Design and implementation of a driving safety assistant system based on driver behavior

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Article Info	ABSTRACT
	These days, road accidents are one of Morocco's biggest problems. Fatigue, drowsiness, and driver behavior are among the primary causes. This research aims to develop an embedded system by image processing and computer vision to ensure driving safety by monitoring driver behavior and assist drivers to awaken from micro-sleep or fatigue due to long driving hours and various other reasons. Indeed, the driver inattention, drowsiness or driver fatigue can be detected. The suggested method is designed to support drivers if needed, based on the vehicle velocity. Once the driver crosses a certain speed limit, the program starts face detection and analyzing this data to determine whether the driver is tired, sleepy, or inattentive. This activates different alarm depending on the criticality level. It can sound a voice alert to help him wake up and drive more cautiously. The system is based on artificial intelligence algorithms in image processing based on OpenCV libraries and the Python language to capture the movements of the driver's eyes and head when starting the automobile. Every algorithm is run on a Raspberry-Pi 4 card, and numerous experimentation series have demonstrated overall credible performance with success accuracy of over 93% in eye aspect ratio (EAR) and mouth aspect ratio (MAR) calculations. *This is an open access article under the [CC BY-SA](#) license.*

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1. INTRODUCTION

In the world, road accidents represent a critical issue, with alarming statistics underscoring the urgent need for effective interventions to enhance road safety. According to recent surveys conducted by the Vinci autoroutes foundation in Morocco, falling asleep at the wheel is the leading cause of mortality on highways, tripling to quadrupling the risk of accidents within thirty minutes after the onset of drowsiness related to fatigue. The severity of the situation is further highlighted by the fact that a vehicle in Morocco is 18.2 times more likely to be involved in a fatal accident than in Sweden and 13.5 times more than in France [1]. Further studies have shown that 20 to 30% of accidents involving professional drivers are related to vigilance disorders, with 39% of highway accidents due to drowsiness and 25% caused by a decrease in alertness due to falling asleep at the wheel. To underscore the gravity of this issue, Figure 1 at the bottom illustrates the comparison between Folkway and Fastway in terms of the primary causes of fatal accidents, derived from a survey executed as part of the 2018 Moroccan barometer of responsible driving project. This comparison elucidates the specific areas requiring urgent attention for intervention.
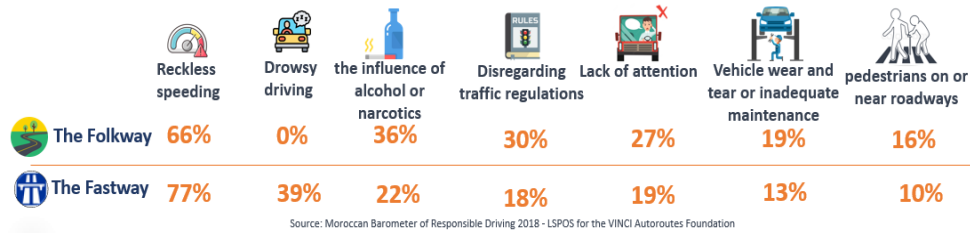
Figure 1. Primary causes of fatal accidents according to Moroccan drivers

Addressing this dire reality, our study introduces a driver assistance safety system based on driver behavior, utilizing image processing and computer vision to detect fatigue and drowsiness. This approach represents a novel and effective solution to monitor driver behavior in real-time, thereby reducing the risk of fatigue-related accidents. The article details the design, implementation, and evaluation of our system, providing a comprehensive overview of the methodology employed, the experiments conducted, and the analysis of the results obtained which success accuracy rate exceeding 97%. Through this study, we aim to make a significant contribution to road safety in Morocco and beyond by offering an innovative technology capable of preventing accidents caused by driver fatigue.

To achieve this, we have developed a comprehensive system that integrates advanced image processing algorithms and machine learning techniques to accurately detect early signs of driver fatigue and drowsiness. By deploying real-time monitoring and alert mechanisms, our system provides timely warnings to drivers, potentially saving lives and reducing the incidence of road accidents. This research not only addresses a critical safety issue but also sets a precedent for future studies in the field, paving the way for the development of more sophisticated driver assistance technologies.

