Journal of Design Intelligence
https://www.ffspub.com/index.php/jdi
ISSN 3104-9001 (print)
E-mail: jdi.office@ffspub.com

Article

Design a Driver Fatigue Intelligent Monitoring Cap Based on the Fusion of EEG and Blink Signals

Rui Zhu[1,2], Zhaohui Wang[1,2,†]
[1] *College of Fashion and Design, Donghua University, Shanghai 200051, China*
[2] *Key Laboratory of Clothing Design & Technology, Ministry of Education, Donghua University, Shanghai 200051, China*
[†] *E-mail: wzh_sh2007@dhu.edu.cn*

Received: February 25, 2026 / Revised: April 7, 2026 / Accepted: April 22, 2026/ Published online: April 28, 2026

Abstract: This study proposes a hat-based wearable intelligent monitoring system for driving fatigue, aiming to address the limitations of traditional wristband or helmet-style devices, such as difficulties in accurately reflecting fatigue levels, unstable signal acquisition, and insufficient comfort. From the perspective of apparel engineering, a modular hat design scheme was developed. By optimizing the inner structure, pressure distribution, and electrode attachment method of the hat, stable acquisition of electroencephalogram (EEG) and blink signals in driving scenarios was achieved. On this basis, a monitoring and feedback platform was constructed, incorporating a dynamic threshold blink detection method and an improved Long Short-Term Memory (LSTM) fusion model, the experimental results show that the selected brain-computer interface and blinking fusion method achieves an accuracy rate of over 92% in identifying different stages of driving fatigue. Finally, the monitoring system was tested using real driving data to evaluate its performance in various aspects such as signal acquisition, fatigue detection, grading feedback, and subjective wearing experience. This verified the practical application potential of the designed intelligent monitoring cap in monitoring driving fatigue.

Keywords: Intelligent Wearable Monitoring; Driving Fatigue; EEG; Blink Signal; Cap Structure Design
https://doi.org/10.64509/jdi.12.78

1 Introduction

Driving fatigue is one of the key causes of traffic accidents, with typical manifestations including reduced attention, delayed cognitive response and decreased visual concentration. The mainstream fatigue monitoring methods include vehicle operation behavior analysis, expression recognition based on cameras and heart rate monitoring through wearable devices such as wristbands. However, all of these methods have certain limitations: behavior and visual monitoring are easily disturbed by environmental light, occlusion and posture changes, while physiological indicators based on heart rate or pulse can only indirectly reflect fatigue status and have limited ability to capture early cognitive fatigue. Research indicates [1] that early signs of driving fatigue include heavy eyelids, changes in blink frequency and closed-eye duration, as well as brief lapses in consciousness, all of which directly reflect the decline in cognitive function. At the same time, EEG signals are widely regarded as the most reliable "gold standard" physiological indicator for reflecting cognitive fatigue [2]. Blink signals, as the most direct and sensitive fatigue manifestation among facial behaviors, overlap highly with the main EEG collection area - the frontal cortex - in spatial location.

Based on this natural commonality of physiology and behavior, this study holds that the structural feature of the cap covering the forehead area gives it an inherent advantage in signal collection. The cap can not only simultaneously cover the key positions of EEG and blink signals, but also its stable fit, natural shielding, and high user acceptance make it the optimal clothing carrier for integrating brainwave and facial behavior monitoring. In contrast, traditional physiological monitoring devices such as wristbands cannot access the head signal areas directly related to cognitive fatigue, making it difficult to achieve early and intuitive monitoring of fatigue.

Although head-mounted EEG devices have gradually gained attention, the existing products mostly adopt rigid structures or single sensing modules, which have problems such as poor wearing stability and easy sliding due to head

[†] Corresponding Author: Zhaohui Wang
[*] Academic Editor: Yan Hong

movement, making them unsuitable for long-term data collection in driving scenarios. There is also a lack of systematic research on "clothing structure engineering + multi-modal signal fusion". Based on the above background, this study proposes a driving fatigue intelligent monitoring cap that integrates EEG and blink signals. The research is based on the perspective of clothing engineering, and through optimizing the surface structure of the cap, the pressure distribution of the inner lining, the electrode attachment method, and the modular wiring, it achieves stable collection of physiological and behavioral signals in the frontal area. At the same time, by combining the dynamic threshold blink detection method and the improved LSTM multi-modal fusion model, a real-time fatigue recognition and feedback system that can operate continuously in driving scenarios is constructed. This study not only verifies the natural advantage of the cap as an intelligent clothing carrier in cognitive fatigue monitoring, but also provides a new path for the engineering design of physiological signal clothing and intelligent head-worn devices.

2 Related Work

In this section, In the field of driving fatigue monitoring, methods can be broadly classified into three categories: those based on subjective scales (such as the Stanford Sleepiness Scale [3], Visual Analogue Scale [4], Karolinska Sleepiness Scale [5]), those based on vehicle behavior (such as lane deviation [6], vehicle trajectory, steering wheel control [7, 8]), those based on head and facial features (such as blinking [9], pupil changes, head tilt angle [10, 11], PERCLOS time when eyes are closed [12–14]) and those based on physiological signals (such as heart rate variability [15], low-frequency high-frequency components [16], electromyography [17, 18], EEG). Among them, the monitoring wristband devices based on photoplethysmography (PPG) technology are widely used due to their simple implementation and high user acceptance [19]. However, these indicators mainly reflect the activities of the autonomic nervous system and have relatively weak specificity for cognitive fatigue or attention resource attenuation, and are significantly affected by movement, temperature and emotions. Therefore, their sensitivity in early fatigue detection is limited. In contrast, EEG can directly reflect the activity changes in the brain cortex in specific frequency bands, such as the power of alpha, beta, theta, delta [20] waves, various entropy values, $(\alpha+\beta)/\delta$ relative energy [21], etc., which have been proven to be effective in identifying fatigue. EEG is also regarded as the "gold standard" for fatigue detection [22, 23]. A large number of simulation and real driving studies have used EEG features combined with learning models to achieve high classification performance in fatigue recognition [24–26], with an accuracy rate as high as 98.3% [27]. However, these studies are often conducted in controlled environments or using professional helmet-type electrodes, making it difficult to directly extend to wearable solutions for daily driving. Additionally, blinking and eye-closing time are considered the most intuitive indicators of fatigue at the visual and behavioral levels, with early indication significance, but visual detection based on cameras is susceptible to changes in lighting, occlusion or driver posture.

Numerous studies in the field of driving fatigue monitoring have confirmed [28–30] that the input of multi-modal data can complement the weaknesses of each modality and significantly improve the recognition accuracy. Therefore, this paper proposes a multi-modal scheme based on frontal EEG and blinking: EEG provides the gold standard for the cognitive level. Blinking detection through the regular twitching of frontal muscles not only provides immediate behavioral evidence for visual fatigue and eye closure behavior, but also effectively avoids misjudgment in lighting or shading conditions, thus outperforming a single modality in robustness and early detection capabilities. The cap, as a common type of clothing, naturally covers the frontal area in structure and has advantages such as stable adhesion, natural concealment, and high user acceptance, making it an ideal carrier for EEG and blinking signal acquisition.

The current practice of head-mounted wearable devices can be roughly divided into two paths. One is the flexible wearable solution using textile electrodes, which mainly integrates conductive fibers, embroidered electrodes, or fabric electrodes into headbands or hats to achieve higher wearing comfort and daily applicability[31–33]. However, this path still faces some application limitations: Firstly, conductive threads and silver-plated materials tend to degrade under washing and repeated bending[34]. Secondly, textile electrodes are more suitable for single-modal monitoring and difficult to integrate with high-performance amplifiers and multi-modal sensing modules, which leads to the fact that textile electrodes still have difficulty being directly applied in driving fatigue scenarios. The other realization approach is to embed mature electronic modules into head-mounted devices, such as the already launched head-mounted products like Emotiv and OpenBCI. Its advantage lies in higher signal amplification performance, detachable and maintainable modules, ease of integrating multi-modal sensors, and the ability to achieve reliable real-time processing and wireless transmission. However, the semi-rigid nature of the hardware modules may affect wearing comfort and stability. Therefore, it is necessary to make up for the shortcomings in comfort and stability from the perspective of human head and facial ergonomics and clothing engineering.

