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Fatigue Driving Recognition Using Improved YOLOv8

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***Abstract*—Fatigue driving contributes to 21% of fatal accidents, leading to slower driver responses and increases crash risks. This study presents research to detect driver fatigue. Fatigue driving systems face challenges in real-time detection due to limited computing resources and poor accuracy detection. To address this, we introduce the YOLOv8-FCA model, enhancing the YOLOv8 algorithm to boost detection accuracy and efficiency in controlled environments. YOLOv8 was selected for its proven performance in object detection tasks. Our model integrates a feature pyramid network (RepFPN) to improve detection of subtle fatigue indicators and details, and utilizes the convolutional block attention module (CBAM) to focus attention on critical regions. Experimental results demonstrate a 1.3% increase in detection accuracy (mAP50), achieving 99.1%, while reducing computational costs by 40.73%, thus significantly enhancing detection and response capabilities.**

***Keywords*—Fatigue driving, YOLOv8, real-time detection, RepFPN, CBAM, detection accuracy, computational efficiency**

I. INTRODUCTION

In recent years, with the change in people's quality of life and the surge in travel demand, cars have become the primary means of transportation used by families, and cars are an essential way for people to travel. According to statistics, 9.27 million cars were sold in 2023**Error! Reference source not found.** [1]. W hile cars offer significant convenience in daily life, they also pose considerable risks. Fatigue driving is a key factor in many road traffic accidents [2], with serious consequences for drivers, passengers, and pedestrians.

National Highway Traffic Safety Administration estimates that 91,000 police-recorded crashes in 2017 involved fatigued drivers, resulting in about 50,000 injuries and nearly 800 deaths [3]. In 2021, drowsy driving accounted for 21% of all fatal crashes, which, based on 39,508 fatal crashes recorded that year, implies that more than 8,300 people could have died as a result of drowsy driving [4]. Given this stark reality, developing and deploying effective fatigue monitoring systems to alert drivers in real time is particularly urgent.

Since 2011 [5], although some vehicles have begun implementing monitoring applications, only some vehicle systems have fatigue driving monitoring functions. The wide application of fatigue monitoring systems is limited by the cost of vehicles, and most models do not yet have onboard cameras. In addition, while updates to software applications have improved the accuracy of fatigue driver identification, the vehicle's engine system can be a limiting factor in the upgrade process. Therefore, to improve road safety, there is a need to continuously improve fatigue driving monitoring technology and seek cost-effective solutions for broader deployment.

This study proposes YOLOv8-FCA, an enhanced version of the YOLOv8 object detection framework that integrates RepFPN (Re-parameterized Feature Pyramid Network) and CBAM (Convolutional Block Attention Module) to improve multi-scale feature fusion and enhance both spatial and channel attention. This study discusses the application of different machine learning methods in fatigue driving recognition, in order to further improve the recognition efficiency and accuracy by introducing the YOLOv8-FCA model.

RepFPN and CBAM in the model are used to enhance the detection rate while simultaneously eliminating most of the computational processes. Therefore, through the use of the model incorporated, the study objectives are to increase the accessibility and application of fatigue detection technology to reduce related accidents and enhance road safety in a timely manner.

This paper is structured as follows: Section II represents the literature review and methodology in Section III. Results and analysis are illustrated in Section IV. Finally, the conclusion and recommendations are stated in Section V.

II. LITERATURE REVIEW

This section reports on previous research papers related to image recognition of tired driving and the YOLO series in different fields.

A. Fatigue Definition

Fatigue is caused by a lack of adequate sleep, prolonged wakefulness, different phases of circadian rhythms, and excessive workloads (including mental and physical activity) that reduce cognitive ability and the ability to perform safety-related tasks. This status not only affects their alertness but also impairs their ability to perform security-related tasks and responsibilities. This includes driving, operating machinery, performing emergency tasks, and other activities that require a high degree of concentration and quick reflexes [6]. When the driver continues to drive the vehicle in a state of fatigue, he will experience drowsiness, sleepiness, weakness of limbs, lack of concentration, decreased judgment, and other behaviors, and may also experience trance or instant memory blank, resulting in slow or premature movement, operation pause or error, and other unsafe factors. These conditions will significantly increase the risk of road traffic accidents, posing a threat to the safety of drivers and other road users [7]. According to statistics, when a traffic accident occurs, if the driver's response can be half a second faster, 60% of traffic accidents can be avoided [8]. To ensure individual and public safety, it is crucial to take measures that reduce dangerous behaviors caused by fatigue, thereby protecting people's lives and property. Studies have shown that by analyzing the driver's physiological characteristics (such as heart rate, eye movement, etc.), behavioral characteristics (such as facial expression, head posture), or vehicle driving state (such as steering wheel operation, speed fluctuations), the fatigue recognition technology can monitor the fatigue degree of the driver in real-time and give an early warning when necessary [9].

