Deck officer drowsiness detection based on Improved GhostNet-SSD and grey correlation analysis

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Abstract. Deck officer drowsy driving has become a major cause of shipping accidents, while traditional drowsiness detection methods have struggled to cope with the complex detection environment of a ship's cockpit. In this paper, we propose a deck officer drowsiness detection method based on the improved GhostNet-SSD.A multi-scale feature extraction network is constructed on the basis of lightweight GhostNet to generate redundant feature maps by depthwise separable convolutions. Extracting features of small targets at multiple scales facilitates that the model can be deployed on shipboard low-performance devices and enhances the detection accuracy of the model at the same time. In the inference stage, an improved soft-NMS algorithm is proposed to optimize the process of removing overlapping prior bounding box, reduce the miss rate of overlapping targets, and boost the detection speed of the model.

Keywords: Drowsiness detection; GhostNet, Grey correlationanalysis; Single Shot MultiBox Detector (SSD); Non-Maximum Suppression (NMS).

1. Introduction

In the past decades, shipping has been an important logistics access for the world. However, frequent transportation has also led to many marine incident, the main cause of which is crew drowsiness[1]. Drowsiness driving is a safety issue, and it is also the main cause of the accident. According to the report of European Marine Incident Information Platform (EMCIP), there are at least 4,000 marine casualties per year on average, causing huge economic losses and serious human casualties.

Tthis paper newly proposes to build a lightweight multi-scale object detection network. We uses a lightweight backbone network to reduce the size of the network and lower the performance requirements of the hardware. At the same time, it extracts the features of the deck officer’s eyes and mouth at multiple scale to improve the accuracy of object detection and further reduce the miss rate. Considering the complex environment of drowsiness detection on board, an improved soft-NMS algorithm is used, thus significantly reducing the miss rate of overlapping targets. Meanwhile, the detection rate is further improved so as to meet the requirements of real-time drowsiness detection on board. At the step of drowsiness state discrimination, grey correlation analysis is innovatively used to adjust the threshold value adaptively for different detection environments, achieving a high drowsiness detection accuracy under various conditions.

2. Related Work

It is likely that drowsy driving brings great risks and hidden dangers to the transportation industry. Hongzhe et al. detected the driver's state during accidents by means of face detection and eyes location, confirming that drowsy driving could lead to major traffic accidents[2]. Borghini et al. further conducted a safety assessment for the transportation industry, and proposed that drowsiness is an important factor affecting safety assessment[3]. Many scholars have conducted profound researches on drowsy driving warning strategies to avoid casualties and property loss caused by drowsy driving, which further ensures transportation safety.

However, human fatigue is a very complex physiological mechanism. No absolute criterion has been found for fatigue, so there is no optimum warning strategy for drowsy driving [4]. Sagila et al. proposed using wearable EEG devices for drowsiness detection of drivers, extracting information features in EEG signals, and then differentiating fatigue from wakefulness by information features[5]. Perrier et al. proposed using driving performance indexes to discriminate fatigue state, analyzing statistically the steering wheel rotation status, vehicle braking status, etc., and thus assessing the driver's drowsiness level[6]. Wang et al. proposed using the driver's facial information to discriminate the fatigue state by tracking and recognizing the driver's facial image through the camera, so as to extract the eye feature information and discriminate the fatigue state[7]. However, the first two schemes cannot achieve good expected results in the ship environment. The detection scheme based on physiological signals requires sophisticated detection equipment, which is difficult to adapt to the environment of larger noise and hull vibration. At the same time, the behavior of detecting physiological signals such as EEG is invasive and difficult to be accepted psychologically by the deck officers[8]. The detection scheme based on navigation performance index can capture performance data based on ship condition monitoring system, but the accuracy of drowsiness discrimination is low due to the influence of deck officers and navigation environment.

