DESIGN AND IMPLEMENTATION OF FATIGUE DRIVING MONITORING SYSTEM BASED ON DEEP LEARNING

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ABSTRAK

Kepenatan memandu sentiasa menjadi faktor penting yang menyebabkan kemalangan jalan raya. Ia adalah isu keselamatan lalu lintas global yang sering menimbulkan ancaman keselamatan kepada pemandu dan pengguna jalan raya yang lain. Memandu keletihan biasanya merujuk kepada ketidakselesaan fizikal pemandu atau keadaan mental yang lemah dalam persekitaran pemanduan jangka panjang, yang membawa kepada ketidakupayaan untuk menumpukan perhatian yang tinggi, dan juga disertai dengan reaksi perlahan dan penghakiman yang menurun. Oleh itu, untuk memantau dengan berkesan sama ada pemandu keletihan dan mengelakkan kemalangan jalan raya, projek ini bertujuan untuk mereka bentuk dan melaksanakan sistem pemantauan status keletihan berasaskan CNN untuk mengurangkan kemalangan lalu lintas dan menyumbang kepada keselamatan lalu lintas. Sistem yang dicadangkan akan menggunakan Rangkaian Neural Konvolusi (CNN) untuk menganalisis dan mengesan keletihan pemandu dalam masa nyata dengan menangkap ciri muka utama seperti penutupan mata, kekerapan berkelip, menguap dan postur kepala. Dengan memanfaatkan pembelajaran mendalam dan teknologi pengecaman muka, sistem akan mengklasifikasikan keadaan keletihan yang berbeza menggunakan teknik pemprosesan imej. Model pembangunan tambahan akan diguna pakai untuk memastikan ujian berulang dan penambahbaikan berterusan, membolehkan penyesuaian yang lebih baik kepada keadaan pemanduan yang berbeza. Hasil yang dijangkakan daripada projek ini ialah sistem pemantauan keletihan yang cekap dan tepat yang boleh mengesan keletihan pemandu dalam masa nyata dan mengeluarkan amaran yang sesuai untuk mengelakkan kemalangan. Sistem ini akan beroperasi dengan pasti dalam persekitaran pemanduan yang pelbagai sambil meminimumkan pengesanan palsu. Kesimpulannya, projek ini bertujuan untuk meningkatkan keselamatan jalan raya dengan menyediakan sistem pengesanan keletihan pemandu berasaskan pembelajaran masa nyata yang boleh membantu mencegah kemalangan dan melindungi nyawa. Penggunaan CNN dalam pengesanan keletihan akan menyumbang kepada pengangkutan yang lebih selamat dan mengurangkan kerugian ekonomi yang berkaitan dengan perlanggaran lalu lintas.

ABSTRACT
Fatigue driving has always been an important factor causing traffic accidents. It is a global traffic safety issue that often poses a safety threat to drivers and other road users. Fatigue driving usually refers to the driver's physical discomfort or poor mental state in a long-term driving environment, which leads to the inability to concentrate highly, and is also accompanied by slow reaction and decreased judgment. Therefore, in order to effectively monitor whether the driver is fatigued and avoid traffic accidents, this project aims to design and implement a CNN-based fatigue status monitoring system to reduce traffic accidents and contribute to traffic safety. The proposed system will utilize Convolutional Neural Networks (CNNs) to analyze and detect driver fatigue in real-time by capturing key facial features such as eye closure, blinking frequency, yawning, and head posture. By leveraging deep learning and facial recognition technologies, the system will classify different fatigue states using image processing techniques. The incremental development model will be adopted to ensure iterative testing and continuous improvements, enabling better adaptation to different driving conditions. The expected outcome of this project is an efficient and accurate fatigue monitoring system that can detect driver fatigue in real-time and issue appropriate warnings to prevent accidents. The system will operate reliably in diverse driving environments while minimizing false detections. In conclusion, this project aims to enhance road safety by providing a real-time, deep learning-based driver fatigue detection system that can help prevent accidents and protect lives. The application of CNNs in fatigue detection will contribute to safer transportation and mitigate the economic losses associated with traffic collisions.

1.0 INTRODUCTION

With the increasing number of vehicles on the road and the accelerated pace of life, driver fatigue has become one of the leading causes of traffic accidents worldwide. Traditional fatigue monitoring systems usually rely on on-board sensors with limited sensitivity and accuracy. These traditional systems are not effective in detecting early signs of driver fatigue, especially in different driving environments.

To address this challenge, advances in deep learning offer a promising solution to enable real-time monitoring of driver facial expressions and behaviors through computer vision. This project proposes to develop a fatigue driver monitoring system based on convolutional neural networks (CNNs). The system aims to accurately identify fatigue-related indicators such as eye closure, blinking rate, yawning, and head movements, thereby issuing timely alerts before the driver's condition becomes dangerous.

