

# Effective driver distraction warning system incorporating fast image recognition methods

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## ABSTRACT

Modern cars are equipped with advanced automatic technology featuring various safety measures for car occupants. However, the growing density of vehicles, especially in areas where infrastructure development lags, poses potential dangers, particularly accidents caused by driver subjectivity. These incidents may occur due to driver distraction or the presence of high-risk obstacles on the road. This article presents a comprehensive solution to assist drivers in mitigating these risks. Firstly, the study introduces a novel method to enhance the recognition of a driver's facial features by analyzing benchmarks and the whites of the eyes to assess the distraction level. Secondly, a domain division method is proposed to identify obstacles and lanes in front of the vehicle, enabling the assessment of the danger level. This information is promptly relayed to the driver and relevant individuals, such as the driver's manager or supervisor. An experimental device has also been developed to evaluate the effectiveness of the algorithms, solutions, and processing capabilities of the system.

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## 1. INTRODUCTION

It can be noted that modern car technology has significantly enhanced safety measures, contributing to the reduction of losses resulting from accidents. However, in many accident cases, the root cause does not stem from the vehicle itself but rather from the subjectivity of the driver. Incidents often occur due to driver distraction, fatigue, or drowsiness. During such instances, drivers experience reduced alertness and responsiveness to external factors that may pose danger. This phenomenon is referred to as "Micro Sleep," defined as a brief and involuntary period of sleep that can occur at any time due to fatigue or prolonged sleep deprivation. Micro-sleep episodes typically last for a few seconds and can pose a severe risk, especially for individuals operating a vehicle.

Several signs indicate that individuals are not fully awake while driving, such as frequent yawning, continuous and slow eye blinking, a bowed or tilted head, and drifting from the lane. Previous studies have explored various methods to assess distraction and assist drivers based on facial variables. Two primary approaches to evaluating fatigue or sleepiness include physiological-based techniques and behavioral-based techniques. Physiological techniques involve the use of electrodes to measure indicators on the body. However, this method can be inconvenient for the driver. On the other hand, the behavioral-based approach assesses eye, face, and head movements, as well as yawning behavior, to detect sleepiness. Most studies suggest that, to ensure comfort and avoid impacting driving, assessing driver behavior through camera image processing is a viable option.

Several works utilize eye images to assess the driver's fatigue state. For example, Horng *et al.* [1] proposed a vision-based real-time driver fatigue detection system that locates the driver's face using skin color characteristics, employs an edge detection method to identify eye regions, and uses the obtained eye images for sleepiness detection, generating warning alarms for the driver. However, this system must run on a personal computer and faces challenges in rapid application within a car. Another non-intrusive prototype computer vision system monitors a driver's vigilance in real-time, based on a hardware system for acquiring driver images. It uses an active infrared (IR) illuminator to monitor eyelid movements and facial pose, characterizing the driver's level of vigilance [2]. Nevertheless, this system is tailored to a specific individual rather than being applicable to a broader range of drivers. Rahman *et al.* [3] proposed an eye blink monitoring algorithm that uses eye feature points to determine the state of the eye and activates an alarm. However, this article does not account for specific blinking patterns and facial expressions. Another embedded monitoring system was introduced to detect symptoms of driver drowsiness by exploiting the bright pupils' phenomenon. The algorithm detects and tracks the driver's eyes, but encounters issues with light poles being misclassified as eyes due to their shape and size [4]. Flores *et al.* [5] presented a system designed to track and analyze the face to determine a drowsiness index. It operates under different light conditions. However, the system still exhibits a high percentage of error and false alarms, indicating a need for improvement. Similar directions of research can be found in other publications [6]–[8].