Since only part of the feature information presented in the fatigue state could be captured and extracted for quantitative analysis, many current studies of drowsiness detection based on facial features focus on analyzing the feature information of eyes or mouth[9]. Abdelmalik et al. set the features corresponding to the fatigue state as continuous and rapid blinking and frequent yawning. Detects the driver's fatigue level by tracking and monitoring the driver's facial information[10]. Choi et al. developed a feature gaze zone detection algorithm based on convolutional neural networks to detect driver fatigue state with SVM by identifying feature information such as blinking or frequent yawning. Recently, Caio et al. proposed a model based on ML to accurately identify the early features of fatigue by comparing the aspect ratio of the eyes and then applied the model based on ML to process and classify the user state in real-time. However, it is still challenging to carry out drowsiness detection on ships for deck officers. On the one hand, it is difficult for ships to carry larger scale drowsiness detection models due to the scarcity of high-performance hardware equipment. On the other hand, since the ship's cockpit space is much larger than that of a car, and the cockpit background is more complex, it is difficult to obtain feature information of small targets under low-performance equipment conditions, thus it is hard to detect the fatigue state of deck officers accurately.

3. Improved GhostNet-SSD network

3.1. Lightweight Backbone Network

In the practical application scenario of drowsiness detection, due to the lack of high-performance hardware resources, in order to reduce the scale of the network model used for object detection, the whole network model is considered to be lightweight and improved, thereby lowering requirement for hardware of the object detection network. A lightweight backbone network replaces the backbone feature extraction network, which realizes the lightweight of the network structure, improving the detection rate, and further reducing the performance requirements for hardware.

GhostNet is an efficient and lightweight network, it adopts the structure of lightweight CNN. Therefore, it has outstanding performance in terms of computer performance and memory footprint. Compared with other lightweight network structures, GhostNet has better overall performance in accuracy and computational complexity, so GhostNet is selected to improve the network structure. GhostNet uses MobileNetV3 as the reference network structure and uses Ghost Bottlenecks as the basic block of the network structure.

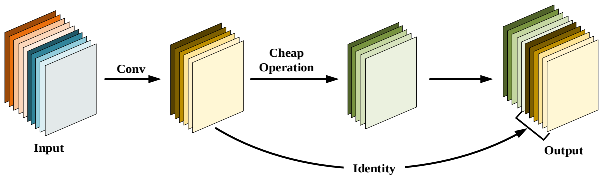

Fig. 1 Ghost module structure

Ghost module structure is shown in Fig. 1, the Ghost module is the core of GhostNet. The Ghost module first uses convolutional layer to generate part of the feature maps, then increases the number of channels with the help of depthwise separable convolutions, and finally merges the feature maps generated by both methods into the output feature map.The use of Ghost modules greatly reduces the total parameters of the whole network, thus significantly reducing the calculation cost, while maintaining the network performance, and helping to adjust and deploy the network on low-performance hardware.

3.2. Multi-scale object detection network based on GhostNet-SSD

For drowsiness detection of deck officers, it is necessary to locate and classify the eyes and mouths of deck officers at first. The background of the ship cockpit is complex, while the size of the eyes and mouth is smaller and have less feature information, which may lead to missed detection of the eyes and mouth. Hence, we consider extracting eye and mouth features at different scales to improve the accuracy of object detection as well as to further reduce the rate of missed detection.

SSD network is a feedforward multi-scale feature extraction network, which can extract features from the feature layers generated by the backbone network at different scales. Compared with other single-level object detection networks, the SSD object detection network has a better overall advantage in detection speed and accuracy, so SSD is chosen as the back-end multi-scale feature extraction network for drowsiness detection.

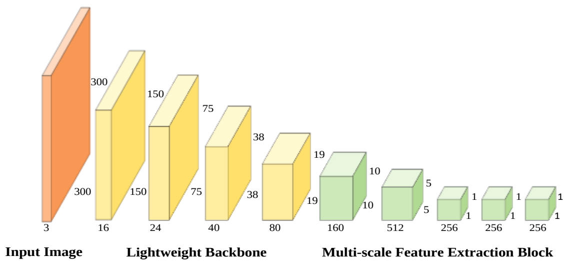

Fig. 2 GhostNet-SSD Network Structure Diagram

The constructed GhostNet-SSD network structure is shown in Fig. 2. On the one hand, a lightweight GhostNet-SSD network is used to replace the backbone network in SSD, reducing the overall network scale. On the other hand, a feature extraction network at the back end of SSD is used to dig small object feature information from multiple scales so as to achieve accurate positioning of the deck officer's eyes and mouth. The combined GhostNet-SSD network can meet the demands of drowsiness detection for real-time and accuracy, along with further enhancement of feature extraction capability for small objects and further reduction of hardware performance requirements.