2.   RELATED WORK

To mitigate the precarious situation of road accidents caused by drowsiness, fatigue, or even lack of vigilance, researchers have considered several approaches to detecting these factors. The drowsiness detection landscape comprises two main categories of techniques. The first category focuses on driver performance, monitoring the driver's actions for signs of drowsiness [2], [3]. Steering wheel jolts and the standard deviation of lateral position (SDLP) are employed to detect drowsiness. While steering wheel jolts look for erratic movements, SDLP keeps an eye on the vehicle's lane position. The second category, known as driver state monitoring technique, involves direct monitoring of the driver's physical state. This approach utilizes image-processing methods to analyze factors such as eye closure, yawning, and head nodding. Additionally, it incorporates physiological signal-based methods that track changes in heart rate or brain activity as indicators of drowsiness [4]-[7]. By integrating these techniques, researchers can develop more accurate and reliable drowsiness detection systems for enhanced driver safety.

2.1. Face detection

Detecting faces, especially those with visible eyes, is effortless for humans but poses a challenge for machines. Indeed, machine learning plays a crucial role in extracting desired elements from complex environments, taking into account factors such as scale, orientation, and lighting. Moreover, face detection has diverse applications, including monitoring driver fatigue. In this context, researchers, led by Kortli *et al*. [8], categorized facial detection methods into four groups. Firstly, model-based: this approach compares face and facial part models with candidates using correlation functions. Almabdy and Elrefaei [9] emphasized the importance of eyes but also noted potential accuracy issues and computational costs. Secondly, invariant characteristics: focuses on detecting faces despite variations in pose, lighting, and angles. Thirdly, facial characteristics: this method locates five key facial features to describe a typical face [10], [11]. Lastly, appearance and machine learning: quickly and accurately applies models acquired from a variety of images.

Regarding object detection techniques, popular methods include the Viola-Jones algorithm (Haar cascade) and the histogram of oriented gradients (HOG) by Dalal and Triggs [12]. Specifically, face detection in real-time is one area where the Viola-Jones algorithm excels [13]. The process involves four steps: classifier cascade design, AdaBoost training, image creation, and Haar-like feature selection. Notably, due to their ease of use and quick computation time, Viola and Jones employ Haar features, sometimes referred to as Haar-like features. Additionally, to speed up feature calculations, they make use of an idea

known as integral images. A significant invention by Viola and Jones is the integral image, which makes feature calculations more efficient by reducing the frequency of summing pixel values.

As depicted in Figure 2 illustrates the Haar features, explaining how they are calculated and highlighting their importance. Particularly, Figure 2(a) depicts the Haar-like features employed by the Viola-Jones algorithm for face detection, showcasing simple rectangular patterns that assess contrasts between different image regions, such as the eye area versus the cheek. These patterns use black and white rectangles to represent positive and negative areas, thereby demonstrating the algorithm's capacity to detect faces by contrasting light and dark regions. Simultaneously, Figure 2(b) presents a facial image as a typical input for feature detection. This illustration clarifies the algorithm's objective: to identify invariant facial characteristics despite variations in expression and orientation, thus emphasizing the role of Haar-like features in achieving accurate face detection. However, Figure 2(c) introduces a novel representation, the integral image, conceptualized by Viola-Jones. This integral image, of the same size as the original, contains at each point the sum of the pixels located above and to its left, aiming to streamline the feature calculation process. The idea is to calculate the sum of all pixels in the image just once, meaning the pixel at position (x, y) in the full image is the sum of the pixel values above and to the left of (x, y), significantly enhancing computational efficiency [12], [13]. As shown in Figure 2(c), the integral image at the yellow pixel (20) equals the sum of all blue pixels (1+3+12+4), where "$img_{intg}(x,y)$" is the integral image at position (x, y), representing the sum of all pixels in the original image, "$img_{source}(x',y')$", up to and including (x, y). The general formula is articulated by (1):

$$img_{intg}(x,y) = \sum_{x' \leq x, y' \leq y} img_{source}(x',y') \tag{1}$$

Sequentially applied, cascade classifiers make a pivotal decision: if a sub-region contains the object, the operation is deemed complete and progresses to the next classifier; otherwise, it is rejected. According to Viola and Jones, the vast majority of sub-regions that test negative (non-face/non-eyes) can be promptly dismissed using classifiers at the beginning of the cascade, allowing more focus on positive (face/eyes) inputs. However, the Haar cascade faces several limitations. Firstly, it may struggle to detect faces under challenging lighting conditions, potentially resulting in high false detection rates or inadequate detection rates. Additionally, Haar cascade may find it difficult to detect faces in images where faces are partially obscured, such as those hidden behind glasses or hats. Finally, Haar cascade might face challenges in detecting faces within images exhibiting large angle changes or complex facial expressions [14].