Other works combine eye images with additional facial features to assess sleepiness status. Kumar *et al.* [9] presented an analysis of a fusion method for eye blinking and yawning detection based on changes in mouth features. The algorithm employs OpenCV with the Haar cascade function for detecting facial features and the active contour method for lip activity. However, this research does not consider head movement to enhance the proposed method's accuracy. Teyeb *et al.* [10] developed a drowsy detection system using image processing to analyze eye blinking status for measuring eye closure period and head posture determination. However, the method for determining the angle of head inclination is not optimal, particularly in cases of the head tilted forward. Khunpisuth *et al.* [11] addressed driver drowsiness by creating an experiment to evaluate the level of sleepiness. Using the Haar cascade classifier, the frequency of head tilting and eye blinking was used to warn driver drowsy status. However, various light conditions might impact the accuracy of the proposed method. Similar combinations were explored in another study [12].

Several contributions to fatigue detection involve the incorporation of various facial factors. Saradadevi and Bajaj presented driver fatigue determination based on monitoring the mouth [13]. The method locates and tracks the driver's mouth using a cascade of classifiers for faces. Support vector machines are used to train face images. It is evident that combining more eye elements and head movement is necessary for better results. Another work proposed an efficient system for evaluating fatigue using face and yawning extraction based on support vector machines and circular Hough transform for mouth detection [14]. The system does not require any training data and could work with a low-cost webcam under various lighting conditions. Tawari *et al.* [15] presented a system which tracks facial features and analyzes their geometric configuration to estimate the head pose using a 3D model. Liu *et al.* [16] presented a space-time restrained AdaBoost method to increase the detection rates. In this work, a space-time restriction strategy is designed to restrain the detection window and scale of the AdaBoost method to reduce false-detection cases. Recently, another drowsiness detection system by analyzing the driver's face with a standard camera was proposed [17]. In this case, a set of facial landmark locations are detected by a fuzzy inference system (FIS). This is a relatively accurate proposal but still not complete for practical application. Akrouf and Mahdi [18] proposed work to recognize driver behavior by determining the characteristics of the face. This is a fusion system based on the detection of yawn, somnolence, and 3D head pose estimation. However, the results of the study are still influenced by lighting conditions.

In cases where the driver has specific factors, such as wearing glasses or staying in low-light conditions, different approaches are also suggested. Assari and Rahmati [19] proposed and implemented an infrared light based hardware system. They follow face detection steps, with facial components considered the most important and effective for drowsiness detection. Ahmad and Borole [20] implemented a system using the object identifier within the MATLAB vision toolbox, which detects face, mouth, nose, eyes. In this system, yawning is determined and considered based on the mouth opening portion. The algorithms are formulated under various categories, such as a normal driver, a driver with glasses under different light situations. Li and Zhou [21] presented a wearable eye tracker that detects both the 2D position and diameter of a pupil based on its light absorption feature. This research uses infrared lights to illuminate the eye from different directions, while photodiodes sense the reflected light, which are used to infer the pupil information. The system can exploit characteristics of various eye movement stages and can be applied for drowsiness detection.

Several recent studies have adopted a neural network approach to detect short periods of sleepiness. Doppala *et al.* [22] proposed a drowsiness identification system by capturing image frames of the driver's face from the video stream. In this study, a deep convolutional neural network (D-CNN) model is suggested

to detect drowsiness under various circumstances, such as drivers with and without glasses. In another system, the driver is alerted when they are drowsy using convolutional neural networks (CNN) [23].

In addition to detecting the state of a drowsy face, determining the direction of the vehicle's movement on the road and detecting obstacles also helps warn of unexpected incidents. Nugraha *et al.* [24] used the you only look once network (YOLO) as the object detector and polynomial regression as the road guidance. Kemsaram *et al.* [25] presented a neural network to detect lane markings, objects, using a monocular. Another work presented a lane detection algorithm based on the combined CNN with the random sample consensus (RANSAC) approach [26]. It can be seen that the works mentioned are partially or incompletely resolved for drowsiness detection and driver warning systems.