3.3. Improved soft-NMS algorithm

In deck officer drowsiness detection, the conventional NMS algorithm may miss the overlapping objects when the cockpit crew gather or turn sideways. Therefore, the improved soft-NMS algorithm is adopted. Both differ in the treatment of prior bounding box having high overlap; the NMS algorithm directly removes the detection frames with higher overlap, while soft-NMS reduces the classification confidence score of the overlapping detection frames. A drowsiness detection using the soft-NMS algorithm can significantly decrease the miss rate and improve the mAP. In addition, the soft-NMS algorithm has to be improved to further raise the detection rate since the drowsiness of the driver's cab personnel needs to be monitored in real-time.

$$S_i = \begin{cases} S_i, & iou(M,b_i) < N_t \\ S_i(1-iou(M,b_i)), & N_t \le iou(M,b_i) < N_t^{'} \\ 0, & iou(M,b_i) \ge N_t^{'} \end{cases} \tag{1}$$

The improved soft-NMS algorithm directly removes the detection frames with excessive overlap, while the classification confidence score reduction method is applied to the detection frames with high overlap but not reaching the threshold $N_t^{'}$. It can promote the detection rate further and ensure real-time drowsiness detection while lowering the rate of missed detection.

4. Comprehensive drowsiness evaluation model

During detection, the real-time state information of the eyes and mouth is firstly captured based on the object detection network, followed by comprehensive discrimination of the drowsiness state based on the real-time state information. Aiming to further improve the accuracy of judging the drowsiness state, a drowsiness evaluation model based on multiple indexes is considered, whilst considering an adaptive drowsiness discrimination algorithm based on gray correlation analysis in order to improve the robustness of the drowsiness discrimination model under different conditions.

4.1. Selection of drowsiness index

In case of drowsiness, the ship's pilot usually experiences physiological changes, such as prolonged eye closure, reduced blink frequency, yawning, etc. Given the physiological phenomena that emerged during drowsiness, PERCLOS value P , blink frequency f_{blink} and yawn frequency f_{yawn} were taken as the evaluation indexes of drowsiness.

Suppose that during a period of time t_0, the GhostNet-SSD network detects n_0 frames of the video stream, E_k is the index variable characterizing the eye opening and closing information of the kth frame image, and M_k is the index variable characterizing the mouth opening and closing information of the kth frame image. Table 1 Comparison table of indicated variable value and state information is shown in Table 1.

Table 1 Comparison Table of Indicated Variable Value and State Information

indicator variable	variable value	State information
E_k	0	Eyes open
	1	Eyes closed
M_k	0	Mouth open
	1	Mouth closed

4.1.1. Perclos

PERCLOS is the ratio of eye closure time to total time over a period of time, which can measure the drowsiness level of deck officers to some extent. There is a positive correlation between PERCLOS and the fatigue degree of deck officers during ship driving[20]. For video streams in t_0, the sum of frames with eye closure is expressed as the eye closure time, and the total number of frames in t_0 time is expressed as the total time, so the ratio of the sum of frames with eye closure to the total number of frames in t_0 approximates the PERCLOS value.

$$P = \frac{\sum_{k=1}^{n_0} (E_k \wedge 1)}{n_0} \tag{2}$$

4.1.2. Blinking frequency

Initially, we analyze the real-time state information of the deck officer's eyes in the video stream to determine whether the driver is blinking or not. Each time a blink is performed, the eye state changes from open to closed and then from closed to open, so the change in the E_k value from 0 to 1 is recorded as one blink.

Based on the analysis of single blink actions, blink frequency is further calculated. The blink frequency is the number of blinks per unit time and fatigue will lead to an increase in blinks per minute during driving. So for live video streams within t_0, the blink frequency is approximated by the sum of the blink counts to the t_0 ratio.

$$f_{blink} = \frac{\sum_{k=1}^{n_0 - 1} ((E_k \wedge 0) \wedge (E_{k+1} \wedge 1))}{t_0} \tag{3}$$

4.1.3. Yawning frequency

In the state of fatigue, the frequency of yawning will increase significantly, so yawning frequency is selected as an index to evaluate the fatigue degree of deck officers. The process of mouth state change in yawning is similar to the process of eye state change in blinking action, so the calculation method that resembles blink frequency is used to approximate the yawning frequency.

$$f_{yawn} = \frac{\sum_{k=1}^{n_0 - 1} ((M_k \wedge 0) \wedge (M_{k+1} \wedge 1))}{t_0} \tag{4}$$

4.2. Drowsiness discrimination based on grey correlation analysis

Different drivers have different eye and mouth states in drowsiness state, besides, they are prone to encounter situations such as strong sunlight, gale at sea and heavy rain at sea during the voyage, etc. Stronger light, gale, and rain will make drivers show abnormal eye and mouth states, for example, deck officers blink more frequently and the percentage of eye closing time rises in the waking state, which will easily cause misjudgment of drowsiness state.