Based on this, this study selects the hat body as the wearable carrier, relying on modular hardware embedding and clothing engineering optimization, to design a real-time monitoring and feedback driving fatigue monitoring hat, and verify the practicality and recognition performance of the designed monitoring hat in driving scenarios.

3 System Design and Wearable Hat Engineering

3.1 User Requirement and Design Considerations

The balanced approach of integrating technological innovation with user-centered design principles is crucial for the successful development and adoption of wearable devices [35]. Therefore, this study conducted user research in the early design stage, involving daily drivers, wearable device users, and professionals related to traffic safety. The research collected users' preferences regarding the wearing experience, signal collection stability, and feedback methods. The results showed that 78.6% of users did not accept head-mounted devices with a distinct medical device feel, and preferred designs with an appearance similar to ordinary hats and functional modules that could be hidden; 91.8% of users generally emphasized that the forehead area was sensitive to pressure, and the device must be lightweight, snug, non-slip, and have soft, breathable, and adjustable head circumference materials; users' concerns included concerns about unstable electrode contact due to head movement during driving, interference from wires with activities or signal interruption. The main user needs were identified to be concentrated in the four aspects of "comfort, stability, accuracy, and aesthetics".

3.2 Sensor Placement and System Architecture

To determine the optimal placement of electrodes in the fatigue monitoring cap, a prefrontal functional area screening experiment was conducted before the formal design. The experiment used the Dutch Artinis Brite MKIIIportable fNIRS device to monitor the changes in blood oxygen concentration (HbO) in the frontal lobe region of the subjects [Figure 1(a)]. This was because previous studies have shown that fNIRS can sensitively reflect the local neural activity in brain regions during fatigue [36, 37]. Four subjects who were excluded from left-handedness, heart disease, cerebrovascular diseases or other health problems, and had at least 2 years of driving experience were selected. The subjects slept for no less than 8 hours the night before the experiment, and did not take alcohol, coffee or other drugs within 24 hours before the experiment. The subjects conducted a 90-minute monotonous driving experiment based on the SCANeR™ studio driving simulation platform and steering wheel components, including 10 minutes of driving environment familiarization instructions and 5 minutes of resting baseline collection. The experiment officially began, and a continuous 75-minute simulated highway monotonous driving experiment was started, with Karolinska sleepiness scale (KSS) fatigue self-assessment conducted before and after the driving task. Paired sample t-tests were performed on the HbO signals before and after the driving task, and significant difference channels were determined based on $p < 0.05$. The results are shown in Table 1. Among the 24 channels covering the prefrontal lobe, a total of 13 channels showed significant differences. Various machine learning methods were used to rank the channel sensitivity, [Figure 1(b)] shows that the three channels with the most prominent activation differences are CH2, CH3, and CH4, and the corresponding regions are all located in the medial prefrontal cortex (MPFC) region. This is consistent with the research conclusions that "in complex tasks, the MPFC plays a key role in behavioral regulation and decision-making [38]" and "the MPFC dominates during the fatigue stage [39]". Finally, considering the fatigue sensitivity of EEG and the capture characteristics of blink signals, the frontal midline near Fpz was determined as the optimal position for EEG signal collection in the fatigue monitoring cap [Figure 1(c)].

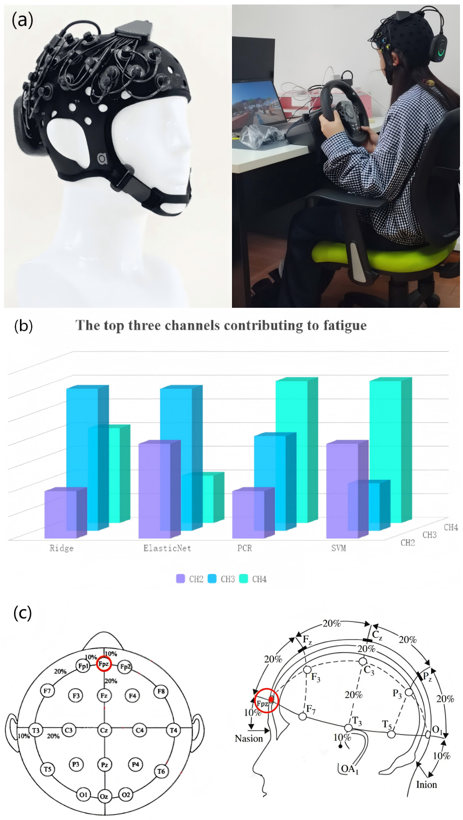

Figure 1: Sensor Location Determination.(a)Experimental Setup;(b) the Top Three Channels Contributing to Fatigue;(c)Final Fpz Selection.

Table 1: Channels with Significant HbO Changes (Paired t-Test)

Channel Number	Paired Points	Comparison Before and After Driving	
		z	p
CH1	'Rx2-Tx1'	-2.521	**0.012***
CH2	'Rx2-Tx4'	-2.521	**0.012***
CH3	'Rx3-Tx4'	-2.38	**0.017***
CH4	'Rx3-Tx10'	-2.38	**0.017***
CH5	'Rx7-Tx10'	-2.521	**0.012***
CH6	'Rx7-Tx8'	-2.1	**0.036***
CH7	'Rx5-Tx8'	-0.14	0.889
CH8	'Rx5-Tx7'	-1.68	0.093
CH9	'Rx1-Tx1'	-1.82	0.069
CH10	'Rx2-Tx3'	-2.521	**0.012***
CH11	'Rx4-Tx4'	-2.24	**0.025***
CH12	'Rx3-Tx5'	-1.12	0.263
CH13	'Rx8-Tx10'	-1.54	0.123
CH14	'Rx7-Tx9'	-1.4	0.161
CH15	'Rx6-Tx8'	-0.84	0.401
CH16	'Rx5-Tx6'	-2.521	**0.012***
CH17	'Rx1-Tx2'	-0.7	0.484
CH18	'Rx1-Tx3'	-2.38	**0.017***
CH19	'Rx4-Tx3'	-2.521	**0.012***
CH20	'Rx4-Tx5'	-2.24	**0.025***
CH21	'Rx8-Tx5'	-1.96	0.05
CH22	'Rx8-Tx9'	-0.42	0.674
CH23	'Rx6-Tx9'	-1.26	0.208
CH24	'Rx6-Tx6'	-2.38	**0.017***

