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Fatigue Driving Detection Based on Convolutional Neural Network Model Connected to New Energy Vehicles

Xiang Li

Kunming University of Science and Technology Oxbridge College

ABSTRACT
Fatigue driving detection based on Convolutional Neural Network (CNN) is a method that utilizes deep learning technology to monitor and identify whether a driver is in a fatigued state in real-time. This method analyzes the driver's facial features, eye status, and other information, combining multiple algorithms and techniques to achieve accurate detection and early warning of fatigue driving. This paper takes the application comparison of Yolov8 model as an example to conduct research on the idea of integrating fatigue detection systems with the Internet of Vehicles. During driving, if fatigue driving occurs, the system will make a judgment. Then, the autonomous driving system will take over the driving of the car and remind the driver to enter a rest area or stop to rest.

KEYWORDS
Internet of Vehicles; fatigue driving; accurate detection; Yolov8; Convolutional Neural Network

1 Introduction

Fatigue driving is one of the significant factors leading to traffic accidents. Therefore, developing a system that can monitor the driver's fatigue state in real-time and provide timely warnings is crucial. Traditional fatigue detection methods often rely on driver self-reports or simple physiological measurements, which have issues such as delayed response times and low accuracy. In contrast, fatigue detection technology based on Convolutional Neural Networks (CNN) analyzes the driver's facial features through deep learning algorithms to achieve more accurate and real-time monitoring of fatigue states. In this study[1], when the detection system identifies that the driver is in a fatigued state, the autonomous driving system can take over the driving based on the driver's habits and prompt the driver to rest in a rest area. The new energy vehicle industry in the country has gone through five main stages, starting from the "863 Program" for electric vehicles initiated in 2001 during the "Tenth Five-Year Plan," and has now entered a new stage of rapid popularization and market development. With the continuous expansion of the new energy vehicle market and the advancement of technology, autonomous driving has become a prominent selling point for new energy vehicles, and the demand for related safety technologies is also increasing. YOLO (You Only Look Once) is a one-stage object detection algorithm that converts the object detection problem into a regression problem and solves it through a unified neural network framework. The core idea of YOLO is to divide the input image into a fixed-size grid, with each grid responsible for predicting the position of the bounding box and its category. The YOLO series models have been continuously developed, from the initial YOLOv1 to the latest YOLOv10, with each generation enhancing speed and accuracy. Among these updated versions, YOLOv8 is relatively stable.

2 Literature Review

2.1 Historical Development

Convolutional Neural Networks (CNN) are deep learning models primarily used in image recognition and speech recognition. Their basic structure includes convolutional layers, pooling layers, and fully connected layers. Initially designed to solve image recognition problems, CNNs can automatically extract features and classify patterns, significantly reducing the complexity of application. In this review, we focus on the YOLO model.

2.1.1 Introduction to Convolutional Neural Networks

This is a deep learning technology used for image and speech recognition. It simplifies the complexity of traditional machine learning by automatically extracting features and classifying them.

2.1.2 Development of YOLO Algorithms

Since its debut in 2015, the YOLO algorithm has been continuously updated and upgraded, becoming a key advancement in the field of object detection. Here are the main versions of the YOLO algorithm:

YOLOv1 (2015): Pioneered one-stage object detection, fast but less accurate for small object detection.

YOLOv2 (2017): Introduced batch normalization and anchor boxes, improving stability and accuracy.

YOLOv3 (2018): Adopted a new architecture and feature pyramid networks, enhancing multi-scale object detection capabilities.

YOLOv4 (2020): Further optimized based on YOLOv3, improving performance.

YOLOv5 (2020): Innovated in data processing and network structure, enhancing real-time performance and accuracy.

YOLOv6 (2020): Continued improvements, contributing to the field of computer vision.

YOLOv7 (2022): Continued the core ideas with optimizations and adjustments.

YOLOv8 (2023): Offered multiple versions suitable for different scenarios, improving accuracy and processing speed.

YOLOv9 (2024): Addressed information loss issues, enhancing multi-task performance.