4.2.1. Data preprocessing

It is necessary to analyze the opening and closing state of the eyes and mouth of each frame when processing the real-time video stream and obtain the m drowsiness indexes corresponding to each frame. Assuming to judge the drowsiness state at the moment of t_{now}, t_{past} is a certain moment before t_{now}, the drowsiness indexes of n frames are analyzed and available during this period, and the drowsiness indexes are listed in a drowsiness matrix $Z^{'}$ of $m \times n$.

$$(Z_1^{'}, Z_2^{'}, \cdots, Z_n^{'}) = \begin{pmatrix} z_1^{'}(1) & z_2^{'}(1) & \cdots & z_n^{'}(1) \\ z_1^{'}(2) & z_2^{'}(2) & \cdots & z_n^{'}(2) \\ \vdots & \vdots & \vdots & \vdots \\ z_1^{'}(m) & z_2^{'}(m) & \cdots & z_n^{'}(m) \end{pmatrix} \tag{5}$$

In the comprehensive evaluation of drowsiness indexes, due to the inconsistency of drowsiness indexes, which will affect the final drowsiness detection results. it is recommended to standardize the drowsiness indexes so that the different drowsiness indexes of deck officers are comparable.

Since the values of indexes P, f_{blink} and f_{yawn} are positively correlated with the degree of deck officer drowsiness, the larger the index value of matrix $Z^{'}$, the more tired the driver is. Thus directly standardizing the index data of matrix $Z^{'}$. After standardization, each element of the generated matrix Z follows a distribution with a mean of 0 and a standard deviation of 1. The normalization formula is as follows.

$$z_i(k) = \frac{z_i^{'}(k) - \mu_i}{\sigma_i} \tag{6}$$

μ_i, σ_i are the mean and standard deviation of the elements in column i of matrix $Z^{'}$, respectively.

4.2.2. Drowsiness evaluation algorithm based on grey correlation analysis

The gray correlation analysis can analyze the geometry of the corresponding curves of the index sequences, and judge the degree of correlation between the sequences from the similarity of the curve shapes. When analyzing the drowsiness index data of drivers, the gray correlation analysis method can access the degree of correlation between the drowsiness state to be discriminated and the reference drowsiness state, thus calculate the evaluation score, so that the drowsiness state can be accurately discriminated.

In this paper, we adopt gray correlation analysis to calculate the drowsiness state score sequence, and the specific steps of the algorithm are as follows.

(1)Reference drowsiness index sequence

After data pre-processing, the maximum value of the row is taken out from each row of matrix Z respectively as the reference drowsiness index sequence Z_0, which can reflect the drowsiness characteristics of deck officers and provide a reference index sequence for the subsequent drowsiness discrimination.

$$Z_0 = (z_0(1), z_0(2), \cdots, z_0(m)) \tag{7}$$

(2)Drowsiness correlation coefficient

The following equation is used to calculate the correlation coefficients of the corresponding drowsiness index sequences for each frame separately according to the reference drowsiness index sequences.

$$\zeta(k) = \frac{\min\limits_i \min\limits_k \left| z_0(k) - z_i(k) \right| + \beta \bullet \max\limits_i \max\limits_k \left| z_0(k) - z_i(k) \right|}{\left| z_0(k) - z_i(k) \right| + \beta \bullet \max\limits_i \max\limits_k \left| z_0(k) - z_i(k) \right|} \tag{8}$$

(3)Drowsiness degree scoring sequence

For the reference drowsiness index sequence, calculate the mean value of the corresponding correlation coefficient sequence for each frame of the images separately. Thus, we obtain the degree of correlation between the drowsiness state of the ship driver and the reference drowsiness state at each moment, and consequently obtain the drowsiness score sequence D. D_k represents the driver drowsiness degree score corresponding to the kth frame of the images.

$$D = (D_1, D_2, \cdots, D_n)$$
$$D_i = \frac{\sum\limits_{k=1}^{n} \zeta_i(k)}{m} \tag{9}$$

It can judge the degree of association between the current drowsiness state and the reference drowsiness state by using the gray correlation analysis, calculating the current drowsiness state score, and finally obtaining the drowsiness score sequence.