Key questions explored in this research include: which facial behaviors are the most reliable indicators of fatigue; how to design a robust deep learning-based system that can detect fatigue under various real-world conditions; and what alert mechanisms are most effective in prompting fatigued drivers to rest or refocus.

The main goal is to implement a highly accurate fatigue detection system using convolutional neural networks (CNNs), supported by data augmentation and model optimization techniques. The system must be able to capture and interpret facial features in real time and issue appropriate warning signals based on the level of fatigue detected. These alerts should effectively prompt drivers to take a break while ensuring minimal disruption to driving safety.

The objectives of this research are threefold: (1) identify key facial features that indicate fatigue; (2) develop and validate a reliable deep learning-based monitoring system; and (3) evaluate the effectiveness of different alert strategies in reducing fatigue-related risks.

The scope of the system is strictly focused on vision-based monitoring, specifically facial features and movements captured during driving. It does not include vehicle-based behavioral indicators (such as braking frequency or steering control) and biometric data (such as heart rate or EEG signals) to keep the system simple and responsive in real time. The system will be trained using publicly available datasets (such as those on Kaggle) as well as self-collected data to ensure robustness under different lighting and environmental conditions. An alert mechanism will also be integrated to issue appropriate warnings when fatigue is detected.

However, the development process may encounter some limitations. The availability of high-quality, annotated datasets specific to fatigue detection may be limited due to privacy and data sharing concerns. Environmental factors such as poor lighting, weather conditions, or facial occlusion (e.g., sunglasses or masks) may affect system performance. Additionally, the use of facial recognition technology raises ethical and legal challenges related to user privacy that must be carefully addressed during system deployment.

To effectively implement the proposed fatigue driving monitoring system, the project adopted an incremental development approach. This approach enables concurrent design, development, and verification activities in different versions of the software. Each version builds on the previous one, enabling independent testing and optimization of system components. Compared to the traditional waterfall model, this strategy enhances flexibility in responding to user feedback and reduces the cost of modifying design specifications. It also speeds up delivery time, which is critical for systems that require iterative improvements and real-time performance.

The implementation process included multiple development phases, starting with the identification of key system requirements, including facial detection, real-time video stream analysis, fatigue feature extraction, and alarm activation. The system architecture consists of multiple core modules, such as facial feature point detectors, convolutional neural network-based classification models, fatigue level assessment logic, and audio/visual alarm mechanisms. Tools such as OpenCV and MediaPipe were used for facial tracking and feature extraction, while TensorFlow was used to train deep learning models on Kaggle datasets and custom annotated images to capture behaviors such as yawning, blinking, and eye closure.

After development, testing and evaluation were carried out. The results showed that the system can accurately identify fatigue indicators in different driving environments. Black-box testing verified the functionality of all major modules, and user acceptance testing was conducted to evaluate the usability and performance of the system. The alert mechanism successfully triggered visual and audio cues when the driver's fatigue level exceeded the specified threshold. The convolutional neural network model achieved high accuracy in both the training and validation phases through model optimization techniques such as data augmentation and dropout regularization. The real-time performance was considered acceptable in real-world driving scenarios.

In summary, the system provides a reliable and non-intrusive solution for detecting and mitigating fatigue-related risks while driving. By integrating deep learning, facial recognition, and alerting technologies, it improves road safety without relying on physiological sensors or vehicle behavior monitoring. The adoption of an incremental development model enabled modular testing and improvements, ultimately resulting in a stable and effective system. Although there are still some limitations, such as data availability, environmental changes, and privacy issues, this project demonstrates the potential of AI-driven fatigue detection in preventing accidents and improving public safety. Future improvements may include expanding the range of detectable fatigue symptoms, incorporating more biometric signals, and refining alert personalization based on driver profiles.

2.0 LITERATURE REVIEW

Over the past decade, fatigue driving detection technology has made significant progress, thanks to advances in artificial intelligence, computer vision, and sensor technology. Modern systems prevent accidents by monitoring the driver's physical or behavioral state in real time, using a variety of methods. These methods are generally divided into four categories: image-based facial recognition monitoring, physiological signal monitoring through biosensors (such as EEG, heart rate), vehicle behavior analysis, and hybrid systems that combine two or more methods (Ramzan et al., 2019). Among them, non-invasive image-based methods - especially those using facial feature points - have gained the most attention due to their practicality and ease of integration into vehicles without causing driver discomfort (Saradadevi et al., 2008). Invasive methods such as those based on brainwave or heart rate sensors, although accurate, often affect driver comfort and increase hardware complexity and cost (Zhang et al., 2018). Non-invasive methods using visual systems are able to analyze fatigue indicators such as eye closure, blinking frequency, yawning, and head posture without requiring the driver to wear any equipment. However, they are sensitive to environmental factors such as lighting, occlusion, and facial diversity (Liu et al., 2020). Hybrid systems attempt to balance these trade-offs by combining data from facial features and physiological signals, but they require significant computational resources and advanced sensor integration, which complicates real-time applications (Keyvanara et al., 2018).

