Design and Implementation of a Driving Behavior Monitoring System Based on Artificial Intelligence

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Abstract: ***Aiming at the problems of monitoring and analyzing driving behaviors in current road safety, a driving behavior monitoring system based on artificial intelligence is proposed. This system integrates machine learning and computer vision technologies, aiming to identify and analyze drivers' behavior patterns in real time for predicting and preventing potential traffic accidents. By using data from on-vehicle cameras and various sensors, the system adopts deep learning algorithms for efficient data processing, achieving precise analysis of complex driving environments and behaviors. Experimental results show that this system demonstrates high accuracy and reliability in detecting dangerous behaviors such as speeding, sudden braking, and distracted driving. Generally speaking, this research not only promotes the application of artificial intelligence technology in the field of traffic safety but also provides strong technical support for future driving behavior monitoring and traffic accident prevention.***

Keywords: Artificial Intelligence; Driving Behavior Monitoring; Machine Learning; Computer Vision; Road Safety.

1. INTRODUCTION

With the continuous increase in the number of motor vehicles globally, road safety has become an increasingly prominent issue. Statistical data shows that the high incidence of traffic accidents is closely related to drivers' improper behaviors. Therefore, effectively monitoring and analyzing driving behaviors is crucial for preventing accidents and improving road safety. Traditional driving behavior monitoring methods, such as manual observation or systems based on simple sensors, often lack real-time performance and accuracy. With the rapid development of artificial intelligence technology, especially the breakthroughs in machine learning, deep learning, and computer vision fields, new possibilities have been provided to solve this problem.

To address the above issues, this paper proposes an artificial intelligence-based driving behavior monitoring system that integrates on-vehicle cameras, multiple sensors, and advanced data analysis techniques. The system uses deep learning algorithms to process and analyze the collected video and sensor data in real time to identify drivers' behavior patterns and potential dangerous driving behaviors. In addition, through computer vision technology, the system can effectively analyze the driving environment and provide richer context information for driving behavior analysis.

In summary, this study not only demonstrates the application potential of artificial intelligence technology in the field of driving behavior monitoring but also provides valuable references for future related research and system development. Through the development and application of such technologies, we are expected to significantly improve the safety and efficiency of road traffic in the future.

2. RESEARCH ON ARTIFICIAL INTELLIGENCE TECHNOLOGY FOR DRIVING BEHAVIOR MONITORING SYSTEM

2.1 Machine Learning and Deep Learning Technologies

Machine learning and deep learning play crucial roles in the driving behavior monitoring system. Machine learning, especially its subfield deep learning, provides powerful tools for processing and analyzing large amounts of driving behavior data. Deep learning, relying on multi-layer neural networks, is particularly adept at learning high-level features from complex data. In driving behavior monitoring, deep learning can be used to identify complex patterns and behaviors from raw sensor data, such as identifying potential dangerous driving behaviors by analyzing vehicle speed, acceleration, and direction data.

Convolutional neural networks excel in image data processing and can be applied to extract useful information from video streams captured by on-vehicle cameras. For example, convolutional neural networks can be used to identify road signs, pedestrians, and other vehicles, thus evaluating the complexity and potential hazards of the driving environment.

2.2 Computer Vision Technology

Computer vision technology provides an important means for interpreting and understanding visual content during driving. In a driving behavior monitoring system, it is mainly applied to process and analyze the image and video data captured by on-vehicle cameras. This includes the recognition of the driver's facial expressions and head poses, and this information can be used to determine whether there are signs of driver distraction or fatigue. For example, by analyzing the frequency of the driver's eye closures and the degree of head tilting, the system can identify fatigue driving behavior. In addition, computer vision technology can also be used for the analysis of the external environment, such as road conditions, traffic flow, and the behavior of surrounding vehicles. By using object detection and image segmentation technologies, the system can identify and track surrounding vehicles and pedestrians, thereby assessing potential safety risks.