B. Fatigue Driving Identification Method

Fatigue driving identification methods can be categorized as shown in Fig. 1.

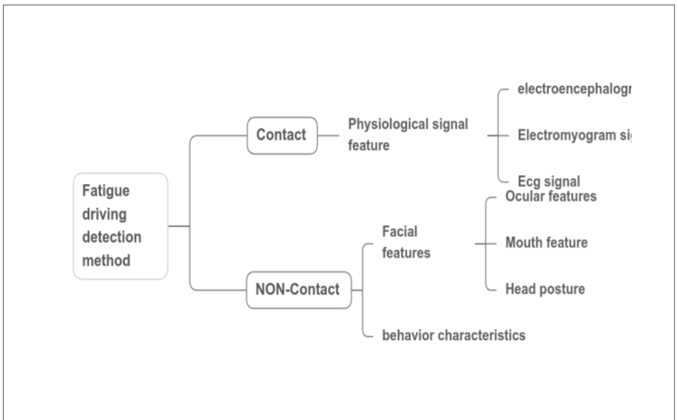

Fig. 1. Fatigue Driving Detection Method

1) Fatigue Driving Detection Method Based On Physiological Signal Characteristics

Contact fatigue driving detection technology mainly collects physiological signals through direct contact with the driver's body sensor and then analyzes the driver's fatigue state. Such techniques include the use of physiological indicators such as electroencephalography (EEG), electrocardiogram (ECG), electromyography (EMG), etc.

2) Electroencephalogram (EEG) Signal Detection

The University of Sydney Health Research Centre has conducted in-depth research on the acquisition and extraction of EEG signals from different drivers and the processing of these signals using neural networks to identify fatigue states [10]. The characteristics of the fatigue state can be extracted from EEG data, and the accuracy and efficiency of detection can be improved. EEG signals are sensitive to data acquisition, but acquisition and analysis can be computationally expensive, especially for real-time monitoring and processing [11].

3) Electrocardiogram (ECG) Signal Detection

Jeong and his team assessed driver fatigue by analyzing heart rate variability in electrocardiogram (ECG) signals. Now, the configuration can be monitored through the steering wheel, bracelet, and other monitoring equipment [12]. If the system detects signs of drowsiness in the driver, it sends an alert. The device is simple in design, easy to implement, and cost-effective. However, due to the significant variation in heart rate patterns among individuals, this approach may carry a particular risk of miscalculation. Therefore, it is best used as an auxiliary tool to assist other fatigue monitoring techniques rather than as the sole basis for judgment.

4) Electromyography (EMG) Signal Detection

Electromyography (EMG) signals are usually measured using evoked potential technology, which involves placing surface electrodes at the muscle site to transmit the captured EMG signals to an EMG recorder for analysis. Hostens and colleagues [13] used this approach to study driver fatigue during long periods of driving. Their results showed that when fatigue occurred, the amplitude of the surface EMG increased while the average frequency decreased.

EMG signal detection has similar advantages and disadvantages to pulse detection. The difference is that EMG signal detection performs better in terms of application scalability. It can be used more widely in different monitoring scenarios and devices. However, like pulse detection, EMG signal detection can also be affected by individual differences, requiring further algorithmic optimization and personalized adjustments to improve accuracy and reduce miscalculation rates. Nevertheless, EMG signal detection as a non-invasive, real-time monitoring tool has important application potential in assessing and preventing tired driving.