Numerous studies have proposed innovative techniques to improve the accuracy of fatigue detection. For example, Alioua et al. (2019) combined support vector machines (SVMs) with circular Hough transforms (CHTs) to detect facial and yawning features, achieving up to 98% accuracy in a simulated driving environment. Zhang et al. (2018) applied a genetic algorithm-based model for real-time eye tracking, which enhanced the ability to resist interference from head motion. Lee et al. (2020) demonstrated the possibility of detecting fatigue through hand movements using smartwatch sensor data, highlighting the potential of wearable-based monitoring. Monadjemi et al. (2019) proposed a hybrid detection framework combining Haar wavelets, principal component analysis (PCA), and SVM, achieving an accuracy of 96.8%. These studies highlight both the opportunities and limitations of existing systems, especially in terms of robustness and adaptability to various real-world driving conditions.

Deep learning, especially convolutional neural networks (CNNs), has become a transformative tool in the field of fatigue detection. Compared with traditional machine learning models, CNNs are able to learn complex spatial patterns and show superior performance under dynamic conditions. Liu et al. (2020) developed a CNN-based facial fatigue detection model with an accuracy of 94.7%, while Kawanala et al. (2018) proposed a hybrid architecture combining CNN and RNN to achieve an accuracy of 95.3% by tracking yawning and blinking frequency. Saradavi et al. (2008) demonstrated a multi-stream CNN architecture combining facial images and EEG signals with an accuracy of 97.1%, demonstrating the significant benefits of integrating multiple data modalities.

Despite these advances, challenges remain. Current datasets often lack demographic diversity, reducing generalizability (Honn et al., 2020). Environmental factors such as poor lighting or strong light reflections, as well as individual differences in biometric features, further complicate detection (Zhang et al., 2018). In addition, while some systems are able to effectively detect fatigue, few provide adaptive alert mechanisms based on changes in fatigue levels to minimize distraction or annoyance (Alioua et al., 2019). Real-time multimodal systems remain computationally demanding and require further optimization for scalability and integration into commercial vehicles.

This project builds on these insights by using a non-intrusive, deep learning-based approach to detect driver fatigue through facial feature analysis. By prioritizing driver comfort, detection accuracy, and real-time response, the proposed system addresses the limitations observed in previous studies. The adoption of convolutional neural networks (CNNs) enhances robustness in complex environments, while future work may explore dynamic alert systems and integration with other vehicle safety features to advance the development of intelligent transportation systems.

3.0 METHODOLOGY

Fatigue driving has been identified as one of the major contributors to traffic accidents worldwide. Due to the decrease of attention, the effect of reaction edge easing on the driver's autonomous judgment ability. Tired driving poses a great threat to road safety and the lives of other road users. On this issue, the fatigue driving monitoring system designed in this paper aims to detect the early phenomenon of driver fatigue by real-time analysis of facial expressions, eye movements and head posture. The goal of the system design is consistent with that of organizations and communities, and by integrating into existing traffic facilities, it can ensure that drivers are warned of fatigue before it reaches dangerous levels.

3.1 DEFINITION OF USER NEEDS

The fatigue driver monitoring system is designed to improve road safety by detecting and alerting drivers when they show signs of drowsiness or fatigue. The system uses advanced facial recognition technology to continuously monitor drivers' facial expressions, eye movements and behavior to assess their alertness. When fatigue is detected, the system provides real-time, non-intrusive alerts via visual, auditory or tactile signals to help drivers stay focused and avoid potential accidents.

The system has an easy-to-use interface that requires almost no interaction, allowing drivers to focus on the road while receiving clear feedback. Users can customize the sensitivity of fatigue detection based on their driving habits, and the system records fatigue events to help drivers track and improve their driving patterns over time.

The fatigue driver monitoring system is integrated with existing vehicle safety features to ensure seamless operation across different vehicle types. It has high accuracy in a variety of lighting and environmental conditions. In addition, to ensure user trust, all collected data is securely stored, while strict measures are taken to protect privacy.

By meeting these needs, the system plays a key role in reducing fatigue-related accidents, fostering a safer road environment, and promoting responsible driving habits.