In order to improve the accuracy and speed of facial information processing, as well as the detection of objects on the road, this study introduces new approaches. Two cameras are used to directly observe the driver's face and objects on the road, employing rapid image processing methods to recognize and assess the driver's drowsy situation. This image processing method utilizes a novel approach to determine benchmark points and characteristic white areas on the face and in the eyes. Additionally, lanes, obstacles, and traffic signs are identified to assess the level of danger to vehicles and drivers. In the event of distraction, an on-board warning system will trigger a signal to alert the driver. Simultaneously, the driver's information will be transmitted to the monitoring system or the vehicle management department.

The article comprises three main parts. Section 2 introduces a method to identify distractions based on benchmarks and white areas of the face. The image separation method, applying the fast image recognition algorithm, is proposed in section 3. Section 4 provides a description of the complete monitoring system, outlining the practical application of the results. Finally, Section 5 contains conclusions.

## 2. FACE IMAGE RECOGNITION ALGORITHM

The observations and studies clearly indicate that the most prominent signs of driver distraction are the tilt of the head and eye gestures. In such cases, the eyes tend to remain closed for a longer duration than during regular blinking, and the head is typically bent or slightly tilted for an extended period. The position of the head may suggest that the driver is either distracted due to drowsiness or focused on objects not on the road ahead. The algorithm for determining the head tilt and eye-closed state is illustrated in Figure 1. The process involves analyzing the original camera image to ascertain the position of the driver's head. Subsequently, the degree of head tilt and eye closure is transmitted to the evaluation and analysis block. In situations of potential danger, both the on-board warning system and the remote management alert are activated.

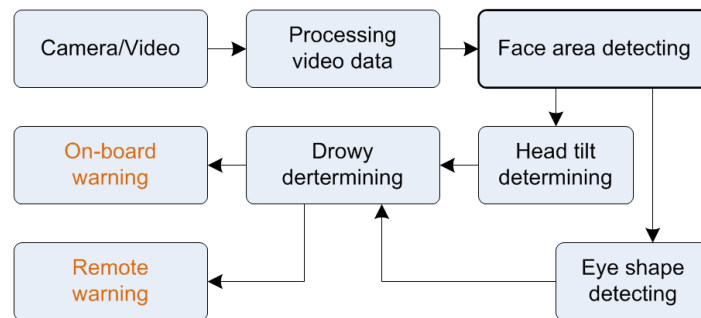


Figure 1. Distracted state identification process

### 2.1. Determine head tilt angle

To assess facial features, it is essential to determine the position of the head in the image. Digital camera images undergo preprocessing steps, including conversion to grayscale and filtering image noise. The resulting image is then input into the initial face recognition model. Face recognition can be achieved through various methods, such as the AdaBoost classification algorithm using Haar-like features, which is available in the OpenCV library. Additionally, methods like histogram of oriented gradients and linear support vector machine, pre-trained for face detection, can be applied. Deep learning algorithms are also employed for locating face coordinates in images.

Due to its effectiveness, this study utilizes the Haar-like feature-based AdaBoost detection method. The Haar-like feature employs a simple but efficient transformation, calculating its characteristic as the difference between the sum of geometric domains. Through this method, the coordinate frame for the face boundary is determined for further inclusion in subsequent algorithms.

To identify changing facial features, this study employs a novel approach by utilizing the improved facial Landmark model. The method applied to this model is capable of detecting crucial facial features, including mouth, eyes, eyebrows, nose, and facial corners such as the corners of the eyes and eyelids. Most landmark detection methods are applied based on a regression problem where the detector redefines the mapping from an image to landmark locations. The technique employs the Softmax regression method, utilizing neural networks to learn facial properties, and end-to-end regression with tiered architecture to update face landmark estimates. This technique still harnesses the inherent advantages of the CNN network. Existing detectors are trained from sets of available databases with images of different lighting conditions, various facial expressions, and diverse face rotations. Therefore, the algorithm typically achieves a high accuracy, usually exceeding 94%.