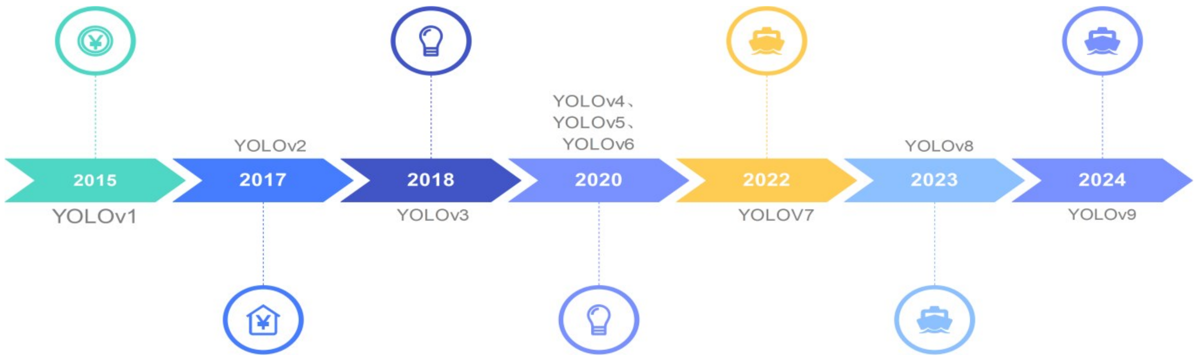

Figure 1 The Evolutionary Journey of YOLO

2.1.3 History of Fatigue Detection in New Energy Vehicles

The technology for fatigue detection in new energy vehicles originated from hydraulic fatigue testing machines in the 1960s. Initially unreliable due to manual control, digital computers later resolved these issues. Germany was once a leader in this field, with the laboratory established by Gassner and Svenson advancing the development of fatigue detection technology. Early techniques relied on direct contact with drivers, detecting fatigue through physiological indicators. Nowadays, detection technologies based on vehicle operation data have become mainstream, capable of accurately determining fatigue states in real-time.

The new energy vehicle industry in China began with the "Ten Cities, Thousand Vehicles" project in 2009, and fiscal subsidies were extended nationwide in 2013. With the promotion of environmental protection and energy policies, the new energy vehicle market has grown rapidly. In the future, automotive electronic systems will increasingly take on driving assistance functions, such as fatigue detection and automatic braking.

2.1.4 Application of YOLOv8 in Fatigue Detection

YOLOv8 is used to detect signs of driver fatigue, such as closed eyes or nodding. Images are collected through network cameras for training to achieve accurate detection.

Fatigue State Detection Project: Using the YOLOv8 model to detect signs of fatigue such as closed eyes or nodding.

Improved YOLOv8 Fatigue Detection Algorithm: Introducing variant models to improve detection efficiency.

Fatigue Driving Detection System: Integrating the YOLOv8 algorithm and comparing it with earlier versions to accurately identify fatigued driving behavior.

2.1.5 Current Development Level

The latest advancements in fatigue detection technology for new energy vehicles include:

High-frequency fatigue testing technology: Testing machines operate at higher frequencies to more accurately simulate real-world usage environments.

On-board environmental monitoring systems: Sensors collect physiological and behavioral data of drivers, monitoring fatigue states in real-time.

Differential gear torsional impact fatigue testing: Evaluating the stress concentration areas of key differential gear components.

Gear fatigue testing machine technology: Providing support for gear technology testing.

Electric six-degree-of-freedom noise testing platform: Precisely simulating the multi-degree-of-freedom motion of components.

Chassis fatigue life simulation and optimization: Using finite element models and strength simulations to assess the fatigue life of chassis.

2.1.6 Effectiveness Evaluation of YOLOv8 Model

The effectiveness of the YOLOv8 model in improving the accuracy and response speed of fatigue detection includes:

Accuracy Assessment:

Mean Average Precision (mAP): Evaluates the overall performance of the model.

Precision and Recall: Precision is the proportion of correct predictions, and recall is the coverage range of correct predictions.

F1 Score: Comprehensively evaluates the accuracy and stability of the model.

Response Speed Assessment:

Frames Per Second (FPS): Measures the processing speed of the model, with higher FPS indicating faster response.