3.2 SYSTEM REQUIREMENT SPECIFICATIONS

- Hardware requirements for development:

Components	Specifications
CPU	AMD Ryzen 7 4800H with Radeon Graphics
RAM	16GB
Disk space	250GB SSD
GPU	NVIDIA GeForce GTX 1650

Table 1 Hardware requirements for development

- Software requirements for development:

Components	Specifications
Operating system	Windows11
Programming language	HTML python SQL
Database software	PostgreSQL
Data processing / Machine learning tools	Pandas NumPy TensorFlow Keras Matplotlib Seaborn Plotly OpenCV MediaPipe Flask SocketIO
Deep learning framework	TensorFlow

Table 2 Software requirements for development

3.3 SYSTEM MODEL

This fatigue driving monitoring system detects the driver's fatigue status through facial recognition and real-time monitoring technology. After the system is activated, the camera captures the driver's facial image in real time, and the built-in deep learning model analyzes features such as the duration of eye closure and the frequency of yawning to assess the fatigue level. Once fatigue signs are detected, the system will immediately trigger local auditory alerts (such as sound prompts) and visual alerts (such as interface changes) to alert the driver. All data processing, event detection, and alert triggering are completed in real time on the local device, ensuring low latency response. The relevant information of fatigue events (such as time and type) will be recorded as local log files for subsequent review.