To clearly assess the facial features, this study separates the important points from  $p_1$  to  $p_{15}$ . The locations of these points are shown in Figure 2. These points have features that are easy to identify by algorithms using face benchmark model. To assess eye status, six points around the border of each eye should be identified and two points on either side of the mouth image are determined to assess head status.

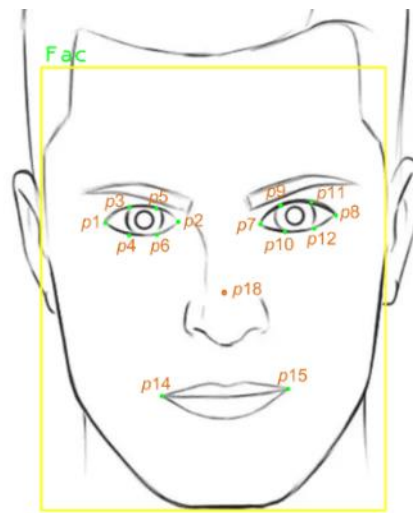


Figure 2. Characteristic defining points for face states

To determine head tilt, this study proposes to use four points of the eyes and mouth. These points are  $p_1$ ,  $p_8$ ,  $p_{14}$  and  $p_{15}$ . These points are characterized by their large bends, so they are easy to identify by Facial Benchmark model with high accuracy. The location of these points and the changes of the points when the face moves are shown in Figure 3. The center point of the face  $p_{18}$  is defined as the midpoint of the line segment connecting the midpoints of the lines  $p_1p_8$  and  $p_{14}p_{15}$  in Figure 3(a).

Normally, when the driver looks ahead, the  $y$ -axis position on the image coordinates of point  $p_{18}$  has a small value. When bowing forward in Figure 3(b), this coordinate increases, corresponding to the point  $p_{18}$  being lower in the frame. In the case of the head tilted as shown in Figures 3(c) and 3(d), the coordinates of point  $p_{18}$  also drop dramatically in the frame. The coordinates of point  $p_{18}$  are determined as (1).

$$y_{18} = \frac{|y_1 + y_8 + y_{14} + y_{15}|}{4} \quad (1)$$

When the driver is sitting upright, the head tends to tilt to one side rather than forward. The inclination of the head is determined by the deflection angle of the line passing through the point  $p_{18}$  and the inclination of the line segment  $p_1p_8$ . By determining the position of the  $p_{18}$  point and the tilt of the head, it is possible to assess the state of distraction. If the driver tilts his head for long enough, distraction begins to appear.



Figure 3. Results of identifying facial points with different tilt states of the head, including (a) normal head state, (b) forward head tilt state, (c) slight head tilt to the left, and (d) strong head tilt to the left

## 2.2. Eye state recognition

In most cases, a medium-quality camera can be used to receive images of the eye for recognition algorithms. In case of necessity, different types of cameras can be used to improve the results of eye status assessment such as infrared cameras [17], or glasses with specialized cameras [21]. The work in this paper implements an algorithm for analyzing eye states using a standard camera in normal lighting conditions.

Many methods have been presented to automatically detect blinks in a sequence of images in a video. Nevertheless, a major drawback of previous approaches is their dependency on various factors when setting up the recognition model. These approaches are influenced by factors such as camera angle, image resolution, light source hitting the eye, or movements of the driver being detected. To address this problem, this study continues to use the points identified, as shown in Figure 2. From the position coordinates of the recognized eye landmarks, determining the state of sleepiness is possible by relying on the longer duration of the blinking state. Each person has a different blink pattern in terms of how fast they open and close their eyes, how wide the eyes are when opened and closed, and the blink cycle or average time between blinks. Normally, a blink lasts about 100 to 400 ms. In this study, blinks lasting more than 1,200 ms are considered distracting.