5) Fatigue Driving Detection Method Based on Vehicle Characteristics

Vehicle characteristic behaviors are usually monitored and recorded by sensors or monitoring systems inside the car [14]. By analyzing these behavioural characteristics, the system can identify potential signs of fatigued driving, issue warnings in advance, and reduce the risk of traffic accidents. This method combines the information on driver behaviour (steering wheel Angle, steering wheel grip, pedal open fit, etc.) and vehicle behaviour (lane departure, speed, angular speed, etc.) to improve the accuracy and reliability of fatigue driving detection [15]. Fatigued drivers show instability in speed and acceleration, frequently change speed or excessive acceleration or braking because the driver's reaction time is long, it is difficult to maintain smooth driving; More likely to deviate from the lane, the driver is not focused, it is difficult to stay in the correct lane; Excessive steering or erratic steering behaviour where the driver tries to keep the vehicle in the lane: slow or untimely braking response; Frequent deviation from lane centre line; Vehicle vibration may increase, and the driver may lose control of direction or cause irregular driving behaviour [16].

The fatigue driving detection method based on facial features refers to relying on facial video data, collecting data through image sensors such as cameras, and applying machine vision technology, such as facial critical point positioning, to analyze various changes in the driver's face. These changes include a percentage of eyelid closure over time (PERCLOS) per unit time of the eye, blink rate, concentration, eye aspect ratio (EAR), mouth opening degree (mouth aspect ratio (MAR), head movement, and head rotation angle [17]. These feature data are extracted, and a specific algorithm is used to detect whether the driver is in a sleepy driving state. The fatigue detection methods based on facial features can be divided into three types, namely, the methods based on the state of eyes, the state of mouth, and the head posture, and the fatigue of the driver can be judged according to the state of different facial regions.

Vehicle driving behavior characteristic detection has the advantage of being non-contact and easy to extract signals; however, it is susceptible to influence from vehicle models, road conditions, weather, and individual driving habits, making it difficult to distinguish between normal and dangerous abnormal states [14], [15], [16].

6) YOLO Series and Object Detection

YOLO was published by Joseph Redmon *et al.* in the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2016 [18]. It presents a real-time end-to-end object detection method for the first time. YOLO's name stands for "You Only Look Once, "referring to its ability to complete detection tasks in a single pass over the network, unlike previous methods that either used sliding Windows followed by classifiers that needed to be run hundreds or thousands of times on each image, or more advanced methods that split the task into two steps. The first step detects a possible region or region proposal with an object, and the second step runs a classifier on the proposal. In addition, YOLO uses a more direct output, based only on regression to predict the detection output, rather than using two separate outputs like Fast R-CNN [19], one for the classification of probabilities and the other for the regression of bounding box coordinates [20].

In 2024, YOLOv8 was adopted and applied to various fields, including comparisons with YOLOv10 and YOLOv9. It has been utilized for tasks such as target detection in adverse weather conditions, highlighting its value in autonomous driving [21]. YOLOv8 has also demonstrated reliability in real-time detection under mixed traffic conditions [22]. Moreover, studies have explored its integration with deep belief networks for aerial vehicle detection [23], as well as simple agricultural applications such as tomato detection [24]. The versatility of YOLOv8 is reflected in its deployment across diverse domains, including driving, agriculture, surveillance, and aerial image analysis. It has also been successfully implemented on resource-limited platforms and embedded systems.

Although originally a one-stage detection framework, YOLOv8 supports multiple tasks—such as object detection, image segmentation, and tracking — thus expanding its applicability. Among its variants, YOLOv8n has outperformed more complex models in certain scenarios, such as autonomous driving, industrial inspection, and intelligent monitoring, due to its low computational cost (8.7 G FLOPs) and fast inference speed (latency of 0.99 ms). Consequently, YOLOv8n is considered one of the most versatile and portable real-time object detection models currently available.

Table I presents a performance comparison of YOLOv8n [25] with other recent lightweight detection models, including YOLOv9t [25], YOLOv10-N [25], PP-PicoDet-S, NanoDet-Plus, EfficientDet-D0, SSD-MobileNetV3-Small, YOLOX-Nano, MobileNetV3-Small, and ShuffleNetV2-1.0x.

According to the characteristics of YOLOv8 and its versatility in supporting multiple vision tasks, this study selects YOLOv8n as the baseline model for further improvement in developing the proposed fatigue driving detection system.