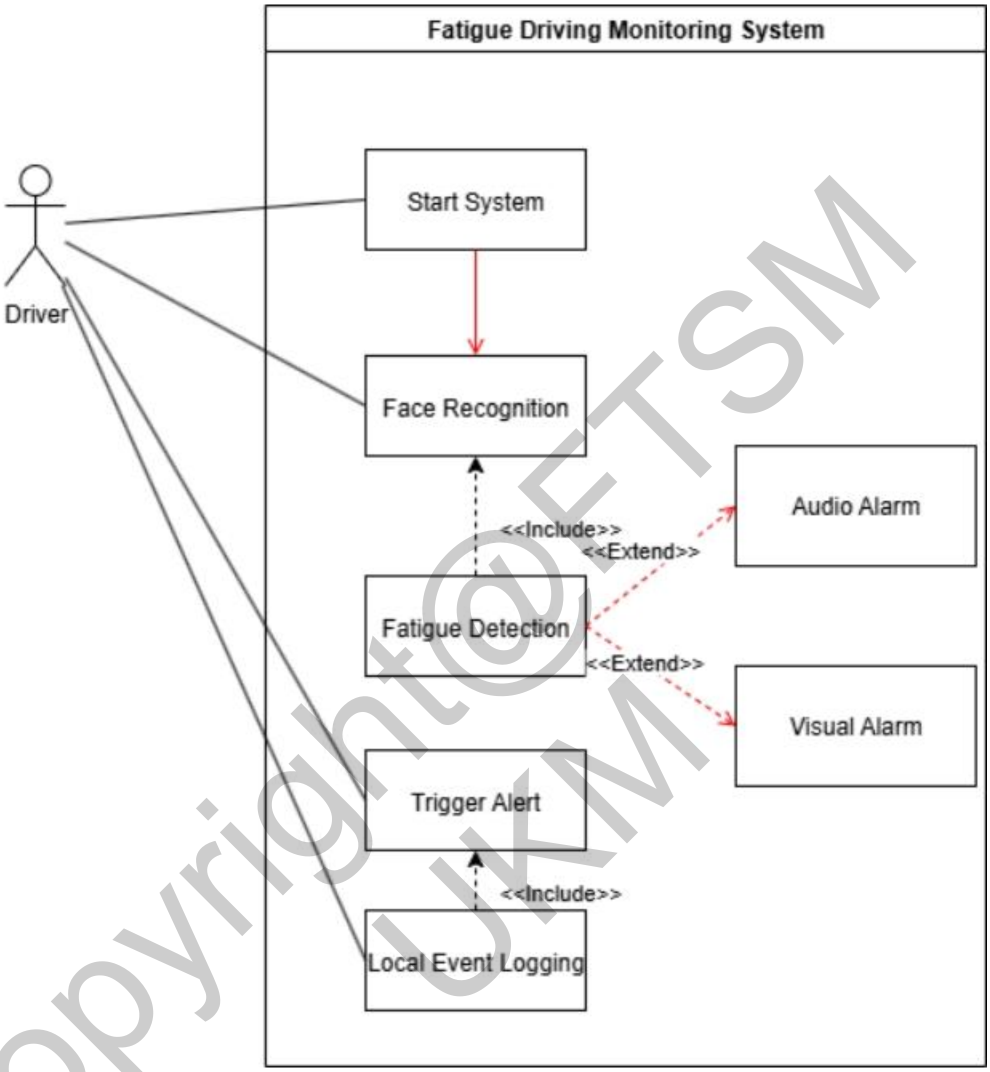

Figure 1 Use case diagram

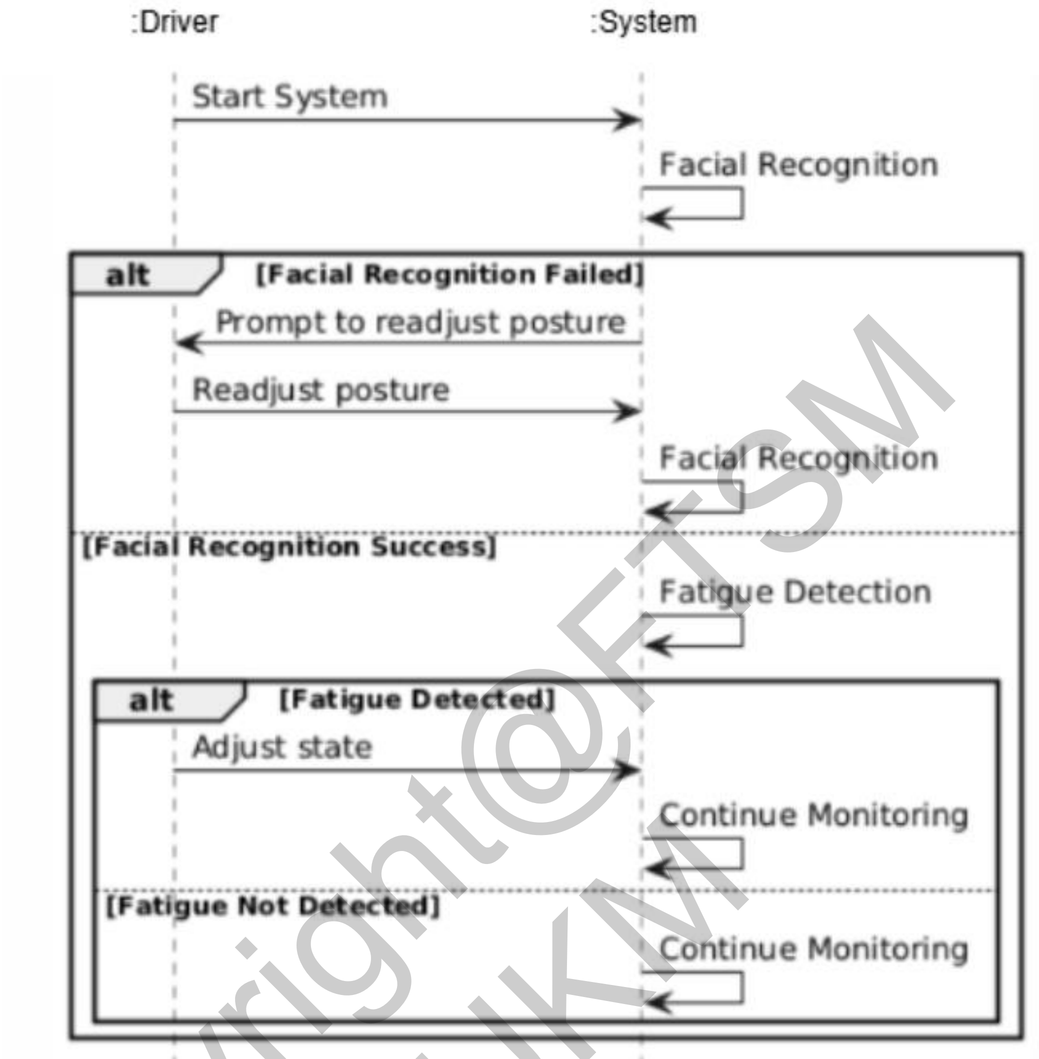

Figure 2 Sequence Diagram

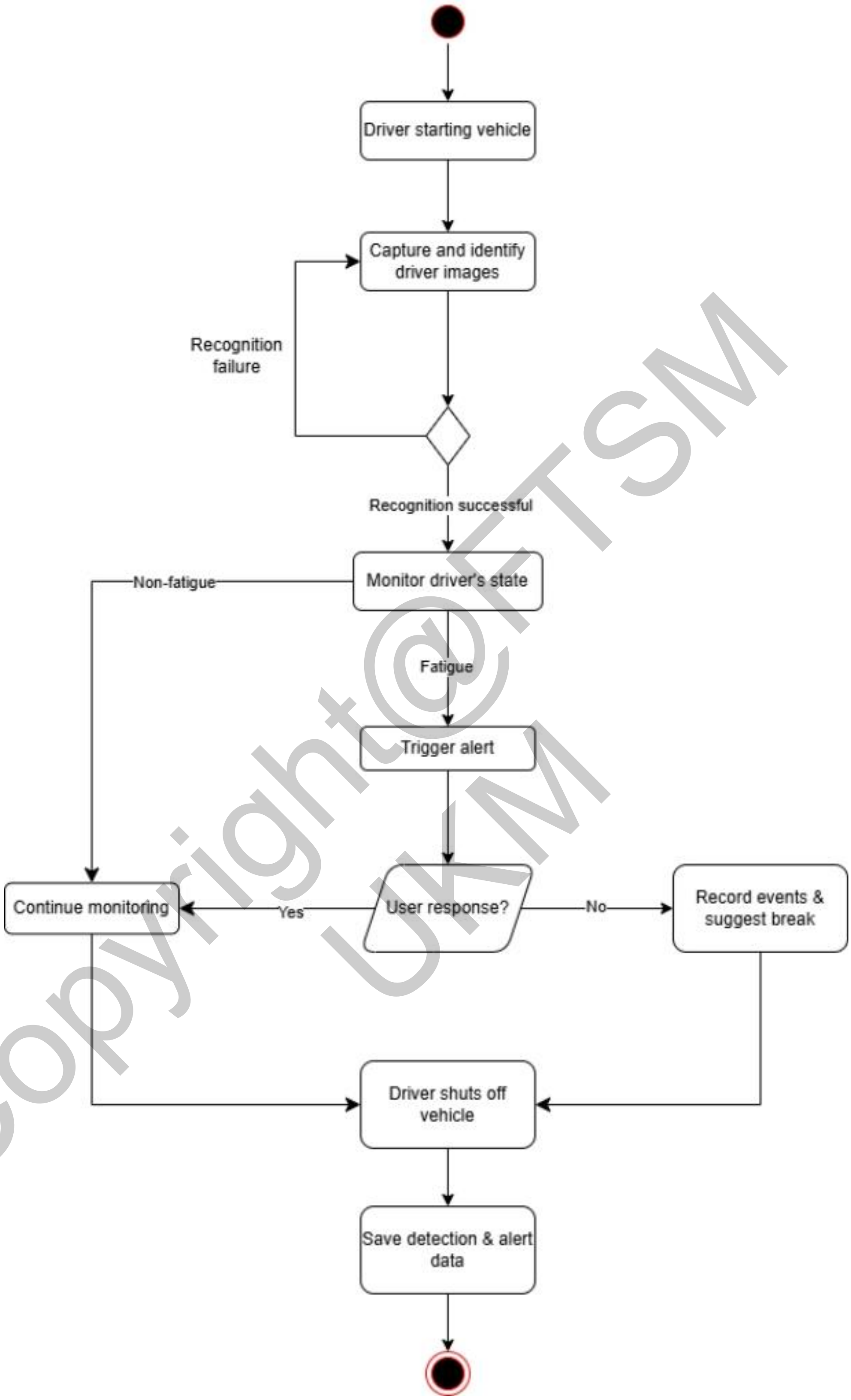

Figure 3 Activity Diagram

4.0 RESULTS

This section will, through a typical user scenario and with the aid of interface screenshots, visually demonstrate the core operation process of this fatigue driving monitoring system, and simultaneously explain its internal working principle to prepare for the subsequent tests.

Step 1: System Initialization and Normal Monitoring

Figure 4 Main Interface in Normal Monitoring State

Before the user starts the system and initiates the detection process in the browser, clicking "Start Detection" will lead to the main monitoring interface as shown in the figure. At this point, the backend of the system (app.py) will start a real-time processing loop. To avoid the limitations of the device's performance, this loop first uses the OpenCV library to capture video frames from the camera at a rate of approximately 10 frames per second. Each frame image is immediately sent to the MediaPipe Face Mesh module, which is responsible for performing high-performance facial detection in the image and accurately locating its 468 facial key points.

In the "NORMAL" state, the system is continuously analyzing these key points. It mainly processes two information paths in parallel: one is to calculate the eye aspect ratio (EAR) based on the geometric relationships of the eye key points, which is a ratio that can precisely quantify the degree of eye opening; the other is to extract the face area by using all the facial key points, and then analyze the overall facial expression by the ResNet50 deep learning model. As long as the EAR value remains within the normal eye-opening range and the model does not detect fatigue features such as yawning, the system's state will remain "NORMAL".

Step 2: Fatigue event detection and alerting

When the driver shows signs of fatigue, the system's hybrid decision-making algorithm will trigger an alert. This algorithm is mainly based on the following two core judgments:

Yawning Detection: The ResNet50 model of the system is particularly sensitive to the macroscopic facial expression feature of "yawning". When the model detects yawning from the cropped facial images, it will immediately significantly increase the overall fatigue score.

Eye Closure Monitoring: The system monitors the eye state by calculating the EAR value in real time. When the EAR value is lower than the preset threshold (0.20), the system determines it as "closed eyes".

Scene A: Yawning Detection:When a driver shows signs of fatigue, the system's hybrid decision-making algorithm will trigger the corresponding alert status based on different fatigue patterns. The following will present two typical fatigue incidents and their subsequent handling procedures.

Figure 5 The Main Interface For Detecting Yawning Status

As shown in the figure, when the driver shows yawning behavior, the deep learning model (ResNet50) of the system can identify this macro expression feature from the facial image. Once the model detects yawning, it will immediately raise the system's comprehensive fatigue level (Fatigue Level) to 100%, switch the status to "YAWNING", and trigger an alarm. As can be seen in the screenshot, at this time, the fatigue level is 100% and the EAR value is 0.12.