The proposed method in this study leverages the performance of the facial Landmark detector to recognize the position of the eye and the contour of the eye on the image frame. It identifies the bright sclera area of the eye, as the sclera region has the advantage of having the highest brightness on the face, making it more easily detected, especially in low-light conditions. From landmark points, the algorithm calculates the eye aspect ratio (EAR) to estimate the eye's open state. The EAR ratio based on eye height and width is calculated using (2). The positions of the points to determine this ratio are shown in Figure 4. For different eye states, the benchmark points will shift accordingly. The denominator part of the formula is multiplied by the factor  $k$ . This is a factor that depends on eye shape. If the eye opening is small, the  $k$ -factor is usually set to less than 1. This is to improve the sensitivity of the eye state assessment.

$$EAR_1 = \frac{|y_4 - y_3| + |y_6 - y_5|}{k|x_2 - x_1|} \quad (2)$$

$$EAR_2 = \frac{|y_{10} - y_9| + |y_{12} - y_{11}|}{k|x_8 - x_7|} \quad (3)$$

$$EAR = \frac{EAR_1 + EAR_2}{2} \quad (4)$$

With the calculation of the eye-opening characteristic by EAR, the calculated value is less affected by the position and relative tilt of the head. Different individuals will have different EAR rates. To increase

the accuracy of the eye closure detection algorithm, the EAR ratio is calculated for both eyes, and the results are averaged as shown in (4). If the closed-eye state (corresponding to a very small EAR ratio) lasts longer than the standard blink state (1,200 ms), the eyes will be detected as closed. This situation is considered a case of drowsiness, distraction, and potentially dangerous situations.

In the case of low light, this study proposes to use the white area of the eye (sclera area) to assess eye condition. This area is clearly the brightest in the face and is more easily recognized by the grayscale conversion algorithm with a defined threshold level. Figure 4 describes the results of identifying benchmarks around the eyes and the white areas of the eyes in different states. In Figure 4(a), the eyes are normally open, and the benchmarks around the eyes are far apart and the white area is easily identified by its maximum horizontal and vertical length. In Figures 4(b) to 4(d), the eyes gradually close, and the distances of the surrounding points become smaller and the white area is therefore also smaller. The white area in the processing method is simply determined by calculating the length of the white area in the  $x$  and  $y$  axes. Obviously, the larger this length multiplication is, the greater the degree of eye opening. This value is used in conjunction with the EAR ratio to increase the accuracy of the algorithm in different lighting conditions.

The process of recognizing the eye state has achieved good results. Blinks are checked with head states to give accurate alerts. The processing method ensures the determination of eye opening in a short time and evaluates the status promptly. Figure 5 depicts the EAR ratio recognition values with high accuracy at a processing speed of 10 frames per second (FPS). Eye closure time is also accurately calculated with fast processing time in response to the rapid closure of the eyelids.

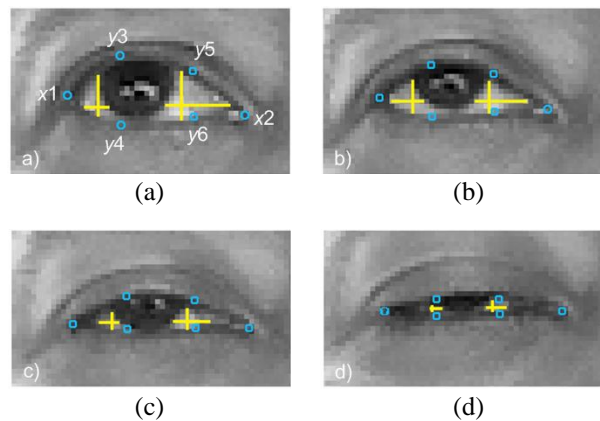


Figure 4. Eye landmarks and regions were identified in different states, including (a) eyes normally open, (b) eyes starting to close, (c) eyes slightly open, and (d) eyes closed