TABLE I. PERFORMANCE COMPARISON OF RECENT LIGHTWEIGHT MODELS [255]-[31]

Lightweight Models					
Model	***Parameters (M)***	***FLOPs (G)***	***mAPval (%)***	***Latency (ms)***	***Notes***
YOLOv8n	3.2	8.7	37.30	0.99	End-to-end detection
YOLOv9t	2.0	7.7	38.30	~1.20	End-to-end detection
YOLOv10-N	6.7	6.7	38.50	1.84	End-to-end detection
PP-PicoDet-S	2.1	4.0	34.60	1.12	End-to-end detection
NanoDet-Plus	1.8	2.6	32.50	1.05	End-to-end detection
EfficientDet-D0	3.9	2.5	33.80	2.60	End-to-end detection
SSD-MobileNetV3-Small	5.0	2.2	25.10	3.10	MobileNetV3 backbone
YOLOX-Nano	0.91	1.08	25.80	1.45	End-to-end detection
MobileNetV3-Small	2.9	0.22	–	–	Classification backbone
ShuffleNetV2-1.0x	2.3	0.15	–	–	Classification backbone

According to the characteristics of YOLOv8and the versatility it supports (such as target detection, segmentation, and tracking), this research chooses to improveYOLOv8for the fatigue driving detection system.

III. METHODOLOGY

Fig. 2 shows the overall framework of the experiment. This study mainly focuses on the YOLOv8 improvement project. The experiment was divided into five phases.

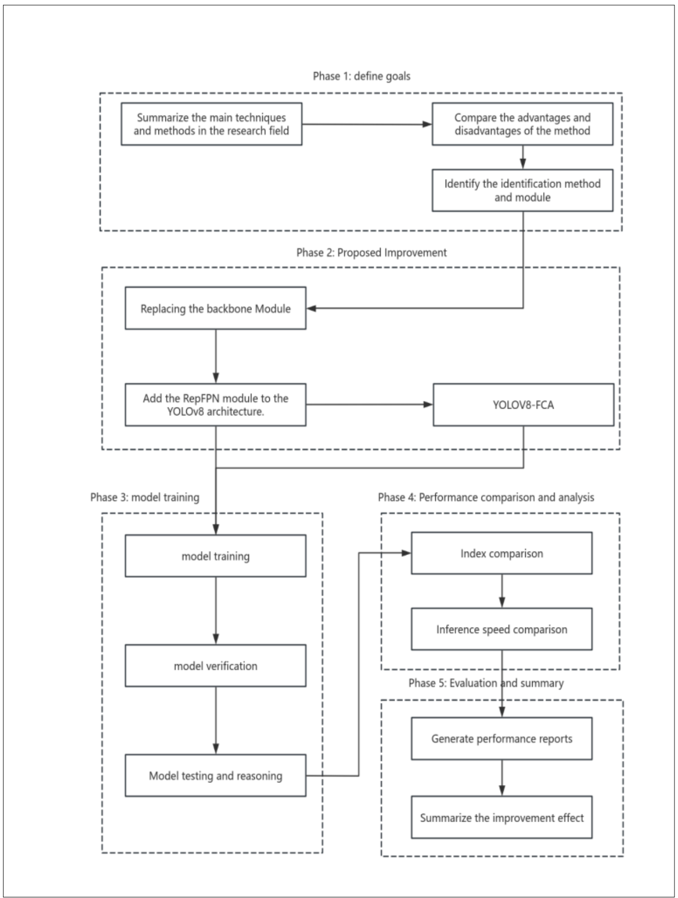

Fig. 2. Research Framework

In Phase 1: Define Goals, according to the existing literature on fatigue driving, the gaps in the current research were understood, and the research objectives were determined. Phase 2: Proposed Improvement involves analyzing the network structure of YOLOv8, replacing the backbone module, and incorporating the RepFPN module into the YOLOv8 architecture to create an improved model named YOLOv8-FCA. Phase 3: Model Training consists of training the model, verifying its accuracy, and conducting model testing and reasoning to ensure its performance. In Phase 4: Performance Comparison and Analysis, the model's performance is evaluated through index comparison and inference speed comparison. Finally, Phase 5: Evaluation and Summary involves generating performance reports and summarizing the effects of the proposed improvements.

The following is the research framework, which consists of 5 phases.

A. Phase 1: Define Goals

According to the review in Section II, the current study focuses on two methods for detecting fatigue: contact-based and non-contact-based. Contact-based methods include EEG, EMG, and ECG, while non-contact methods primarily involve facial and behavioral. Due to the high cost and discomfort associated with EEG and EMG, as well as the individual differences in ECG and behavioral data, facial recognition is identified as a more practical and effective approach for this study.