4.2.3. Drowsiness state discrimination

The drowsiness state score at the moment of t_{now} was recorded as D_{now}, combining the drowsiness degree scoring sequence derived from the gray correlation analysis method with the drowsiness index threshold for drowsiness detection.

(1)Adaptive drowsiness discrimination algorithm based on drowsiness degree scoring sequence

The drowsiness degree scoring sequence reflects the level of drowsiness over a period of time in the current environment. If D_{now} suddenly increases and deviates obviously from the mean value of the drowsiness degree scoring sequence, it indicates that the driver is in a likely state of wakefulness to drowsiness at that moment, so the relative relationship between D_{now} and the drowsiness degree scoring sequence is considered in the drowsiness state detectiontion.

The data distribution of the drowsiness degree scoring sequence D is approximately normal distribution, and statistically, around 99.7% of the data values will be within three standard deviations of the mean, so if the difference between D_{now} and the mean is more than three times the standard deviation, D_{now} is judged to be an outlier. In this case, D_{now} may be either too large or too small, but the driver is drowsinessd only when D_{now} is too large, so if D_{now} is greater than the mean at moment t_{now} and the difference between D_{now} and the mean is more than 3 times the standard deviation, the driver is determined to be drowsinessd at that moment.

With respect to the drowsiness discrimination of different driving crowds under different navigation environments, the adaptive drowsiness discrimination algorithm can dynamically adjust the discrimination criteria according to the drowsiness discrimination environment. For example, the threshold value for detecting drowsiness will be appropriately increased under the strong light environment to prevent the misjudgment of the drowsiness state, thus further improving the precision rate of the drowsiness discrimination algorithm in the complex environment.

(2)drowsiness state discrimination algorithm based on threshold value

The adaptive drowsiness discrimination algorithm is based on the drowsiness degree scoring sequence, and it depends on the historical data to give the relative discrimination of drowsiness degree. Thus, if all moments corresponding to the drowsiness degree sequence are drowsy, then it is impossible to give a correct determination of the drowsiness state at moment t_{now}. This is why we need to further improve the drowsiness determination algorithm to improve the accuracy of drowsiness status determination.

After a large number of experiments, take the average value of drowsiness degree at the moment of multiple drowsinesss as the threshold of drowsiness determination, and record the threshold of drowsiness determination as D_0. If it exceeds the drowsiness degree threshold D_0, the driver is judged to be drowsinessd at that moment.

(3)Comprehensive drowsiness state discrimination model

The above two drowsiness modes are considered for drowsiness discrimination. If one of the criteria is fulfilled, the driver is judged to be under drowsiness at that moment. The integrated drowsiness discrimination model has a strong robustness to discriminate the drowsiness state of different drivers in different navigation environments and has high accuracy in drowsiness determination.

5. Experimental environment and result analysis

5.1. Experimental setup

This experiment was carried out under Ubuntu 18.04 version, the CPU is Xeon E5-2678 v3, the GPU is NVIDIA RTX 2080 TI. The software platform is PyCharm and the deep learning frame is Pytorch 1.6.0. When training the target detection network, Table 2 shows the set training parameters.

Table 2 Specific Parameters Of Network Training

parameter name	parameter value
epochs	400
Batch-size	10
Momentum	0.9
Decay	0.0005
Learning_rate	0.0001

5.2. Dataset

At present, there are many open image datasets of fatigue driving of automobiles, but there is no public data set of fatigue driving of deck officers. Therefore, it is necessary to establish fatigue facial dataset of deck officers. Fatigue data can be collected by crawling images on the network, taking videos in the ship cockpit, and collecting related ship fatigue driving videos. The self-established fatigue driving dataset includes image data of the conscious and fatigue state of deck officers. The fatigue dataset is divided into 7:1:2 ratio and used as training, validation and testing for drowsiness detection.