* $p < 0.05$

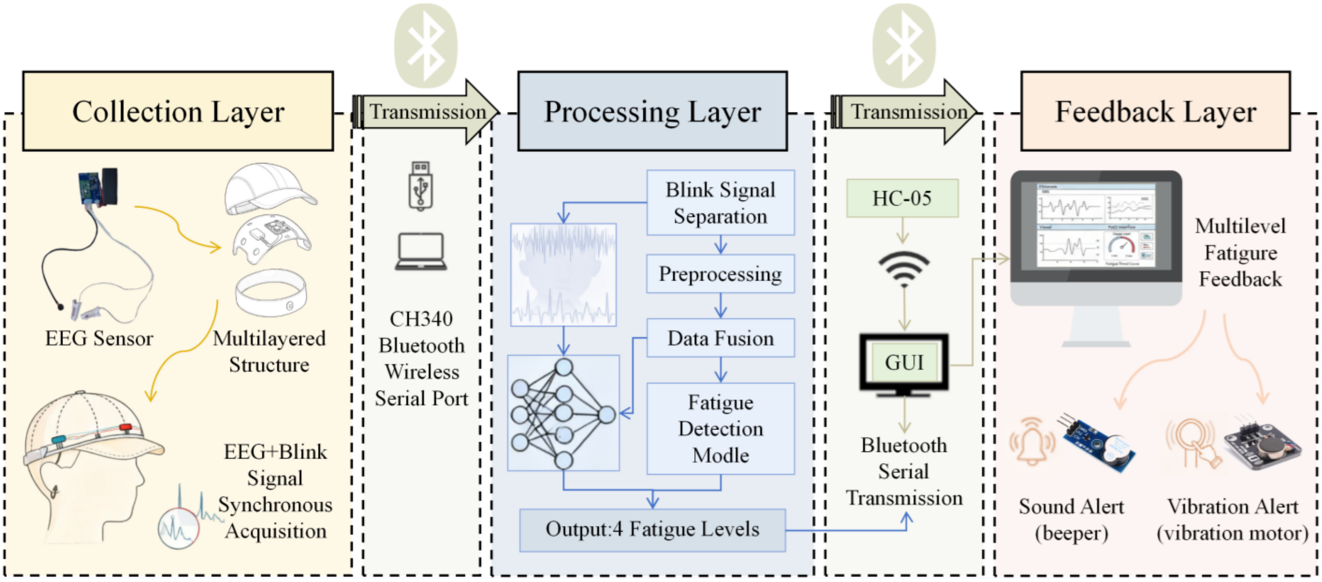

Figure 2: Monitoring Cap System Structure Diagram

The multi-modal fatigue monitoring system constructed in this study follows a hierarchical architecture. It consists of the acquisition layer, the transmission layer, the processing layer, and the feedback layer, achieving real-time monitoring, identification, and feedback of fatigue states [Figure 2]. The acquisition layer selects the Think Gear ASIC Module (TGAM) launched by the American company NeuroSky, which can collect EEG data ranging from 0.5 Hz to 100 Hz from a single point. Compared to medical-grade EEG equipment, the TGAM module has advantages such as high cost-effectiveness, miniaturization, and ease of use, making it suitable for prototype development and testing. The main characteristics of the blinking event originate from the potential fluctuations caused by the movement of the upper eyelid and are captured synchronously from the electrodes placed on the forehead by the TGAM. The transmission layer uses the Bluetooth serial port HC-05 as the wireless transmission method, sending the real-time collected raw EEG data and blinking events to the upper computer. The processing layer is responsible for feature extraction and the construction of fatigue detection models, while the upper computer end is responsible for receiving physiological signals and performing the following functions: separation of blinking signals, preprocessing of EEG, feature extraction and fusion, and model output. The feedback layer controls the sound (active high-level triggered buzzer) and tactile (direct current vibrating flat small motor) through the digital pins of Arduino UNO, activating different levels of feedback for different levels of fatigue. Visually, the monitoring system interface is displayed using PyQt5, and real-time display of EEG waveforms, blinking events, fatigue levels, and historical trends is provided for experimental analysis and user observation.

3.3 Structural and Ergonomic Design of the Hat

To achieve synchronous, stable and highly acceptable EEG and blinking acquisition at the Fpz point, the design should be guided by the cap body structure, taking into account pressure zones, forehead fit and electrode stability. Relevant studies on pressure distribution and wearing comfort of helmet-type products have provided ergonomic basis for this design [40, 41]. This study proposes a ”three-layer composite cap body” structure, which respectively serves as an inner band positioning layer, a functional compartment for bearing weight, and an outer cap collar for covering. The specific design is as follows:

The inner layer skin-contacting band adopts an arc-shaped design centered on the Fpz point electrode area. Based on the multi-level head and facial finite element model established by Yang Wenxiu [42] [Figure 3(a)], the pressure sensitivity gradually increases from the purple area to the red area. The central forehead and bilateral temporal areas are the regions with higher pressure adaptability, while the supra-eyebrow area, zygomatic bone and the top of the head are the most sensitive to pressure. Placing the main electrodes in the central forehead can avoid applying pressure on the zygomatic bone or above the eye socket. The human cranial vault is composed of multiple bone plates such as the frontal bone, parietal bone, and temporal bone, which are connected through bone seams, and each bone plate has a natural convexity and curvature, forming an uneven head surface contour. Traditional rectangular bands tend to have gaps, slippage and local pain at the upper positions of the two ear sides due to their rectangular shape. Therefore, the band shape has been improved, and an arc-shaped fitting structure matching the anatomical curvature of the forehead is designed, while also considering the forehead curvature and the ear side shape. A wavy boundary is adopted to reduce longitudinal and lateral displacement, improve electrode contact stability and distribute pressure [Figure 3(b)]. The rear end of the band is adjusted by Velcro to fit different head circumferences. The inner layer material is selected as 3D air mesh fabric, which has good breathability and moisture absorption performance, is comfortable to fit to the skin, and the physical effect is shown in [Figure 3(c)].

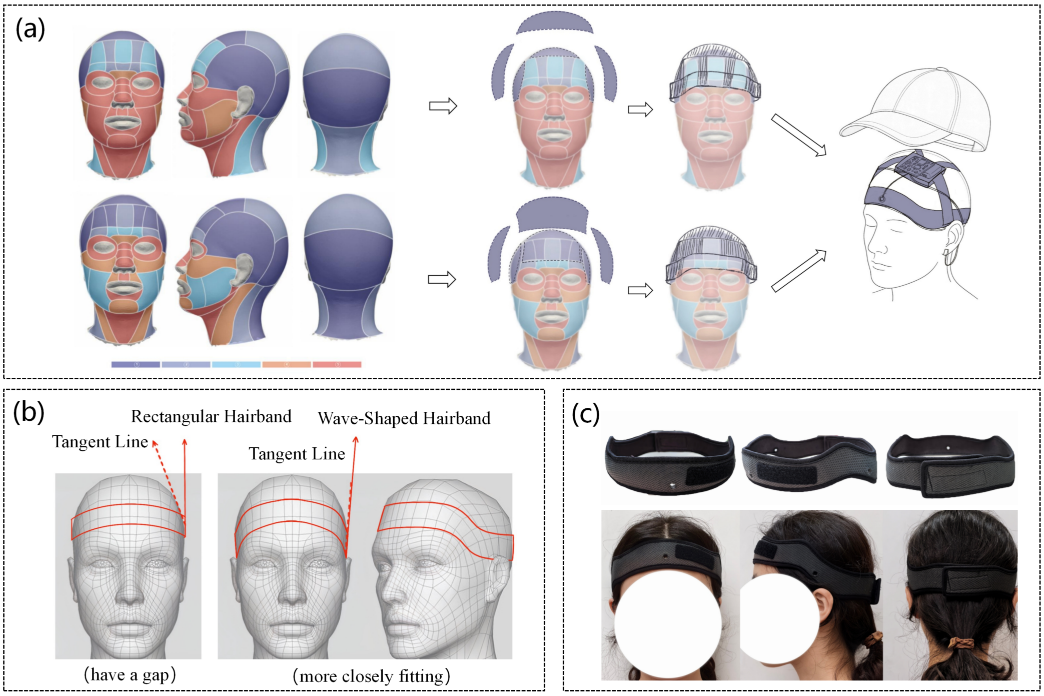

Figure 3: The Innermost Skin-Contacting Hairband Design.(a) Head-face pressure sensitivity map;(b) Comparison of the fitting degree between rectangular and wavy-shaped hairbands;(c)The actual effect of the hairband.

In terms of electrode contact stability, a spring-type dry electrode contact method was designed [Figure 4]. A soft elastic silicone circular gasket was combined with a micro dual-sided spring, which wrapped around the sensor electrode in a circular manner. This design ensures controllable contact pressure while also maintaining comfort and impedance stability. The spring contacts are beneficial for compensating for head shape differences and minor displacements, thereby reducing fluctuations in contact impedance.