Compared with YOLOv10 and YOLOv9 in 2024, YOLOv8 has been widely used in areas such as autonomous driving. AlthoughYOLOv8n has slightly lower mAP compared to YOLOv9, it achieves a better balance between low latency and computational efficiency. This makes YOLOv8n an ideal choice for scenarios requiring real-time performance and resource-constrained deployment.

B. Phase 2: Proposed Improvement

We introduce the Re-parameterized Feature Pyramid Network (RepFPN) and Convolutional Block Attention Module (CBAM) to enhance the detection accuracy and feature extraction capabilities of the YOLOv8 model. RepFPN improves the representation of multi-scale features by repeatedly fusing pyramidal information, while CBAM refines the model’s focus on important spatial and channel-wise regions, particularly useful for detecting subtle signs of driver fatigue. These enhancements are particularly beneficial in detecting subtle fatigue-related features such as eye closure and yawning.

1) Analyze the network structure framework of YOLOv8

The YOLOv8 has been iterated over several generations, building on the advantages of its predecessor while introducing significant enhancements in speed, accuracy, and flexibility. The network structure of YOLOv8 can be roughly analyzed by referring to Fig. 3.

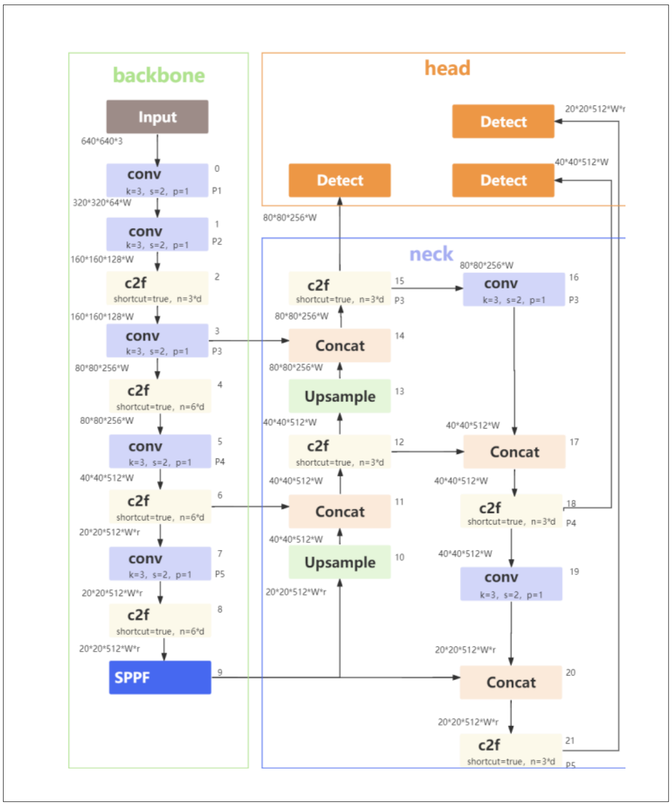

Fig. 3. YOLOv8 network structure diagram

2) Replacing the Backbone Module

MobileNetV4 is the latest architectural design in the MobileNet family, focused on delivering efficient computing performance for mobile devices. It combines innovative module design and optimization techniques to reduce latency and computational costs while maintaining high accuracy significantly. Fig. 4 illustrates the overall network structure of MobileNetV4, detailing its layer composition, module arrangement, and data flow, which together enable high-performance inference under resource-constrained environments.

Primarily for mobile, at its core, Danfeng Qin *et al*. introduce the Universal Inverted Bottleneck (UIB) search block[1], a unified and flexible structure that incorporates Inverted Bottleneck (IB), ConvNext, Feedforward networking (FFN), and a new Extra depth(Rendition) variant. In addition to the UIB, we also introduced the Mobile MQA, an attention block specifically tailored for mobile accelerators that significantly improves speed by 39%.

An optimized neural structure search (NAS) formula is introduced to improve the search efficiency of MNv4. The integration of UIB, Mobile MQA, and refined NAS formulations has resulted in a new set of MNv4 models that are mostly optimal on mobile CPUs, DSPS, GPUs, and dedicated accelerators such as the Apple Neural Engine and Google Pixel EdgeTPU. This is a feature not found in any other model tests.

Finally, in order to further improve the accuracy, we introduce a new distillation technique. With this technology enhancement, our MNv4-Hybrid-Large model delivers 87% ImageNet-1K accuracy, and the Pixel 8 EdgeTPU runs at just 3.8ms.