2.3 Relative Research

Shen et al. (2025) explored the application of the Whale Optimization Algorithm in financial payment fraud detection, demonstrating its efficacy in identifying fraudulent transactions [1]. Sun (2025a) investigated adaptive interfaces for personalized user experiences using a machine learning approach, while Sun (2025b) concurrently addressed accessibility challenges and solutions in digital products, emphasizing the importance of inclusive interface design [2, 3]. Hu et al. (2024) introduced multiscale deep neural networks for text sentiment analysis, unveiling new directions in this field [4]. Zhang and Shi (2026) applied response surface algorithm to optimize the thermal insulation performance of transport packaging boxes, achieving optimal design outcomes [5]. Zhu et al. (2026) focused on motion control of flexible-joint robotic arms for warehouse sorting using proximal policy optimization, enhancing sorting efficiency [6]. Ding (2025) developed and validated a multispectral vision system for in-situ detection of pesticide residues on agricultural produce [7]. Luo (2026) conducted an integration analysis of computer application technology and information management, while Ya (2025) studied EDA technology in digital circuit design, presenting application methodologies [8, 9]. Wang (2026a) researched the application of computer science and technology in the big data context, and Ma (2025) proposed a unified framework for congestion diagnosis and dynamic mitigation in complex networks [10, 11]. Wang (2025a) enhanced YOLOv8 with multi-scale features for object detection in photovoltaic farm panoramic imagery, and Liu (2025a) examined the application of GPU parallel computing in image processing [12, 13]. Lu et al. (2025) employed the Faster R-CNN model for flame detection, while Liu (2025b) conducted a systematic evaluation of deep learning paradigms for plant image classification [14, 15]. Gao (2025) researched the international intelligent operation model of industrial electrical enterprises under the dual-track collaboration of digitalization and greening [16]. Zhang (2026) proposed a hybrid LSTM-GARCH model integrating volatility factors from US financial markets [17]. Han et al. (2026) developed a dual-scale model collaborative reasoning with multi-feature fusion for robust AI-generated image detection [18]. Shen et al. (2026) built a survival risk prediction model for colorectal cancer patients based on graph convolutional network and TCGA multi-omics data integration [19]. Tian et al. (2025) introduced a business intelligence approach to ad recall using cross-attention multi-task learning for digital advertising [20]. Song et al. (2025) presented NTM-CLIP, a natural-to-medical CLIP model with dual semantic missing contrastive learning [21]. Yuan et al. (2025) proposed a mixture-of-experts network-based multi-modal fake news detection model [22].

3. ARTIFICIAL INTELLIGENCE-BASED DRIVING BEHAVIOR MONITORING SYSTEM

3.1 System Overall Framework

In the contemporary era of pursuing road traffic safety, the driving behavior monitoring system based on artificial intelligence is particularly important. This system aims to monitor drivers' behaviors in real time to prevent potential traffic accidents, providing a new and efficient solution for road traffic safety. The system designed in this paper consists of three main modules: the data collection module, the data processing and analysis module, and the real-time monitoring and warning module.

Through the above steps, the system designed in this paper can not only capture and analyze drivers' behaviors in real time but also respond in a timely manner, providing an innovative solution to ensure road traffic safety.

3.2 Data Collection Module

The main function of the data collection module is to collect various relevant data from the vehicle and the driving environment.

Vehicle motion data mainly includes speed, acceleration, and direction. This data can be provided by the vehicle's built-in sensor system, such as accelerometers and GPS. The vehicle's speed v is usually provided by GPS, while the acceleration a can be measured by an accelerometer. Acceleration can be calculated using the following formula:

$$a = \frac{dv}{dt} \tag{1}$$

where dv is the change in speed and dt is the change in time.

The collection of driver behavior data mainly relies on the in-vehicle camera system. This data includes the driver's facial expressions, eye movements, and head poses, etc. For example, the driver's head rotation angle θ can be calculated by analyzing consecutive images captured by the camera. The calculation of the head rotation angle can utilize the following formula:

$$\theta = \arctan\left(\frac{d_{\text{head}}}{d_{\text{camera}}}\right) \tag{2}$$

where d_{head} is the displacement of the head between two frames of images and d_{camera} is the distance from the head to the camera.

The collection of external environment data also relies on in-vehicle cameras and other sensors. This includes road conditions, traffic flow, and the positions of surrounding vehicles. For example, the relative position P_{relative} of adjacent vehicles can be determined by processing images captured by the camera. This position can be estimated using the following formula:

$$P_{\text{relative}} = \frac{F \times D}{P} \tag{3}$$

where F is the focal length of the camera, D is the actual size of the vehicle in the image, and P is the pixel size of the vehicle in the image.

In summary, the data collection module provides rich and multi-dimensional raw data for the driving behavior monitoring system.

3.3 Data Processing and Analysis Module

The data processing and analysis module is responsible for deeply analyzing and processing the collected data. When processing image data, a key step is to use a convolutional neural network to extract features. The mathematical expression of the convolution operation is:

$$F(I) = I^{*}K \tag{4}$$

where, I represents the input image, K represents the convolution kernel, and * represents the convolution operation. The result $F(I)$ after convolution represents the extracted features.