In terms of wiring details, the TGAM module is connected to the forehead electrodes through flexible wires, reducing the influence of cable tension on the forehead electrodes. All signal wires run along the intermediate layer structure channels, and air holes rings and sewing fixation points are set at key nodes such as the center of the forehead and above the ears to prevent relative displacement of the electrodes caused by cable traction (Figure 5).

The middle-level functional compartment is a detachable modular compartment, which is achieved through "four-directional snap-locking" for modular disassembly. The structure and wearing effect inside the hat are shown in Figure 6.

4 Data Processing and Model Construction

4.1 Fatigue Data Acquisition

A total of 20 participants were recruited for the simulated driving experiment. The participants were aged between 22 and 30 years (mean: 27.35,standard deviation: ± 2.11), including 12 males and 8 females. All participants had valid driving licenses with driving experience ranging from 2 to 5 years,and the driving task was executed with a 20-minute duration unit. After each unit duration ended, the KSS scale score was recorded. This was repeated three times, and the entire driving task was carried out continuously without interruption. The purpose of this step is to obtain the trend of fatigue increase in different driving stages, which is convenient for subsequent classification and tagging of different degrees of fatigue. See Figure 7. Through serial communication between Realterm and Matlab, real-time EEG reading and analysis were achieved, and a fatigue physiological data set of 20 subjects in 4 driving stages within 90 minutes was constructed for subsequent model training and validation.

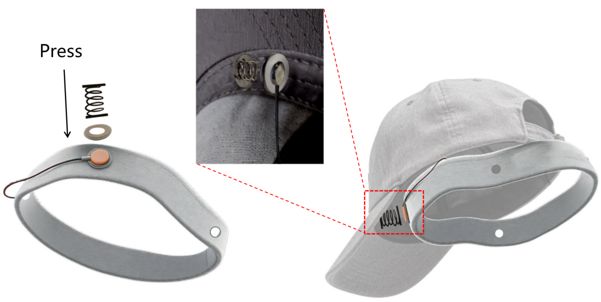

Figure 4: Design of Dry Electrode Contact Method

Figure 5: Signal Wires Layout and Channel Design

Figure 6: Structure Design of the Multi-Layer Cap.(a) Three-layer structure assembly diagram; (b) Final wearing appearance.

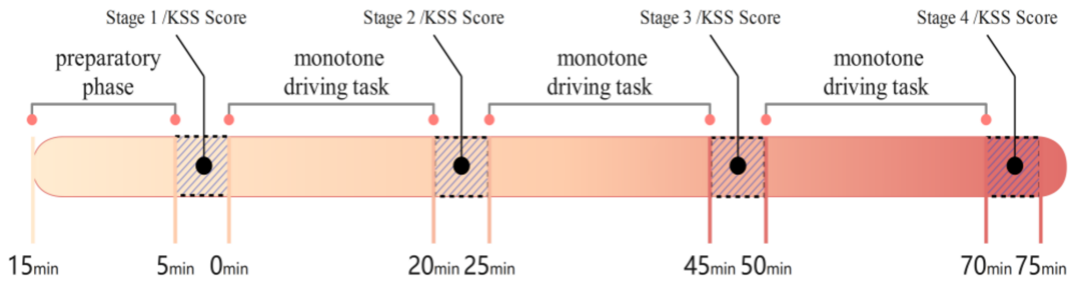

Figure 7: Driving Task Schedule

4.2 Blink Detection and EEG Preprocessing

Previous studies have demonstrated that the blink potential in EEG not only serves as a supplement to EEG signals, improving the accuracy of fatigue detection, but also helps to precisely capture the periods when EEG signals occur under fatigue conditions [43]. The common blink signal detection method involves setting a fixed threshold to detect high-amplitude spike signals in EEG, finding the nearest valleys before and after the peak to capture the blink. However, this static threshold method often struggles to adapt to the dynamic changes of the signal, especially in continuous driving tasks, where the eye state changes dynamically as fatigue deepens, leading to missed detections or false detections. Based on this, this section proposes a blink signal detection method with dynamic threshold setting. The detection threshold is determined based on the standard deviation of the Z-score normalized signal. After multiple experiments, it was found that a detection range of 2 times the standard deviation can effectively improve the detection rate of blink signals. After setting the threshold, the first-order difference of the signal is calculated to identify consecutive segments exceeding the threshold, and their starting and ending indices are recorded for extracting candidate blink events.

The extracted candidate blink events may still contain blink pseudo-events such as noise interference and muscle activity. Further polynomial fitting is performed on each candidate event to ensure that the selected events conform to the periodic characteristics of blinking, that is, a bipolar waveform composed of a negative trough and a positive peak. After the above processing, a relatively stable and low-noise sequence of blink events can be obtained [Figure 8(a)]. After extracting the blink events, the EEG is denoised and cleaned by using a fourth-order Butterworth band-pass filter to remove low-frequency drift and high-frequency noise in the EEG. Then, the sym5 wavelet basis function, 7-layer decomposition, threshold rule as minimum value and maximum value, and threshold method as soft threshold are selected to perform multi-scale decomposition of the signal to remove sudden transient noise. The processed EEG has a higher signal-to-noise ratio and is more suitable for subsequent analysis and input into deep models.

4.3 Multi-modal Feature Extraction

The time-domain dimension of EEG mainly reflects the amplitude and energy changes of the signals, and has the characteristics of directness and rapidity. Independent sample t-tests were used to compare the differences in features before and after driving, and the P-values of variance, standard deviation, and root mean square value within the 95% confidence interval were less than 0.05 [Figure 8(b)], indicating significant differences in the fatigue state. The frequency domain shows the signals with amplitude varying with frequency, which can well compensate for the deficiencies in the time domain. Figure 8(c) shows that the theta, alpha, and beta waveforms in the first driving stage fluctuate up and down but have a small range, indicating that the subject is in the clear stage of driving adaptation. In the second driving stage, the theta and alpha waves begin to show a significant upward trend, indicating that fatigue symptoms begin to appear after 20 minutes of driving, with a gradual decrease in attention level and the brain being in a relaxed state. The beta wave shows a significant downward trend, indicating a decrease in the subject's alertness. In the third and fourth driving stages, the theta, alpha, and beta waves gradually tend to be stable with slight fluctuations, representing that when fatigue reaches a certain level, the relaxation state of the brain also becomes stable. The theta and alpha waves showed a brief small downward trend at the end of driving, which may be that the subject realizes their fatigue state at the end of driving and attempts to