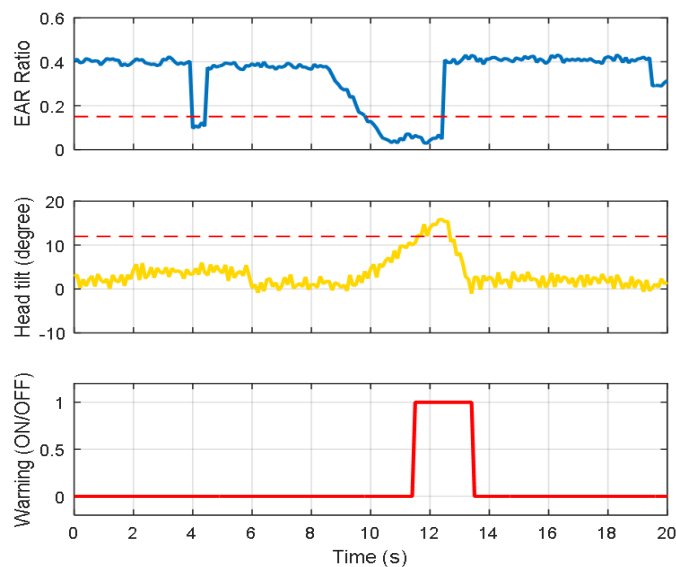


Figure 5. Blink and head tilt image processing results

According to the actual running results in the EAR ratio chart, at the 4<sup>th</sup> second, the eyes blink for a short time. By the 8<sup>th</sup> second, the eyes have a slow closing phenomenon. Nearing the 10<sup>th</sup> second, the EAR rate crossed the 0.15 threshold. From the head tilt chart, as can be seen, from the 9<sup>th</sup> second, the head begins to tilt gradually. When the tilt exceeds the normal threshold, 12 degrees, the eyes are still closed. Near the 12<sup>th</sup> second, the time to close the eyes has exceeded the period of 1,200 ms, along with the head tilt has exceeded the threshold, the alarm system activates (as shown in the last chart). After the warning signal, about 0.5 seconds, the driver started to wake up, his eyes opened quickly. Then the head starts to straighten again. The local siren warning process lasts for about 2 seconds. When the eye and head condition return to normal, the alarm system turns off automatically.

### 3. ALGORITHMS TO RECOGNIZE OBJECTS

#### 3.1. Algorithm to recognize lanes

To observe obstacles on the road as well as the position of the vehicle on the road, a second camera is placed forward to capture the image in front of the vehicle. This camera takes on the task of recognizing lanes, traffic signs, as well as dangerous objects appearing. This risk assessment from the camera image is done using both conventional image processing methods and machine learning approaches. Algorithm flowcharts of the two image processing directions are shown in Figure 6.