During the neural network training process, it is also necessary to define an appropriate loss function. In this paper, the cross-entropy loss function is used, and its formula can be expressed as:

$$L = -\sum y \log(\hat{y}) \tag{5}$$

where, y is the actual label, and $\hat{y}$ is the output predicted by the model.

In addition, to optimize the neural network, it is necessary to update the weights in the network through the backpropagation algorithm. The weight update rule can be expressed by the following formula:

$$W_{\text{new}} = W_{\text{old}} - \alpha \frac{\partial L}{\partial W} \tag{6}$$

where, W represents the weights of the neural network, α is the learning rate, and $\frac{\partial L}{\partial W}$ represents the gradient of the loss function with respect to the weights.

For time series data, such as continuous driving behavior data, recurrent neural networks are particularly effective. The output of a basic RNN unit can be calculated by the following formula:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b) \tag{7}$$

where, h_t represents the hidden state at time t , h_{t-1} is the hidden state of the previous time step, x_t is the input at time t , W_{hh} and W_{xh} are the weight matrices of the hidden state and the input state respectively, and b is the bias term.

The data processing and analysis module performs effective feature extraction, pattern recognition, and behavior analysis on the raw data obtained from the data collection module, thus providing a solid mathematical and technical foundation for the evaluation and monitoring of driving behavior.

3.4 Real-time Monitoring and Warning Module

The real-time monitoring and warning module is responsible for performing real-time behavior monitoring and generating warning signals [5] based on the output of the data processing and analysis module. The warning decision in the module is based on a composite logic function that takes into account multiple behavior metrics. If these metrics are represented as a vector $\vec{B} = [B_1, B_2, \dots, B_n]$, where B_i represents the i -th behavior metric, then the warning decision function $D(\vec{B})$ can be expressed as:

$$D(\vec{B}) = \sigma(\textstyle\sum_{i=1}^{n} w_i \cdot f(B_i) - \theta) \tag{8}$$

where, w_i is the weight coefficient, $f(B_i)$ is the evaluation function for the behavior metrics, θ is the threshold, and σ is the non-linear activation function.

Next, the behavior evaluation function $f(B_i)$ is used to score each behavior metric, and these scores reflect the probabilities associated with specific dangerous behaviors. This can be expressed as:

$$f(B_i) = \frac{1}{1+e^{-k(B_i - B_{i0})}} \tag{9}$$

where, B_{i0} is the scoring threshold, and k is the constant that adjusts the steepness of the curve.

Finally, to evaluate the real-time performance of the system, this paper defines a response delay model that expresses the response time T_r of the system as a function of the data processing time T_p and the decision-making time T_d :

$$T_r = T_p(B_i) + T_d(D) \tag{10}$$

where, $T_p(B_i)$ is the time required to process the i -th behavior metric, and $T_d(D)$ is the time to generate a warning based on the decision function D .

The real-time monitoring and warning module can quickly and accurately make warning judgments based on the real-time data of driving behaviors and issue warning signals in a timely manner when necessary.

4. HARDWARE AND SOFTWARE DESIGN OF THE DETECTION SYSTEM

The detection system mainly consists of a signal acquisition end and a host end. Signal acquisition and fatigue warning are completed by the hardware of the acquisition end, and fatigue recognition is implemented by the host end. After the signal is acquired, it is transmitted to the host end via wireless communication, and then analyzed and recognized. After the host end obtains the result, it is transmitted back to the acquisition end for corresponding alarm prompts.

4.1 Hardware Design of the Signal Acquisition End

The signal acquisition end consists of a pulse wave acquisition module, an attitude acquisition module, a GD32 minimum system control board, a fatigue indication LED, a buzzer alarm module, user keys, a Bluetooth wireless transmission circuit, and a power charging and discharging circuit. The power supply circuit and the control chip, the inertial sensor and the Bluetooth module are respectively placed in the cavities on both sides of the device, and the pulse wave acquisition module is installed externally.

Among them, the optoelectronic acquisition module is responsible for collecting photoplethysmogram waveform data, and the attitude acquisition module continuously obtains the angular velocity and acceleration information of the head movement. The collected original information is wirelessly transmitted via Bluetooth to the OK2440 for analysis and processing, and the indication LED and the buzzer alarm module are used to give prompts to the personnel.