Other Evaluation Indicators:

Confusion Matrix: Compares actual and predicted results to comprehensively evaluate model performance.

Intersection over Union (IoU): Evaluates the overlap between predicted and actual bounding boxes.

Comparative Experiments:

Comparing YOLOv8 with other models to intuitively display its advantages and shortcomings.

Hyperparameter Optimization:

Finding the best parameter combinations through optimization techniques to enhance model performance and response speed.

2.2 Status Analysis

In 2023, Wu Tianhao[2] proposed a Conv-Res module that improved the XCM network classifier, enhancing data accuracy. In January 2024, Luo Guorong[1] noted that the diversity and complexity of driver behavior greatly affect traffic safety, proposing four types of driving. In March 2024, Xu Chang's[6] journal pointed out that intelligent vehicles have changed traditional driving modes, allowing drivers to be relieved of some driving tasks and reducing their burden. However, there are still scenarios where partial autonomous driving systems cannot cover functional boundary scenes, or drivers become distracted or fatigued during long periods of intelligent driving, requiring the system to issue a takeover request. In July 2024, Xu Degang[4] proposed an improved YOLOv8 urban vehicle object detection algorithm. In the YOLOv8 model, a GAM-C2f structure replaces the C2f module to balance computational efficiency and accuracy; a SPPFAPGC module is designed to prevent local feature loss in the SPPF structure, enhancing feature richness and combining small object detection heads to strengthen the detection capability of distant small object vehicles, integrating local and global features. In October 2024, Xia Qingfeng[11] addressed the low detection accuracy, missed detections, and false detections of existing fatigue driving detection algorithms under complex conditions such as low light, drivers wearing sunglasses, and low light with sunglasses. An improved RepVGG fatigue detection algorithm was proposed, optimizing the basic network RepVGG by introducing ASPP and CBAM modules. Experimental results showed that the improved RepVGG algorithm achieved a detection accuracy of 97.34% in complex condition fatigue driving detection datasets, an improvement of 2.51% over the original network. The improved model not only enhanced detection accuracy but also met the standards of a lightweight model. Future research can further focus on the expandability and real-time performance of the improved methods, deploying the improved models to embedded devices such as JetsonNano to enhance model practicality. Finally, in December 2024, Li Bohao's team proposed combining the Sigmoid function and gradient gain coefficient to improve the WIoU loss function, enhancing model stability and robustness. In the backbone part, the feature extraction network of Y0L0v8s was improved to enhance the multi-scale feature extraction capability of small objects and reduce parameter quantity to save computational resources. In the head part, the detection layer network structure was optimized, with the addition of a small object detection layer and the removal of detection layers insensitive to small objects. The WIoU loss function replaced CIoU to improve bounding box regression performance, accelerate model convergence speed, and enhance regression accuracy. At the same time, the 68-point facial annotation method was combined to mark key points in different facial regions for applications such as facial recognition, expression analysis, and posture estimation.

2.3 Trend Prediction

In the future, several emerging technologies or methods may impact the accuracy of fatigue detection systems:

Multimodal Feature Fusion: Combining different types of biometric data (such as heart rate and PERCLOS values) through multimodal fusion can significantly improve the accuracy of fatigue detection. For example, using one-dimensional convolutional neural networks (1D CNN) to establish fatigue detection models based on heart rate and PERCLOS values, and weighting the outputs of the two models to achieve multimodal fusion fatigue detection.

Deep Learning and Computer Vision: The application prospects of deep learning and computer vision technologies in fatigue detection are broad. Through deep learning neural network models for key point localization (such as the contours of eyes and mouth), combined with PERCLOS and other indicators to judge the degree of fatigue, can improve the accuracy and real-time performance of fatigue detection. In addition, the Perclos method based on YoloV5 and MTCNN also shows high feasibility and practicality.

Pose Information Fusion: Utilizing multi-pose face detection methods with integrated pose information and head pose estimation methods based on biometric features can greatly improve the accuracy and reliability of fatigue driving detection.

Improved Image Processing Techniques: Using the Local Binary Features (LBF) algorithm based on regression for facial feature point localization, and improving initialization strategies and classification effects, can balance the accuracy and real-time performance of the algorithm.