Scene B: Monitoring of Severe Drowsiness Incidents

Figure 6 The Main Interface For Detecting Severe Fatigue Events

Another crucial fatigue mode is continuous eye closure. The system monitors this state by calculating the eye aspect ratio (EAR) in real time. When the EAR value is below the preset threshold (for example, 0.20), the system determines it as eye closure and starts timing.

As shown in the figure, the "FATIGUE EVENT" state is triggered by a rule with a higher priority: when the system detects that the eyes have been closed continuously for more than 3 seconds, it will be determined as a serious drowsiness event. At this time, the system will trigger the highest level of alert to ensure the fastest response to the most dangerous driving behavior. In the screenshot, the duration of eye closure has reached 3.10 seconds, the EAR value is as low as 0.07, and the fatigue level is accordingly determined to be 100%.

Scene C: Cooling recovery state

Figure 7 The Main Interface After The Severe Fatigue Incident

After a severe fatigue incident (such as the continuous closing of eyes as mentioned above) is over, to prevent the alarm from triggering too frequently consecutively, the system will enter a brief "COOLDOWN" (cooling-off) state and simultaneously record a video of the entire ten seconds after the occurrence of the severe fatigue incident. During this period, the system will continue to monitor, but will temporarily reduce the sensitivity of the alarm, giving the driver a time to adjust and recover.

As shown in the figure, the driver has opened his eyes. The EAR value has returned to the normal 0.25, and the fatigue level has also dropped to 15.62%. On the interface, it shows a countdown of "COOLDOWN (10s)", and after the countdown ends, the system will return to the fully normal monitoring mode.

Step 3: Event Persistence: Log and Video Recording

Figure 8 New Entry in the Event Log

After a fatigue incident is over, the system's data persistence module is activated. The backend connects to the PostgreSQL database via the psycopg2 library and inserts the detailed metadata of the event - such as the event type (SEVERE_DROWSINESS), start and end timestamps, peak fatigue level, etc. - as a new entry into the fatigue_episodes table.

It is of utmost importance that the system has initiated the video recording function simultaneously when triggering the alarm. After the event concludes, this video segment containing the fatigue behavior will be saved as a local file, and its file path will also be stored in the corresponding entry of the database. Once the "fatigue event log" list on the front-end UI is refreshed through the API, this event that has just been fully recorded will be displayed.

Step 4: Event Review: Video Playback

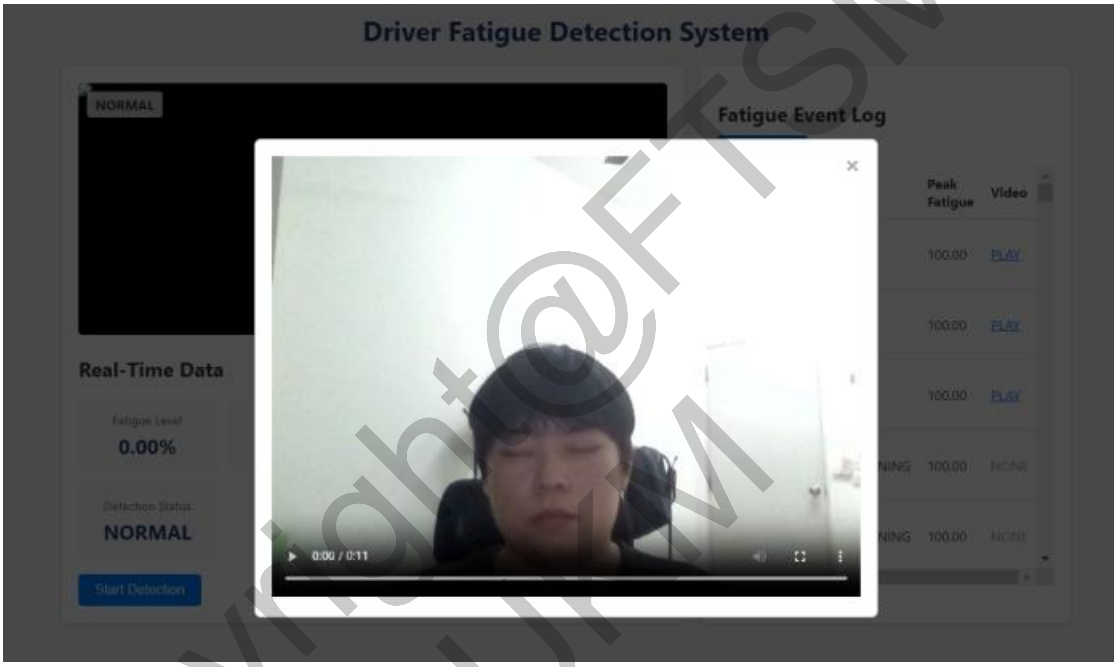

Figure 9 Event Video Playback Modal

The system provides users with the ability to review the data afterwards. When the main.js script at the front end detects the click event on the "Play" button in the log list, it will obtain the video path corresponding to that record. Subsequently, it initiates an HTTP request to the Flask backend for the video file. After the backend receives the request, it finds and returns the corresponding video file stream. Finally, the front end loads and plays the video in a modal (pop-up) window. This feature provides users or managers with clear and objective video evidence for analyzing specific fatigue incidents, forming a complete functional loop from real-time monitoring, intelligent alerts to offline traceability.