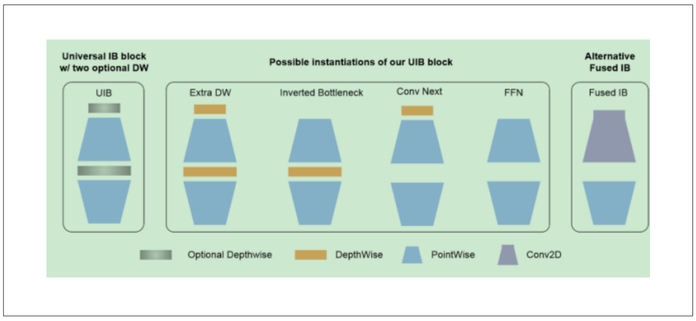

Fig. 4. The MobileNetV4 model [1]

3) Fine-tuning Model Architecture

By introducing RepFPN (Repetitive Feature Pyramid Network) and CBAM (Attention Mechanism Module), YOLOv8 can effectively improve the performance of the fatigue driver recognition system, especially in challenging conditions such as low light or low camera pixel quality. Here is a further explanation of these improvements:

RepFPN is an improved feature pyramid network that enhances the fusion and delivery of features by reusing the feature pyramid structure in the network.

This design helps the model capture and understand the image content at different scales, especially for the recognition of details, which is crucial for tired driving recognition.

Through repeated feature fusion, RepFPN can improve the feature expression ability, so that the model can maintain a high recognition accuracy even when processing low-resolution images, as shown in Fig. 5. The neck changed the way of sampling and feature processing modules.

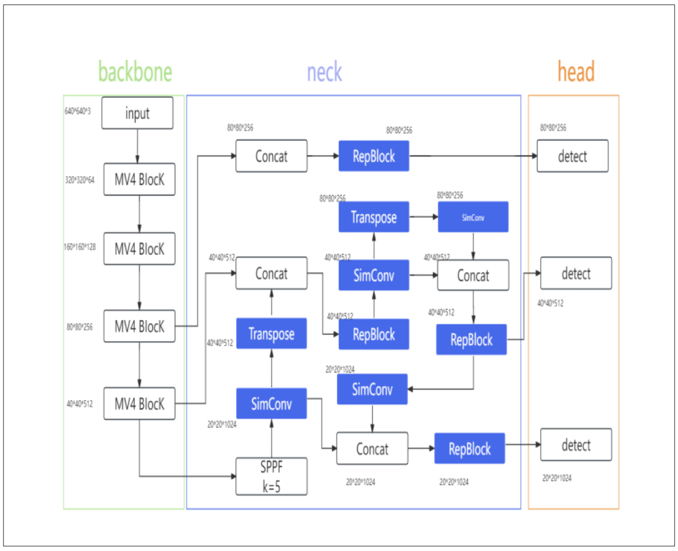

Fig. 5 Proposed YOLOv8-RepFPN network diagram

CBAM is an effective attention mechanism that enhances the model's attention to important features through two submodules: channel attention and spatial attention.

The channel attention mechanism helps the model identify which channels (features) are important, while the spatial attention mechanism focuses on key areas in the image.

In the recognition of tired driving, CBAM can help the model pay more attention to the driver's facial features, such as eye closure, yawning, etc., which are the key to judging the fatigue state.

Combined with these technologies, the YOLOv8 model can more effectively handle fatigue driver recognition tasks, especially in complex environments. This multimodal approach not only improves the accuracy of recognition but also enhances the robustness of the system. As shown in Fig. 6, in addition, a CBAM module is added before the neck output 80x80 size feature map so that small target recognition is increased.

