers, 52*(12), 2726–2738. https://doi.org/10.1109/TCSI.2005.857555

[22] Chai, R., Naik, G. R., Nguyen, T. N., Ling, S. H., Tran, Y., & Craig, A. (2016). Driver fatigue classification with independent component by entropy rate bound minimization analysis in an EEG-based system. *IEEE Journal of Biomedical and Health Informatics, 21*(3), 715–724. https://doi.org/10.1109/JBHI.2016.2532354

[23] Teplan, M. (2002). Fundamentals of EEG measurement. *Measurement Science Review, 2*, 1–11. Available from: https://www.measurement.sk/2002/S2/Teplan.pdf

[24] Gharagozlou, F., Saraji, G. N., Mazloumi, A., Nahvi, A., Nasrabadi, A. M., Foroushani, A. R., et al. (2015). Detecting driver mental fatigue based on EEG alpha power changes during simulated driving. *Iranian Journal of Public Health, 44*(12), 1693–1700. Available from: https://pubmed.ncbi.nlm.nih.gov/26811821

[25] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM, 60*(6), 84–90. https://doi.org/10.1145/3065386

[26] Obaidan, H. B., Hussain, M., & AlMajed, R. (2024). EEG_DMNet: A deep multi-scale convolutional neural network for electroencephalography-based driver drowsiness detection. *Electronics, 13*(11), 2084. https://doi.org/10.3390/electronics13112084

[27] Lee, C., & An, J. (2023). LSTM-CNN model of drowsiness detection from multiple consciousness states acquired by EEG. *Expert Systems with Applications, 213*(PB), 119032. https://doi.org/10.1016/j.eswa.2022.119032

[28] Geoffroy, G., Chaari, L., Tourneret, J. Y., & Wendt, H. (2021). Drowsiness detection using joint EEG-ECG data with deep learning. In *2021 29th European Signal Processing Conference (EUSIPCO)* (pp. 955–959). https://doi.org/10.23919/EUSIPCO54536.2021.9616046

Author's contacts:

Ssang-Hee Seo, Professor
School of Computer Science and Engineering,
7 Kyungnamdaehak-ro, Masanhappo-gu, Changwon-si,
Gyeongsangnam-do, 51767, Republic of Korea
Mobile Phone: +82-010-3454-8737
shseotwin@kyungnam.ac.kr