Functional test results:

Before conducting the system-level functional tests, we first carried out unit tests on the core underlying components to ensure the correctness of their basic functions.

EAR computation module (TC01 equivalent): It was confirmed that the EAR calculation function can return accurate floating-point values that fall within the physiological range by entering several sets of preset facial key point coordinates.

CNN model loading and inference module (TC02 equivalent): For standard input images, the system's ability to load the Keras model (.h5 file) and return the prediction results in the appropriate format (a vector with three probability values) was confirmed.

All the above unit and component-level tests have been successfully completed, laying the foundation for subsequent integration and system tests. The summary of the black-box test results for the core functions of the system's upper layer is shown in Table 4.3.4

Test ID	Test Description	Result
TC03	Start/Stop Detection Function	Pass
TC04	High-Frequency Yawning Alert Trigger	Pass
TC05	Log Entry Validation	Pass
TC06	Audio Alert Trigger	Pass
TC07	Real-time UI Update	Pass
TC08	Socket.IO Connection Recovery	Pass

Table 3: Summary of Core Function Test Results

The tests have shown that all the user interaction functions, event triggering logic and data recording procedures of the system are functioning as expected.

Non-functional Test Results:

The performance, availability, compatibility and recoverability of the system were evaluated. The results indicated that the system performed well in terms of non-functional quality attributes. The summary of the test results is shown in Table 5.3.

Test ID	Test Type	Observed Result	Conclusion
TC09	Performance Test	System ran continuously for 1 hour, average CPU usage was between 20-	Pass

		30%, memory was stable, with no crashes.	
TC10	Usability Test	All 3 surveyed users were able to complete core tasks independently and gave positive feedback on the interface's simplicity.	Pass
TC11	Compatibility Test	The system functioned and displayed correctly on the latest versions of Chrome, Firefox, and Edge, with no differences observed.	Pass
TC12	Recovery Test	After restarting the backend service, the frontend WebSocket was able to automatically reconnect and restore the data stream within 5 seconds.	Pass

Table 4: Summary of Non-Functional Test Results

5.0 CONCLUSION

The project successfully designed, implemented and tested a real-time fatigue monitoring system focused on improving road safety. The system aims to prevent the huge risk of major traffic accidents caused by driver fatigue, which is often difficult to handle accurately and in a timely manner by traditional vehicle sensors. The solution developed is a non-intrusive system that uses computer vision and deep learning technology to monitor the driver's facial state through a standard webcam, accurately detecting and warning the driver's fatigue state while avoiding interference with the driver's driving process.

The development process of this project focuses on an iterative and incremental model, which is crucial to overcoming the initial design challenges.The core algorithm of the system eventually evolved into a hybrid algorithm that intelligently combines a ResNet50-based deep learning model for macro analysis (mainly for yawn detection) with a lightweight geometric eye aspect ratio (EAR) calculation for accurate monitoring of eye closure. The system was built based on a front-end and back-end separation architecture. The back-end used Python, Flask, and Socket.IO, respectively, while the front-end was a simple HTML/JS interface that reduced performance requirements and was used for real-time user feedback. A comprehensive testing phase subsequently validated the system, and finally its overall accuracy on an independent test set reached 85%.

Based on the current strengths and weaknesses of the system, the system can be further deepened and extended in three main directions to improve its performance and practical value. First, at the core algorithm level, the primary task is to improve the recall rate of fatigue status to reduce the risk of false negatives. This can be achieved in two ways: first, fine-tuning the hybrid decision logic, such as optimizing the weights and EAR values of the deep learning model, or exploring more advanced multimodal fusion algorithms; second, expanding and diversifying the training dataset by collecting more fatigue samples in subtle and critical states to enhance the sensitivity of the model. And training a model for judging related to driver facial occlusion to avoid the impact of driver facial occlusion on fatigue monitoring results. Second, in order to enhance the environmental robustness of the system and ensure its reliable operation under all driving conditions, future research can focus on using data augmentation techniques to simulate extreme scenarios that may be encountered in driving conditions such as low light and high light during the model training stage. In addition, studying the integration of infrared (IR) cameras will be a key way to improve nighttime detection performance. Finally, in terms of system functionality expansion, the current local prototype can be developed into a more functional product, including the development of a cloud-based backend to support fleet management and remote data analysis; and the introduction of user-specific adaptive calibration capabilities that enable the system to learn and adapt to the unique physiological characteristics of each driver, thereby achieving accurate monitoring for each driver.

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