5.3. Performance evaluation

Two algorithms are used to detect the eyes and mouth of deck officers respectively. The mean Average Precision and parameters of the algorithm are shown in Table3. From Table3, the accuracy of GhostNet-SSD in detecting mouth opening and mouth closing is slightly higher than that of MobileNetV3-SSD, but the accuracy in detecting eye opening and closing is slightly lower. The mAP of GhostNet-SSD algorithm is 92.61%, which is a slight improvement compared to MobileNetV3. Moreover, GhostNet-SSD algorithm has fewer parameters than MobileNetV3, which makes the network scale lighter, so it has better compatibility with low-performance devices. Therefore, the GhostNet-SSD algorithm has a better overall performance than similar lightweight object detection networks when detecting the eyes and mouths of deck officers.

To meet the requirement of real-time drowsiness detection and improve the detection speed for the eyes and mouths of deck officers, we further propose the improved GhostNet-SSD.

The mAP of the three object detection networks are basically identical. After replacing GhostNet with the backbone network, the calculation and model size of the network are reduced. Improved GhostNet-SSD reduces the detection time on CPU and GPU to a certain extent, increases the detection speed of object detection network, and enables faster deck officers' drowsiness detection on low-performance devices, after improving the soft-NMS algorithm of GhostNet-SSD.

As shown in Fig. 3, eight testers were selected to take videos of drowsy driving, in which the testers would continuously repeat the process of state transition from awake to fatigue, and 1000 frames of fatigue state pictures were extracted from each video as test samples. Detecting the facial fatigue features of testers based on imporoved GhostNet-SSD and MobileNetV3-SSD respectively, discriminating the fatigue state using the traditional fixed threshold drowsiness discrimination algorithm and the adaptive threshold drowsiness discrimination algorithm in this paper, and calculating the accuracy rate of fatigue state discrimination.

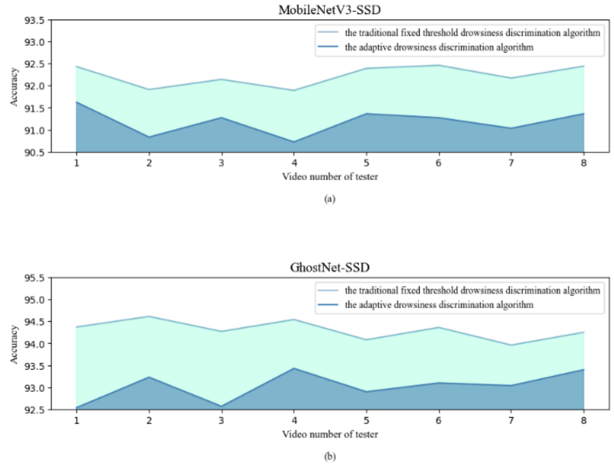

Fig. 3 Comparison between traditional fixed threshold drowsiness discrimination algorithm and adaptive threshold drowsiness discrimination algorithm in deck officers' drowsiness detection performance

After detecting facial fatigue features based on two object detection algorithms, it is concluded that using the adaptive threshold drowsiness discrimination algorithm in this paper has a slightly higher accuracy rate compared to the traditional fixed threshold drowsiness discrimination algorithm. This is due to the adaptive threshold drowsiness discrimination algorithm in this paper that can change the threshold value dynamically according to the change of the detection environment, thus reducing the miss rate and ultimately improving the accuracy rate of drowsiness detection.

6. Conclusion

In this paper, we propose a deck officer drowsiness detection methods based on the improved GhostNet-SSD. Building a multi-scale feature extraction network， which is based on the lightweight GhostNet, has reduced the hardware performance requirements of the object detection network, allowing the model to be deployed on shipboard low-performance devices. The improved soft-NMS algorithm is adopted to reduce the miss rate of overlapping targets, and further enhance the detection speed. Thus it can cope with the complex detection environment in the ship's cockpit, and also meet the real-time requirements of ship drowsiness detection. A drowsiness state discrimination algorithm based on gray correlation analysis is proposed to adaptively adjust the evaluation thresholds toward detection environments of different ships. This maintains a high accuracy rate of drowsiness detection in complex environments. The results show that the size of the improved drowsiness detection model based on GhostNet-SSD is smaller than MobileNetV3-SSD, while achieving great results in terms of detection accuracy and detection time consumption.

Compared with the traditional drowsiness state discrimination algorithm with fixed threshold, the adaptive threshold drowsiness detection algorithm in this paper exhibits a higher average accuracy.

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