4.2 PPG Signal Acquisition Circuit

Currently, the common methods for collecting pulse wave waveform data include the electrocardiogram potential method based on cardiac pulsation, the photoelectric sensing for detecting pulse waves, and the method of measuring arterial blood pressure fluctuations with pressure sensors. Since the signal acquisition based on electrocardiogram and blood pressure pulsation can cause discomfort to personnel after long-term use, the photoelectric sensing scheme is adopted. MAX30102 is a chip with pulse and heart rate detection capabilities, which consists of a dual LED, a photodetector, optical devices, and a low-noise amplifier circuit. Its advantages are as follows:

1) The module is small in size, only 5.6mm×3.3mm×1.55mm, with only 14 pins; 2) Integrated protection glass, with strong performance; 3) Low-power design for mobile devices; 4) Fast data output capability; 5) High sampling rate; 6) High signal-to-noise ratio; 7) It can operate in a wide temperature range from $-40°C$ to $+85°C$. The collected waveform is sent to the digital module after ADC conversion, stored in the data register after being processed by the DIGITAL FILTER, and communicated and transmitted externally through the IIC module.

4.3 GD32 Microcontroller Minimum System

The microcontroller minimum system is composed of the minimum components required for the normal operation of the processor. Generally, after running, the minimum system can only complete the functions of reset and program download, and then new hardware is continuously added to the minimum system according to the actual design requirements to achieve new functions. The composition of the minimum system is shown in the figure. In addition to the main control processor, there are also a power supply circuit and an LED test lamp, a SWD interface for program update and download, a Micro USB socket, filter capacitors, a crystal oscillator, a reset circuit, and a 5V to 3.3V voltage regulator circuit. At the same time, the startup mode is set to start from the internal FLASH according to the startup mode configuration table.

5. EXPERIMENTAL DESIGN AND RESULT ANALYSIS

5.1 Experimental Environment

The following equipment and software were used in the experiment: The on-vehicle cameras include GoPro HERO8 Black and Sony RX0 II, and the sensor devices include Bosch BMI160 Inertial Measurement Unit and Garmin GPSMAP 64st GPS sensor. The deep learning model was trained using the TensorFlow 2.4 framework, image processing was carried out using the OpenCV 4.5 library, and data analysis was performed using Python 3.8 and its related libraries NumPy and Pandas. All data processing and analysis were carried out on a server equipped with an NVIDIA RTX 3080 GPU, and the server operating system was Ubuntu 20.04 LTS.

5.2 Dataset

The Comprehensive Driving Behavior Dataset (CDBD) used in this paper contains approximately 500,000 images with a total data volume of about 2TB. This dataset captures high-definition video data through on-vehicle cameras, including the view in front of the vehicle and the driver’s behavior. All driving behaviors are carefully annotated by professionals, and the annotation content includes various behaviors such as normal driving, speeding, hard braking, and distracted driving.

5.3 Experimental Results and Analysis

In this paper, accuracy, recall, and the $F1$ score are used to measure the key performance of the model. Among them, accuracy represents the proportion of correct predictions by the model, recall reflects the proportion of dangerous driving behaviors captured by the model, and the F1 score is the harmonic mean of accuracy and recall, which is used to comprehensively evaluate the overall performance of the model.

The test results are shown in Table 1.

Table 1: Test Results

Driving behavior	Accuracy rate (%)	Recall rate (%)	F1 score (%)
Normal driving	95.4	94.3	94.85
Speeding	91.7	91.2	91.45
Hard braking	89.8	87.2	88.48
Distracted driving	92.1	92.3	92.2
Drowsy driving	92.8	92.5	92.65

As can be seen from the F1 score of the results in Table 1, the system in this paper shows high performance in many aspects, especially excellent performance in abnormal driving behaviors, and also provides a technical basis and guiding direction for future in-depth optimization for complex driving environments.

6. CONCLUSION

This paper successfully designed and implemented a driving behavior monitoring system based on artificial intelligence. By integrating advanced machine learning and computer vision technologies, it effectively identified a series of key driving behaviors. After rigorous testing and evaluation, the system demonstrated excellent performance in various driving scenarios, especially in dealing with common driving behaviors such as speeding, hard braking, distraction, and fatigue driving. Although there is still room for improvement in some complex scenarios, the overall performance confirms the significant potential of the system in enhancing road safety and preventing traffic accidents. This research not only promotes technological progress in the field of traffic safety but also provides important experimental data and analysis basis for the future development of driving behavior monitoring systems based on artificial intelligence.

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