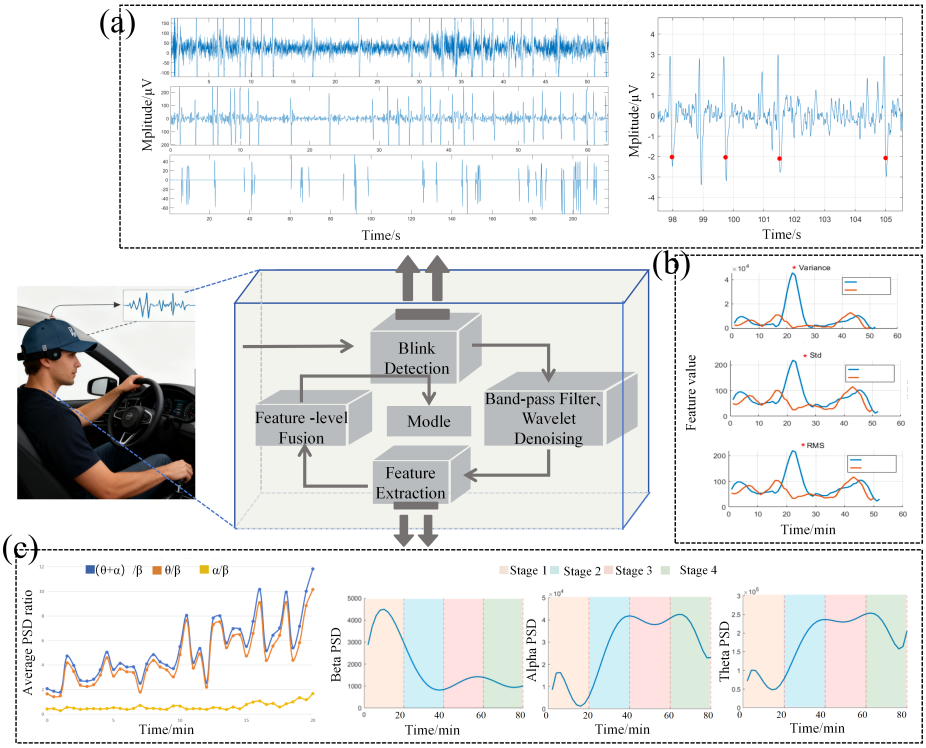

Figure 8: Eye Blinking and Feature Extraction.(a) Dynamic Threshold Blink Recognition; (b) Extraction of EEG Time-Domain Features; (c) Extraction of EEG Frequency-Domain Features.

concentrate their attention or self-regulate to maintain driving performance. Further comparison revealed that $(\theta+\alpha)/\beta$ and θ/β changed significantly over time, showing a significant upward trend. In summary, the five features of α, θ, β, $(\theta+\alpha)/\beta$, and θ/β, which respond better to fatigue, are retained in the frequency domain.

To capture the relationship between blink signals and fatigue states more comprehensively, features were extracted from three aspects: blink frequency, intensity, and stability. The corresponding parameters were blink rate, average blink amplitude, and average blink interval. By comparing the differences in various indicators within different driving stages, the blink rate and average blink interval, two blink indicators, showed a stable trend in the change of fatigue state, which can form a good complement to the EEG features. The multimodal data fusion divides the fusion strategy into data layer fusion, feature layer fusion, and decision layer fusion according to the information processing stage. The core operation of feature layer fusion is feature selection, dimensionality reduction, and concatenation, and in this study, feature layer fusion was selected, which is advantageous because it can balance information integrity and computational efficiency, suitable for applications with strong cross-modal feature complementarity.

4.4 Data Labels and Dataset Division

Since individual differences such as fatigue resistance and lifestyle habits can affect the perception of driving fatigue, using the driving stage as the data fatigue label for the input model is clearly not comprehensive enough.In January 2026, the Ministry of Security of the People's Republic of China issued the "Regulations for Identifying Fatigue Driving of Motor Vehicle Drivers(GA/T 2372-2026)". It clearly designated the KSS scale as the core reference for classifying fatigue severity. This study, in order to focus on the early signs of fatigue and capture the gradual progression of fatigue, further decomposed the three-category classification in the document standard "alert, mild fatigue, severe fatigue" into "1-5 points alert, 6 points mild fatigue, 7 points moderate fatigue, 8 points and above severe fatigue".

In the simulated data of this study, 70% of the data was used for training, 15% for testing, and 15% for validation. In addition to the simulated dataset, a small-scale real-world driving experiment was conducted with 3 participants, these data were not used for model training but served as an independent test to evaluate the practical applicability of the proposed system.

4.5 Construction of Fatigue Model

In the fatigue detection task involving multi-modal physiological signals, both EEG and blink signals exhibit the characteristics of temporal continuity, short-term dependence, and coexistence of long-term trends. Therefore, a time-series-based deep learning model, namely Long Short-Term Memory Network (LSTM), is selected as the basic model to construct the fatigue detection framework.The LSTM model serves as a baseline to capture temporal dependencies in EEG signals. The BiLSTM model extends this by incorporating both forward and backward temporal information, which is beneficial for modeling sequential physiological data. Finally, the Attention mechanism was introduced to enable the model to focus on the most informative time segments, thereby enhancing feature representation.

To evaluate the effectiveness of each component in the proposed model, an ablation study was conducted by comparing three model variants: (1) a baseline LSTM model, (2)

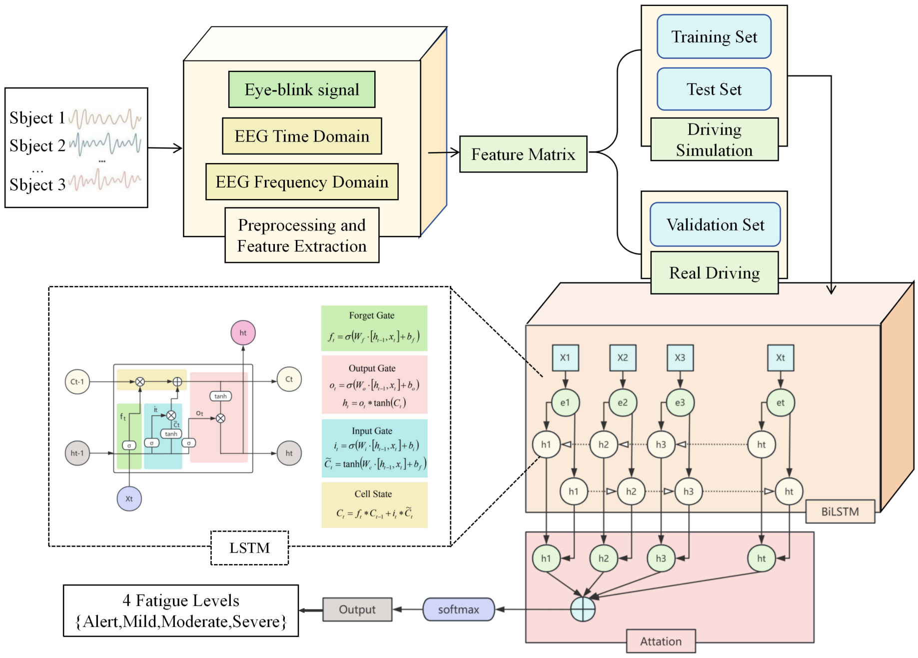

Figure 9: Attention-BiLSTM Model Structure Diagram

a Bidirectional LSTM (BiLSTM) model, and (3) the proposed BiLSTM with Attention mechanism.All models were trained and evaluated under the same experimental conditions and dataset partitioning to ensure a fair comparison,the comparison results are shown in Table 2.The results show that the BiLSTM model outperforms the standard LSTM, indicating that bidirectional temporal modeling improves fatigue detection performance. Furthermore, the integration of the Attention mechanism leads to an additional performance gain, achieving the highest accuracy of 92%.

Table 2: Comparison of Ablation Experiment Results

Model	Accuracy
LSTM	74%
BiLSTM	83%
Attention-BiLSTM	92%

This study proposes the introduction of an Attention-Bidirectional LSTM (Attention-BiLSTM) model [Figure 9]. The improvements include two key parts: changing from unidirectional to bidirectional, where BiLSTM simultaneously learns sequence features from both forward and backward directions, which helps in identifying nonlinear changes in consecutive fatigue segments; an attention layer is superimposed on the output of BiLSTM, by learning trainable weights, to enhance the model's selectivity for key time segments.

The improved Attention-BiLSTM model, after parameter optimization and iterations of training times, achieved an accuracy rate of over 92%. The performance was evaluated using precision (Precision), recall (Recall), and F1-score (F1-score) as indicators, as shown in Figure 10, the precision of all four stages was above 85%, and the F1-score was above 0.88, indicating that the model has high reliability in predicting the four categories, has balanced overall performance, and effectively improves the ability to recognize fatigue states. The Loss and Accuracy curves plotted are shown in Figure 11.