Promotion of Intelligent Driving Technology: With the promotion of intelligent driving technology, driver fatigue detection will become an important part of intelligent driving systems, further enhancing the accuracy and reliability of fatigue detection.

3 Main Text

3.1 Model Optimization and Compression

Quantization: Convert high-precision parameters in the model to low-precision parameters to reduce storage space and computational complexity, improving operational efficiency.

Pruning: Remove unimportant parts of the model to reduce the number of parameters and computational volume, making the model lighter.

Knowledge Distillation: Transfer knowledge from a large model to a smaller one, maintaining high accuracy while reducing model size and computational resource requirements.

3.2 Hardware Acceleration and Adaptation

Selecting Suitable Hardware Platforms: Choose high-performance hardware platforms according to model requirements, such as GPUs, TPUs, FPGAs, or dedicated AI chips, ensuring that computational capabilities, storage capacity, and power consumption levels meet the requirements.

Utilizing Hardware Accelerators: Use hardware accelerators like NPUs to speed up key calculations, shorten inference time, and enhance system real-time performance.

Hardware and Software Co-design: Consider model characteristics during hardware design, optimize memory management, reasonably allocate storage space, reduce memory access latency, and improve hardware resource utilization.

3.3 Software Framework and Tool Support

Selecting Suitable Deep Learning Frameworks: Choose frameworks that support smart car hardware platforms, have efficient computational performance, and good compatibility, such as PyTorch, and use their optimization tools to deploy and optimize models.

Using Model Conversion Tools: Convert trained models into formats suitable for smart car hardware operation, such as ONNX, and then use inference engines like TensorRT for further acceleration.

Developing Efficient Inference Engines: Develop dedicated inference engines for smart car hardware environments and application scenarios, optimize the model inference process, reduce unnecessary calculations, and improve inference efficiency.

3.4 Data Processing and Preprocessing

Data Collection and Annotation: Collect a large amount of image, video, radar, and other data in the smart car usage environment and annotate it accurately to provide rich data support for model training.

Data Preprocessing: Perform operations such as cropping, resizing, normalization, and data augmentation on the collected data to meet the model's input requirements and enhance the model's adaptability.

Real-time Data Processing: Quickly process and analyze real-time data collected during the operation of smart cars to extract useful information and provide real-time input data for the model.

3.5 System Integration and Testing

Integration with Smart Car Systems: Integrate the model closely with the perception, decision-making, and control systems of smart cars to achieve seamless data flow and collaborative work, directly passing the model's output results to the vehicle control unit to generate control commands.

System Testing and Verification: Conduct comprehensive testing and verification of the system equipped with the model in actual operating environments to ensure the model's accuracy and reliability in various complex scenarios.

Continuous Optimization and Updates: Continuously optimize and update the model according to test results and actual operating conditions, and use OTA technology to push optimized models and software to maintain the system's advancement and reliability.

4 Conclusion and Outlook

In the future, the automotive industry will become more intelligent, and traffic safety accidents will definitely become a major challenge. Therefore, fatigue detection of drivers is an important link in traffic safety accidents. It can judge the driving state of drivers and then prompt and persuade drivers to rest. With the continuous development of deep learning technology and the continuous improvement of computer hardware performance, YOLOv8 and its subsequent versions will continue to play an important role in the field of real-time object detection. The future development directions may include:

Stronger Multi-task Learning Capabilities: YOLOv8 and its subsequent versions may be able to handle more tasks simultaneously through multi-task learning, such as object tracking and scene understanding.

Adaptive Network Architecture: Future YOLO algorithms may introduce adaptive network architectures that automatically select the most suitable detection models based on different input scenarios, thereby providing the best detection performance in various application scenarios. Technical fusion: YOLOv8 may be integrated with Transformer structures, self-supervised learning, 3D object detection, and other technologies to enhance the model's performance in a wider range of scenarios.

Model Lightweighting and Real-time Performance Improvement: Future development directions may focus on model lightweighting and real-time performance enhancement to meet the needs of more practical scenarios. Through these measures and future development directions, YOLOv8 and its subsequent versions will play a more important role in the field of real-time object detection in smart cars and other areas.

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