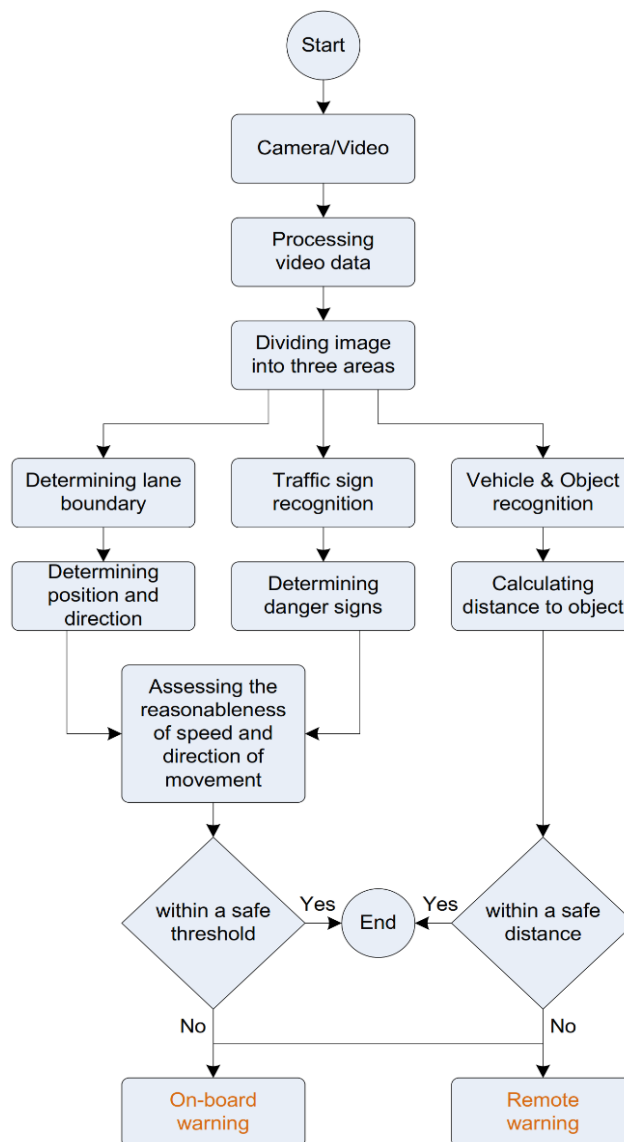


Figure 6. Flow chart for processing image and warning

In order to improve the processing quality and achieve high results, this study proposes to divide the received image area into separate processing regions. Figure 7 depicts the division of image analysis parts and the processing results of each part. The first part is used to detect lanes with an area of one third of the image (light blue in lower part in Figure 7(a). This section features few objects and shows the vehicle's clear position on the road. In addition, in this image area, with normal processing speed, the algorithm ensures timely identification and handling of situations. The upper remaining image area is divided into four equal horizontal sections. The second image processing area is the two small areas in the middle to identify obstacles in front of the vehicle (light yellow area in Figure 7(a). The recognition algorithm can evaluate the speed and direction of the obstacle to assess the level of safety. The third zone is the remaining two small areas on either side (light green area). This area is used to detect traffic signs and give the necessary warnings to drivers. It is clear that dividing the image into recognition regions helps to increase detection performance because the data processing area is significantly decreased. As a result, the recognition accuracy is higher and the safety support properties are also enhanced.

For lane recognition in the first image region, this study applies the canny object boundary finding method to determine the lane and determine the lane center. Since only part of the image is considered, there are not too many obstacles in the lane detection area. Finding the edge of the road also means finding the coordinates of the road and the position of the car on the road. In this image area, there are usually not too many noise factors, so the application of line finding approach in image processing ensures high accuracy and real-time response. Lane detection is performed on the original video with normal image brightness. The solid and dashed line images are accurately recognized, ensuring timely warnings in Figure 7(b). From the vehicle's position, the vehicle's direction is determined by combining multiple continuous images. Based on the direction and traffic signs (described in subsection 3.2), the current safety level of the vehicle is determined to decide whether to activate the warning system or not (as described in the algorithm flowchart in Figure 6).



Figure 7. The image processing process is divided into two stages, which are (a) dividing the image area according to the concentration of objects and (b) identification of objects on each divided area

### 3.2. Algorithm to recognize on-road objects

For the recognition area of other obstacles in the image (cars, people, vehicles, animals, and traffic signs), this study uses CNN network to solve the requirements. Using the well-known object dataset CIFAR 10 and the data collected by the authors, the obstacle recognizer is trained. Moreover, based on the received object area in the image, the study can determine the distance from the camera to the object. From there, the system activates an alert when the distance from the obstacle to the vehicle is within the dangerous range. Furthermore, this result is combined with the vehicle's position information and the vehicle's direction to assess the actual level of safety.

The results of identifying objects on the road are shown in Figure 7(b). Accordingly, the objects in the yellow area are identified quickly because the recognition area is reduced. Traffic signs are mainly recognized in the green zone on the right. The left side area is suitable for identifying signs for countries with vehicles going in the opposite direction, on the left.