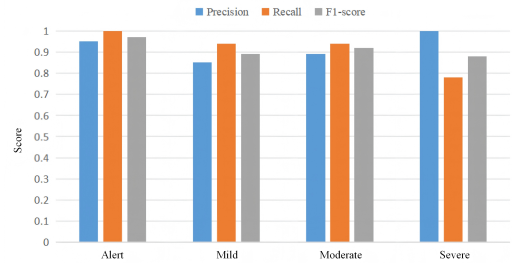

Figure 10: Evaluation of the Model's Recognition Ability at Different Levels of Fatigue

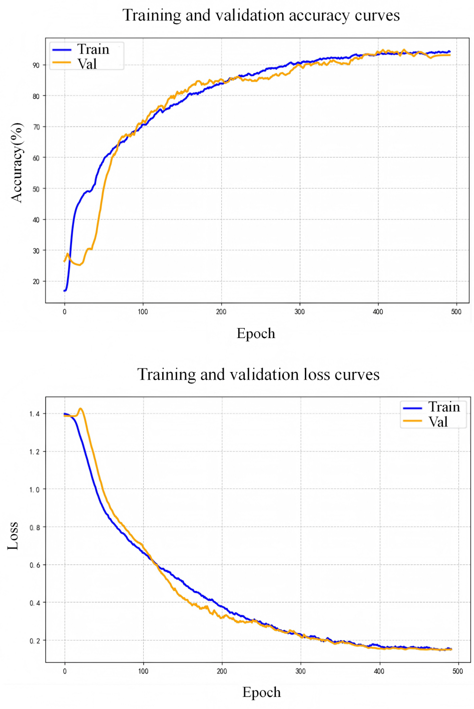

Figure 11: Model Loss and Accuracy Curve Chart

5 System Implementation and Evaluation

5.1 Real-Time Monitoring and Feedback System

The lower-level program design uses the Arduino microcontroller to control the entire data transmission process. The program is written in the Arduino IDE environment and burned onto the UNO control board. Based on the received classification results, corresponding feedback is executed: Input “0”: Turn off all feedback; Input “1”: Start the motor to vibrate for 5 seconds; Input “2”: The buzzer sounds for 5 seconds; Input “3”: The motor and the buzzer are both turned on for 5 seconds. A non-blocking control logic is adopted, and the monitoring is executed in a loop to maintain real-time response.

The upper-level machine is built with PyCharm as the platform and a graphical monitoring interface is constructed. It adopts a modular design concept, mainly including the serial communication module, data processing module, model prediction module, interface display module, and feedback control module (Figure 12). It is developed using Python and GUI design is carried out with PyQt5. Serial communication is achieved through PySerial with Arduino. The information is transmitted and shared through data interaction interfaces among the modules, jointly forming a complete fatigue monitoring system.

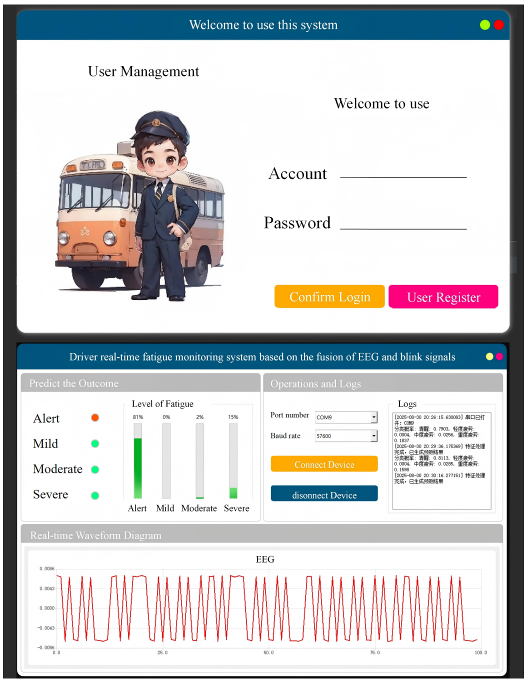

Figure 12: Fatigue Detection System GUI Interface

5.2 Real-world Driving Validation and Evaluation

To evaluate the practical applicability of the proposed fatigue monitoring system, a supplementary real-world driving experiment was conducted with 3 participants. Each participant performed approximately 60 minutes of natural driving in an urban road environment while wearing the developed monitoring hat system. Considering the inherent risks of the real fatigue driving experiment, we chose a closed section similar to the high-speed road conditions instead of the actual high-speed road section. Next, a systematic evaluation system will be constructed from four aspects: signal acquisition, fatigue recognition, feedback response, and wearing experience.

(1) Monitoring performance. Two indicators: the proportion of effective signal segments within a unit time (R_{eff}) and the number of signal interruptions (N_{int}) were selected to evaluate the validity and continuity of the data. In the experiment, the subjects were required to simulate three common actions in the operation of a vehicle (operating the control console, turning the head left and right to observe the rearview mirror, changing the sitting posture). The monitoring cap system recorded the signals in real time. The results are shown in Table 3.

Table 3: Signal Validity and Continuity Test

Number	1#	2#	3#	Mean
R_{eff}	93.2%	94.6%	90.3%	92.7%
N_{int}	0	0	0	0

(2) Recognition performance. In the comparison of the consistency between the model classification results and the subjective fatigue scores, the KSS fatigue scores and the fatigue model classification results were recorded every 20 minutes. The results were summarized in Table 4. During the evaluation, there was one instance where the model judged as mild fatigue while the subject’s subjective score indicated being awake (KSS = 5). After reviewing the literature, it was found that the subjective scale is essentially a delayed perceptual feedback. Compared to the KSS score, EEG detection has higher temporal resolution and sensitivity to subtle neural activity changes, and many studies have shown that EEG can capture early fatigue-related physiological changes and be used for real-time fatigue detection. Therefore, this misjudgment phenomenon to some extent reflects the potential advantages of this system in early fatigue monitoring.

Table 4: Model Fatigue Identification and KSS Consistency Test

Number	Stage (min)	KSS	Corresponding to the degree of fatigue	Model classification result
1#	0-20	5	Alert	Alert
	20-40	5	Alert	Alert
	40-60	6	Mild	Mild
2#	0-20	5	Alert	Alert
	20-40	5	**Alert**	**Mild**
	40-60	7	Moderate	Moderate
3#	0-20	4	Alert	Alert
	20-40	6	Mild	Mild
	40-60	6	Mild	Mild

(3) Feedback performance. It is necessary to verify whether the feedback module can complete the reminder stably, promptly and accurately after the monitoring system identifies the fatigue state. This verification is conducted from three aspects: feedback response delay, Bluetooth communication stability, and multi-level feedback consistency.

The feedback delay test method is as follows: After the upper computer program completes the identification of fatigue state, the log box in the GUI interface automatically prints the timestamp T_1, Arduino receives the command and immediately triggers the corresponding feedback device, and simultaneously returns a confirmation signal via serial port, the time is recorded as T_2. The difference between T_1 and T_2 is recorded as feedback response delay. The average response delay for each level is around 90 ms, and the maximum delay does not exceed 110ms, meeting the real-time requirements of the fatigue intervention system.

The test method for stable Bluetooth communication and consistent multi-level feedback is as follows: the host computer continuously sends fatigue level instructions to Arduino every 5 seconds. After receiving the instructions, Arduino immediately returns a confirmation message. The number of successful instructions received and returned with confirmation and the total number of instructions sent are counted. During the continuous 20 tests of the experiment, no feedback misalignment or accidental touch phenomena were found. The instruction success rate was 100%. This indicates that the Bluetooth communication link is stable and reliable. It is confirmed that the system feedback logic design is reasonable and the operation is stable.