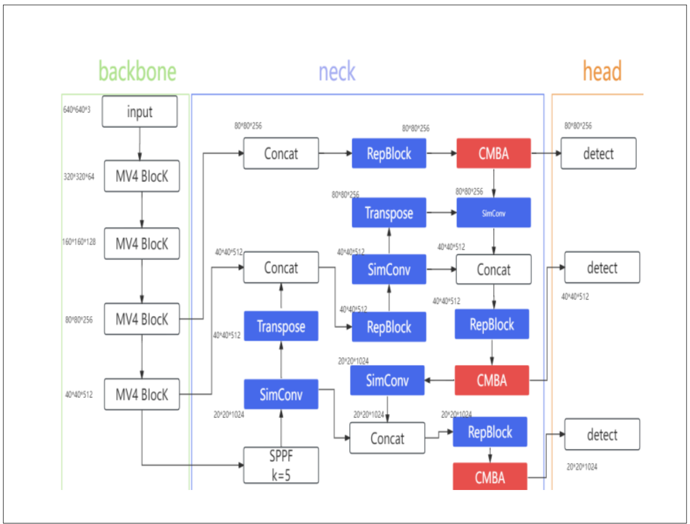

Fig. 5. Proposed improved YOLOv8-FCA network diagram

C. Phase 3:Model Training

The goal of this study is to achieve a significant performance improvement by optimizing the YOLOv8 model. In order to objectively evaluate the actual effect of these improvements, we will conduct a detailed comparative analysis of the performance of the improved model and the original model. In this chapter, we will delve into the training process of the original YOLOv8 model 、 YOLOv8-RepFPN model, and YOLOv8-FCA model, focusing on key links such as data preparation, model configuration, and training process.

D. Phase 4: Performance Comparison and Analysis

The objective of this work was to estimate and compare the efficiency of the changes prior to and after the optimization step and the overall performance of the improved version against the base YOLOv8 model. In this way, the improvement of the model shall be well understood in terms of the accuracy rate and reasoning speed of comparisons. In this study, three models were compared: YOLOv8, YOLOv8-RepFPN, and YOLOv8-FCA.

E. Phase 5:Evaluation and Summary

The last stage of the research work is aimed at assessing the effectiveness of both the basic and YOLOv8 enhanced versions. The following evaluation seeks to present a quantitative analysis of the optimization process in order to determine the efficiency of the changes made during the optimization process. The results are then summarized in order to demonstrate the improvement of the overall performance of the model.

IV. EXPERIMENTATION AND RESULT ANALYSIS

A. Data Sets and Preprocessing

First of all, the significant difference in the number of samples of different categories in the dataset leads to the deterioration of the model's detection performance for a few categories. Therefore, all classifications of the average data set are adopted to avoid the problem of data imbalance. In order to further improve the generalization ability of the model, the multi-stage training strategy can be adopted to divide the dataset according to different classifications and gradually increase the classification difficulty. The model's performance is systematically evaluated under progressively increasing classification difficulty levels. For example, start with a simple classification task and gradually introduce more complex scenarios or categories to see if the performance of the model is stable.

Fig. 6 shows an example of Driver Fatigue Detection Classification, TABLE II, TABLE III, and TABLE IV are the classification of each group data distribution.

Fig. 6. Driver Fatigue Detection Classification

TABLE II. THE FIRST GROUP DATASET DISTRIBUTION SUMMARY

The first set of data			
classification	*train*	*val*	*test*
'focused'	400	40	30
eyes_closed'	400	40	30
'yawning'	400	40	30
'head_up'	400	40	30
'head_down'	400	40	30
total	2000	200	150

TABLE III. THE SECOND GROUP DATASET DISTRIBUTION SUMMARY

The second set of data			
classification	*train*	*val*	*test*
'focused'	400	40	30
eyes_closed'	400	40	30
'yawning'	400	40	30
'head_up'	400	40	30
'head_down'	400	40	30
'seeing_left'	400	40	30
'seeing_right'	400	40	30
total	2800	280	210

TABLE IV. THE THIRD GROUP DATASET DISTRIBUTION SUMMARY

The third data set			
classification	*train*	*val*	*test*
'focused'	400	40	30
eyes_closed'	400	40	30
'yawning'	400	40	30
'head_up'	400	40	30
'head_down'	400	40	30
'seeing_left'	400	40	30
'seeing_right'	400	40	30
eyes_closed_head_right	400	40	30
eyes_closed_head_left	400	40	30
total	3600	360	270

B. Experimental Results and Analysis

Since the YOLOv8-FCA model in this study needs to be deployed in resource-constrained embedded devices, the selection of performance indicators is mainly based on two core requirements of the fatigue driving detection system: real-time (resource consumption) and detection accuracy. Specifically, we chose GFLOPs (computational complexity) and All_mAP50-95 (average accuracy) as the primary evaluation indicators.