From the recognition results, it can be seen that distant objects are also clearly identified. Based on the object type, the algorithm can estimate the size of the obstacle and the distance from the vehicle to the



obstacle with relative accuracy. This information is processed at a distance, when the object is in the danger range corresponding to the current vehicle speed, the warning signal will be activated directly on the vehicle and transmitted to the management department.

#### 4. BUILDING COMPLETE SYSTEM

The complete system is divided into two parts. The first part is a driver assistance device that will be installed on the vehicle, which is responsible for processing images and giving warning statuses. From the requirements of the problem, with two separate cameras containing two different information, the system uses a low-cost multi-threaded architecture processor (Raspberry Pi 4 Model B) to run two image processing tasks in parallel. All hazard estimates from the recognizer are communicated directly to the driver by means of an audible warning. At the same time, a warning image is sent to the host system, to notify all users on the monitoring website belonging to the second part. The two systems connect to each other via the 4G connection in Figure 8.

The construction of a complete warning system aims to monitor and statistic the number of times which the driver's dangerous situations occur. The data is transmitted to the server via 4G platforms. The system can send dangerous warnings to the supervisor or manager, from which it can be timely intervened, minimizing unfortunate incidents. Moreover, this system is also a remote centralized management solution for transport businesses. Enterprises can monitor many drivers at the same time, assess the working quality of each driver, and reduce accidents caused by distracted drivers. From the data collected during operation, the system's database is applied to analyze and give the results of evaluating the time frames with the highest risk of accidents.

Vehicle and driver performance data will be sent and stored in the database. Administrators can access information through the website. The supervisor could be able to see the overall status of all drivers. Information about the driver, concentration history or danger warning is stored and queried through the database. These data can be accessed in the form of statistics, monthly or yearly reports, supporting the supervisor to effectively manage the driver's performance.

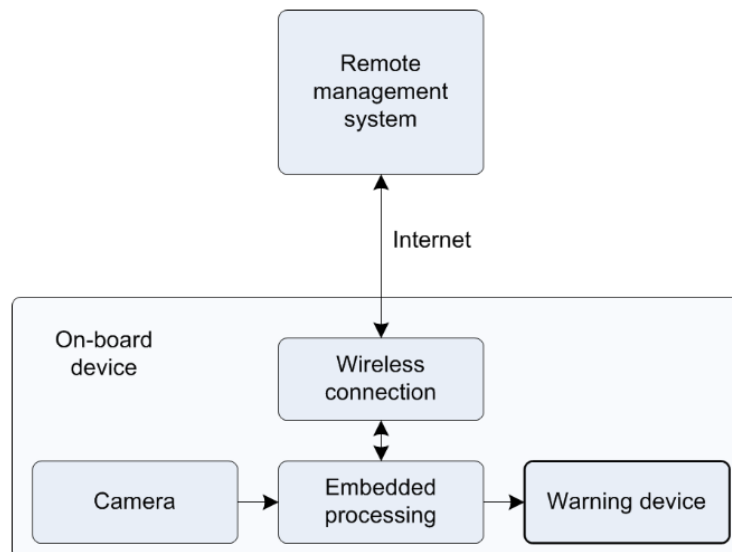


Figure 8. Connection of on-board device and management center

#### 5. CONCLUSION




This study introduces an automatic warning system for drivers and transport managers in case of potential hazards on the road. When the driver is distracted (e.g., drowsy, looking at the phone, not looking ahead), the image processing system perceives different facial expressions and the vehicle's position on the road. The system will activate warnings directly on the vehicle as well as send statuses to the manager. Actual results give accurate information about distractions. In addition, traffic signs and obstacles are also identified. Based on the size of the object, the distance from the object to the vehicle can be determined. From there, the real-time safety factor for the vehicle is also determined on the basis of assessing the

direction of the vehicle's movement. Research results show that the system adapts well in normal conditions with medium light with fast response speed. In low-light conditions, the application of white area recognition gives positive results, improving the system's reliability. The widespread application of this system greatly reduces the risks from the driver's subjectivity, as well as from unusual factors on the road.




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