(4) Subjective feelings of wearing. The subjective perception of wearing focuses on the influence of the hat body structure design, electrode layout method, and weight distribution on the user's wearing experience. A subjective assessment is conducted from seven aspects: comfort, stability, aesthetic, practicality, convenience, effectiveness, and timeliness. The assessment is scored using a five-level Likert scale, where 1 indicates "strongly disagree" and 5 indicates "strongly agree". The evaluation categories and problem descriptions are shown in Table 5.

Table 5: Functional Evaluation Questionnaire for Driver Fatigue Monitoring Cap

Question number	Evaluation category	Description	1 2 3 4 5
Q1	Comfort	Whether it is comfortable without a sense of oppression	
Q2	Stability	Whether it is stable and not easy to shift	
Q3	Aesthetic	Whether to accept the appearance	
Q4	Practicality	Whether it does not block the view	
Q5	Convenience	Whether it is convenient to put on, take off and carry	
Q6	Effectiveness	Does it serve as a reminder?	
Q7	Timeliness	Whether the feedback speed is timely	

The results in Figure 13 show that the average scores for each dimension range from 3.0 to 4.8. The overall mean level is in the medium-high range, indicating that the subjects have a relatively positive subjective attitude towards the comprehensive usage experience of the monitoring cap. From the perspective of dispersion, the standard deviation of the scores for each dimension is all less than 0.75, which means that the evaluation differences among the subjects are small, reflecting that the system shows a relatively stable user experience under different individual wearing conditions.

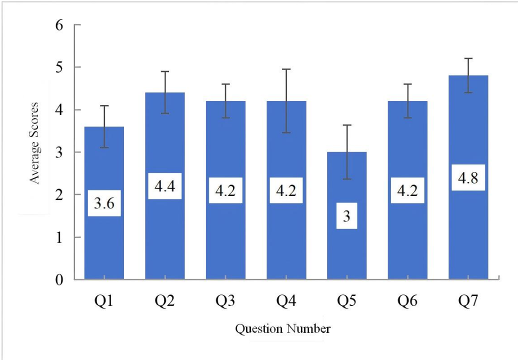

Figure 13: Scores of the subjective wearing scale

6 Conclusions

This research was conducted based on the requirements of driving scenarios. Various methods such as head and facial ergonomics, clothing structure design, and multi-modal physiological signal analysis were adopted, successfully designing a wearable intelligent cap suitable for driver fatigue monitoring. In the research, the fit of the head and facial surfaces, as well as the distribution of pressure-sensitive areas, were analyzed, and a composite cap structure was proposed, including the layout of sensors and other hardware, the contact form with the forehead, and the direction of signal line channels. To enhance the fatigue recognition ability of the monitoring cap, the complementary characteristics of physiological and behavioral features were fully utilized, and a fatigue recognition model based on electroencephalogram and blinking fusion was constructed. The recognition accuracy in different fatigue stages reached 92%, and a real-time feedback system and interface were developed, achieving a complete monitoring process from hardware acquisition, algorithm recognition to feedback intervention. Finally, through actual driving experiments under real road conditions, the designed monitoring cap system was tested from multiple dimensions in terms of subjective wearing experience and objective performance tests. The results showed that the proposed system could demonstrate excellent monitoring, recognition, and feedback performance under actual driving conditions, proving its feasibility in practical applications.

Although this study achieved relatively satisfactory results, it still has limitations: Firstly, the current system is based on a single-channel EEG architecture, although it reduces the complexity of the equipment, it still captures relatively limited brain region information, which may affect the richness of fatigue monitoring. Secondly, the feedback forms for fatigue are relatively simple and cannot achieve personalized intervention feedback for different user groups. Future work will mainly focus on the following directions: Firstly, continue to expand multi-modal sensing channels, such as combining PPG, skin electricity, breathing, etc., to further improve the accuracy and scene adaptability of fatigue recognition. Secondly, the feedback strategy will be further improved, and personalized and adaptive feedback mechanisms will be developed to enhance the safety and comfort of the system in the human-computer interaction dimension.

In conclusion, this study provides a new method path for driver fatigue monitoring and offers a scalable reference for the design and implementation of wearable physiological monitoring systems. With the continuous maturity of technologies such as flexible intelligent textiles and edge computing, it is expected to have more extensive practical value in the fields of traffic safety, public health, and smart transportation.

Funding

This research received no funding.

Author Contributions

The concept proposal, framework construction, and structural design guidance were all provided by Zhaohui Wang; while the user research, physical production, experimental verification, and writing were carried out by Rui Zhu.

Conflict of Interest

All the authors declare that they have no conflict of interest.

Data Available

This dataset was obtained by collecting the physiological signals of 20 drivers with at least two year of driving experience. The personal information involved has signed a confidentiality agreement, and the data is restricted to be used solely for this research project.

References

[1] Shekari Soleimanloo, S., Wilkinson, V.E., Cori, J.M.: Eye-Blink parameters detect on-road track-driving impairment following severe sleep deprivation. Journal of Clinical Sleep Medicine **15**(9), 1271–1284 (2019). https://doi.org/10.5664/jcsm.7918

[2] Li, G., Li, B., Wang, G., Zhang, J., Wang, J.: A new method for human mental fatigue detection with several EEG channels. Journal of Medical and Biological Engineering **37**(2), 240–247 (2017). https://doi.org/10.1007/s40846-017-0224-6

[3] Shahid, A., Wilkinson, K., Marcu, S., Shapiro, C.: Stanford Sleepiness Scale in STOP, THAT and One Hundred Other Sleep Scales. Springer, New York, USA (2011). https://doi.org/10.1007/978-1-4419-9893-4_91

[4] Torrance, G., Feeny, D., Furlong, W.: Visual analog scales: do they have a role in the measurement of preferences for health states? Medical Decision Making **21**(4), 329–334 (2001). https://doi.org/10.1177/0272989x0102100408

[5] Shahid, A., Wilkinson, K., Marcu, S., Shapiro, C.: Karolinska Sleepiness Scale in STOP, THAT and One Hundred Other Sleep Scales. Springer, New York, USA (2011). https://doi.org/10.1007/978-1-4419-9893-4_47

[6] Xu, C., Pei, S.J., Wang, X.: Individualized driving fatigue detection based on non-invasive measurement indicators. China Journal of Highway and Transport **29**(10), 118–125 (2016). https://doi.org/10.19721/j.cnki.1001-7372.2016.10.011

[7] Lee, K., Hyun, S.A., Oah, S.: Detecting driver fatigue by steering wheel grip force. International Journal of Contents **12**(1), 44–48 (2016). https://doi.org/10.5392/IJoC.2016.12.1.044

[8] Li, Z., Li, S.E., Li, R., Cheng, B., Shi, J.: Online Detection of Driver Fatigue Using Steering Wheel Angles for Real Driving Conditions. Sensors **17**(3), 495 (2017). https://doi.org/10.3390/s17030495

[9] Barbato, G., Ficca, G., Muscettola, G., Fichele, M., Beatrice, M., Rinaldi, F.: Diurnal variation in spontaneous eye-blink rate. Psychiatry Research **93**(2), 145–151 (2000). https://doi.org/10.1016/S0165-1781(00)00108-6

[10] Zhao, G., He, Y., Yang, H.: Research on fatigue detection based on visual features. IET Image Processing **16**(4), 1044–1053 (2022). https://doi.org/10.1049/ipr2.12207

[11] Mbouna, R.O., Kong, S.G., Chun, M.G.: Visual analysis of eye state and head pose for driver alertness monitoring. IEEE Transactions on Intelligent Transportation Systems **14**(3), 1462–1469 (2013). https://doi.org/10.1109/TITS.2013.2262098

[12] Chang, R.C., Wang, C.Y., Chen, W.T., Chiu, C.D.: Drowsiness Detection System Based on PERCLOS and Facial Physiological Signal. Sensors **22**(14), 5380 (2022). https://doi.org/10.3390/s22145380