1) Computation (GFLOPs)

Based on the experimental GFLOPs comparison chart, it is evident that the improved YOLOv8 significantly reduces computational cost, even lower than the lightweight versions of YOLOv9 and YOLOv10. This reduction in computational demand makes it more suitable for resource-constrained tasks, further demonstrating its effectiveness for deployment in limited environments such as mobile devices. Fig. 7 shows a comparison of the YOLOv8 and GFLOPs of the improved model.

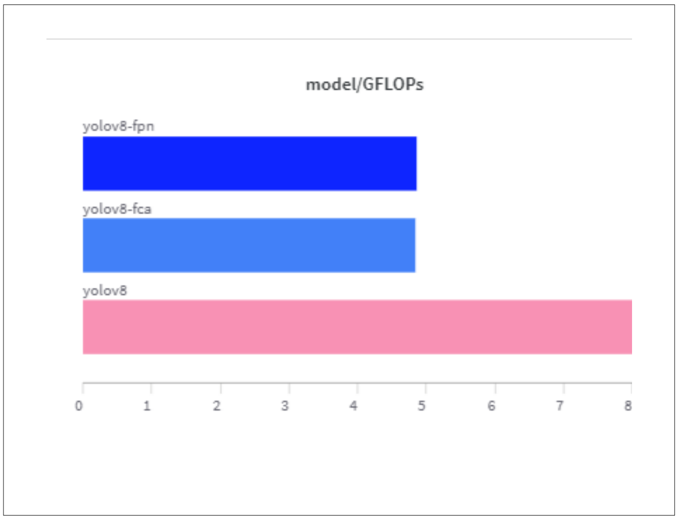

Fig. 7. Computation (GFLOPs)

2) Average Accuracy

The results show that while the improved YOLOv8 RepFPN has the lowest computational cost, YOLOv8-FCA (RepFPN and CBAM) achieves the highest accuracy without significantly increasing the computational load, effectively balancing accuracy and computational efficiency. This makes it well-suited for resource-limited environments such as mobile or embedded systems.

In Tables V, VI, and VII, we compare the model performance across three groups of classification tasks using the All_mAP50–95 metric, where a higher value indicates better detection accuracy.

In the first group, YOLOv8-FCA achieves the highest performance with an mAP50–95 of 0.907, outperforming both the baseline YOLOv8 (0.898) and YOLOv8-RepFPN (0.895). This demonstrates the effectiveness of integrating both RepFPN and CBAM modules when dealing with simpler classification tasks.

TABLE V. ACCURACY COMPARISON FOR THE FIRST GROUP (HIGHER IS BETTER)

The first group	
Model	***All_mAP50-95***
YOLOv8	0.898
YOLOv8_RepFPN	0.895
YOLOv8-FCA	0.907

In the second group, which introduces additional fatigue categories and increases the classification complexity, the baseline YOLOv8 achieves the highest mAP (0.932), followed by YOLOv8-FCA (0.927) and YOLOv8-RepFPN (0.917). Although YOLOv8 still leads slightly, the gap narrows, suggesting that the improved models retain competitive performance in more complex scenarios.

TABLE VI. ACCURACY COMPARISON FOR THE SECOND GROUP (HIGHER IS BETTER)

The second group	
Model	*All_mAP50-95*
YOLOv8	0.932
YOLOv8_RepFPN	0.917
YOLOv8-FCA	0.927

In the third group, which contains the most diverse and challenging classification tasks, YOLOv8 again shows the best accuracy (0.937), while YOLOv8-FCA achieves 0.924 and YOLOv8-RepFPN scores 0.914. This result suggests that while the enhanced models can still generalize well, their relative advantage may be more prominent in simpler settings. At the same time, the original YOLOv8 benefits from fewer added architectural complexities in highly challenging tasks.

TABLE VII. ACCURACY COMPARISON FOR THE THIRD GROUP (HIGHER IS BETTER)

The third group	
Model	*mAP50-95*
YOLOv8	0.937
YOLOv8_RepFPN	0.914
YOLOv8-FCA	0.924

V. CONCLUSION

By combining the Rep-FPN and CBAM modules, significant improvements in detection accuracy (mAP50 and mAP50-95), reasoning speed, and computational efficiency are achieved. The proposed YOLOv8-FCA model shows robustness on different data sets and outperforms the baseline model in both accuracy and recall rates. While the recognition accuracy is improved, the model complexity (GFLOPs) is still reduced by 40.73%. These results verify the effectiveness of the proposed improved method and its potential application in practical fatigue detection systems.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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