[13] Xu, L.M.: Design of a driving fatigue detection system based on improved PERCLOS. Modern Electronic Technology **46**(22), 41–45 (2023). https://doi.org/10.16652/j.issn.1004-373x.2023.22.008

[14] Cheng, Z., Yang, F.: Fatigue monitoring method for power dispatchers based on eyeball openness. Changjiang Information & Communications **37**(3), 46–48 (2024)

[15] Arefnezhad, S., Eichberger, A., Frühwirth, M., Kaufmann, C., Moser, M., Koglbauer, I.V.: Driver monitoring of automated vehicles by classification of driver drowsiness using a deep convolutional neural network trained by scalograms of ECG signals. Energies **15**(2), 480 (2022). https://doi.org/10.3390/en15020480

[16] Piotrow, Z., Szypulska, M.: Classification of falling asleep states using HRV analysis. Biocybernetics and Biomedical Engineering **37**(2), 290–301 (2017). https://doi.org/10.1016/j.bbe.2017.02.003

[17] Sun, J., Liu, G., Sun, Y., Lin, K., Zhou, Z., Cai, J.: Application of surface electromyography in exercise fatigue: a review. Frontiers in Systems Neuroscience **16**, 893275 (2022). https://doi.org/10.3389/fnsys.2022.893275

[18] Yu, N., Luo, X.M., Shu, Z.R.: Driver fatigue state discrimination method based on leg sEMG. Automotive Engineering **47**(5), 951–962 (2025). https://doi.org/10.19562/j.chinasae.qcgc.2025.05.015

[19] Lee, B.G., Lee, B.L., Chung, W.Y.: Wristband-type driver vigilance monitoring system using smartwatch. IEEE Sensors Journal **15**(11), 5624–5633 (2015). https://doi.org/10.1109/JSEN.2015.2447012

[20] Wang, B.S., Wu, X.C., Hu, X.Y.: Fatigue detection system based on single-channel EEG. Computer Science **47**(5), 225–229 (2020)

[21] Kar, S., Bhagat, M., Routray, A.: EEG signal analysis for the assessment and quantification of driver's fatigue. Transportation Research Part F: Traffic Psychology and Behaviour **13**(5), 297–306 (2010). https://doi.org/10.1016/j.trf.2010.06.006

[22] Agrawal, S., Peeta, S., Benedyk, I.: Evaluating the cognitive and psychological effects of real-time auditory travel information on drivers using EEG. Behaviour & Information Technology **42**(10), 1617–1639 (2023). https://doi.org/10.1080/0144929X.2022.2093273

[23] Wang, F.W., Wang, H., Zhou, X., Fu, R.R.: A driving fatigue feature detection method based on multifractal theory. IEEE Sensors Journal **22**(19), 19046–19059 (2022). https://doi.org/10.1109/JSEN.2022.3201015

[24] Parvez, M.M., Allanki, S., Sudhagar, G., R.S., E.R., Santosh, C., Mohammed, A.B., Muqeet, M.A.: Advanced driver fatigue detection by integration of OpenCV DNN module and deep learning. Engineering Proceedings **34**(1), 15 (2023). https://doi.org/10.3390/HMAM2-14158

[25] Wang, M., Guo, L., Chen, W.Y.: Blink detection using AdaBoost and contour circle for fatigue recognition. Computers & Electrical Engineering **58**, 502–512 (2016). https://doi.org/10.1016/j.compeleceng.2016.09.008

[26] Giorgi, A., Ronca, V., Capotorto, R., Vozzi, A.: Beyond the time-on-task: an EEG-driven approach for effective physiological assessment of mental fatigue in simulated and real driving. Frontiers in Bioengineering and Biotechnology **13**, 1682103 (2025). https://doi.org/10.3389/fbioe.2025.1682103

[27] Min, J., Wang, P., Hu, J.: Driver fatigue detection through multiple entropy fusion analysis in an EEG-based system. PLoS One **12**(12), e0188756 (2017). https://doi.org/10.1371/journal.pone.0188756

[28] Wang, J.X.: Driver fatigue recognition based on multi-source information fusion. Master's Thesis, Jilin University (2024)

[29] Xu, G., Zhang, J., Liu, S., Xu, X., Zhang, W.: Driver Fatigue Driving Monitoring System Based on Facial Multi feature Fusion. Auto Time **2024**(22), 186–188 (2024)

[30] Li, H.C., Sun, K.W, Yang, J.F.: A Mine Worker's Vital Signs Monitoring and Status Evaluation System Based on Multi-modal Fusion. Journal of Safety and Environment, 1–14 (2026). https://doi.org/10.13637/j.issn.1009-6094.2025.0443.

[31] Chen, J., He, T., Du, Z., Lee, C.: Review of textile-based wearable electronics: from the structure of the multi-level hierarchy textiles. Nano Energy **117**, 108898 (2023). https://doi.org/10.1016/j.nanoen.2023.108898

[32] Younes, B.: Smart E-textiles: A review of their aspects and applications. Journal of Industrial Textiles **35**, 1–23 (2023). https://doi.org/10.1177/15280837231215493

[33] Azeem, M., Shahid, M., Masin, I., Petru, M.: Design and development of textile-based wearable sensors for real-time biomedical monitoring: a review. Journal of the Textile Institute **116**(1), 80–95 (2025). https://doi.org/10.1080/00405000.2024.2318500

[34] Zaman, S.U., Tao, X., Cochrane, C., Koncar, V.: Understanding the washing damage to textile ECG dry skin electrodes, embroidered and fabric-based: setup of equivalent laboratory tests. Sensors **20**(5), 1272 (2020). https://doi.org/10.3390/s20051272

[35] Seo, Y.W., La Marca, V., Tandon, A., Chiao, J.C., Drummond, C.K.: Exploring the design for wearability of wearable devices: a scoping review. Computers **13**, 326 (2024). https://doi.org/10.3390/computers13120326

[36] Chuang, C.H., Cao, Z., King, J.T.: Brain electrodynamic and hemodynamic signatures against fatigue during driving. Frontiers in Neuroscience **12**, 181 (2018). https://doi.org/10.3389/fnins.2018.00181

[37] Zhang, Z., Xu, F., Yang, H., Jiang, J., Cao, Y., Jiao, X.: Mental fatigue detection based on functional near

infrared spectroscopy. In Proceedings of the International Conference on Optical and Photonics Engineering (SPIE), pp. 271–276 (2017). https://doi.org/10.1117/12.2267307

[38] Papasideris, M., Ayaz, H., Hall, P.A.: Medial prefrontal brain activity correlates with emerging symptoms of anxiety and depression in late adolescence: an fNIRS study. Developmental Psychobiology **63**(7), e22199 (2021). https://doi.org/10.1002/dev.22199

[39] Shen, W.S., Shen, H.J., Su, T.: fNIRS system design for brain fatigue detection. Optical Instruments **46**(4), 46–55 (2024)

[40] Xu, Y., Chen, L.Y., Zhang, H.B., Zhao, X., Tian, Y.S., Ding, L.: Optimal pressure comfort design for pilot helmets. Computer Methods in Biomechanics and Biomedical Engineering **21**(6), 437–443 (2018). https://doi.org/10.1080/10255842.2018.1478966

[41] Forero Rueda, M.A., Cui, L., Gilchrist, M.D.: Finite element modelling of equestrian helmet impacts exposes the need to address rotational kinematics in future helmet designs. Computer Methods in Biomechanics and Biomedical Engineering **14**(12), 1021–1031 (2011). https://doi.org/10.1080/10255842.2010.504922

[42] Yang, W.: Study on head-face pressure sensitivity and comfort of head-worn products. PhD Thesis, Hunan University (2023)

[43] Zhang, B.T., Yan, D.C., Wang, X.M.: Fatigue driving detection method based on fusion of EEG and blink potential features. Journal of Railway Science and Engineering **22**(8), 3738–3747 (2025)