(a)   (b)   (c)
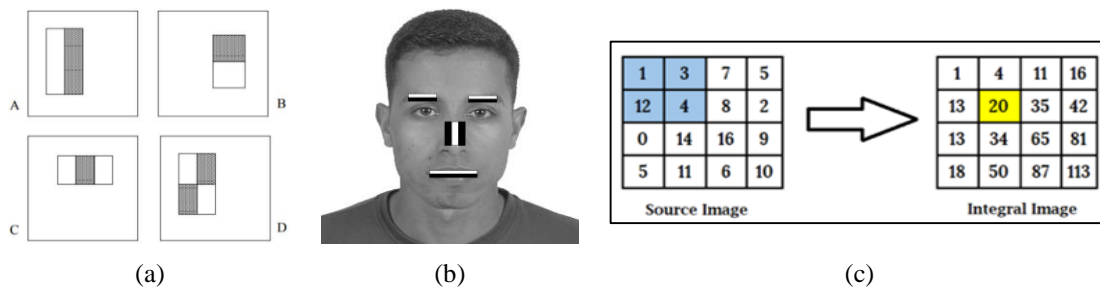
Figure 2. Illustration of Haar's characteristics for computational analysis of feature extraction and summation in image processing: (a) Haar-like features for edge and line detection, (b) Haar feature application on facial features, and (c) source to integral image conversion

On another front, the HOG method emerges as a robust technique in computer vision for object detection within images. Proposed by researchers Dalal and Triggs in their seminal article "histograms of oriented gradients for human detection" [15], the HOG method involves dividing the image into small cells and calculating the gradient orientation of every pixel within each cell. Subsequently, a histogram of gradient orientations is constructed for each block of cells, enabling the representation of the entire image by a vector of HOG descriptors. This representation is pivotal for training classifiers, such as support vector machines (SVM), to detect objects in new images. Crucially, converting the original image into a gray intensity image is necessary to streamline the process [12], [15]. The essence of this approach lies in contrasting the current pixel's darkness with its immediate surroundings, thereby delineating the direction towards increasing darkness. This methodical process, albeit seemingly redundant, ensures that both dark and light areas are uniformly represented based on the direction of brightness change.

Furthermore, by analyzing the image in small 16×16-pixel squares, the flow of light/dark becomes discernible at a macro level, revealing the image's fundamental pattern. In each square, the count of gradients pointing in each principal direction is tallied. These squares are then annotated in the image with the directions of dominant arrows. To locate faces within this HOG image, it suffices to identify parts of the image that closely match a known HOG model extracted from training faces. Conversely, the system's ability to capture faces oriented in various directions could misinterpret the absence of a face, and consequently, a driver. To mitigate this limitation, each image is adjusted to maintain the eyes and lips in direct opposition. This adjustment employs an algorithm known as "face landmark estimation," which identifies 68 specific points, or "landmarks," on each face, such as the top of the chin and the edges of each eye. A neural network is then trained to detect these 68 specific points on any face, enhancing the system's accuracy and versatility.

2.2. Eye status detection

Eye condition is a critical factor in determining whether a driver is tired, asleep, or in their normal state. In essence, eye detection serves as an essential pillar for analyzing driver behavior. Several factors are considered in this operation, including external noise and the diversity of eye appearance. The concept of appearance diversity encompasses shape, size, color variation, and movement of the iris and eyelid, while external noise factors include glasses, hair, shade, quality of imaging conditions, and environmental conditions.

At the heart of this method is the extraction of geometric characteristics of the eye, such as the visible iris and the elliptical shape of the eyelids, which forms the basis for distinguishing whether the eye is open or closed. Furthermore, variations in intensity distribution also facilitate this determination through the presence or absence of the iris and the white region of the eye in an image. Irrespective of the environmental changes, curves representing the differences between opened and closed eyes are generated by the horizontal and vertical projections applied to the eye region. This technique is crucial for determining the degree of eye closure and aligning the detected region. These methods are adept at managing the various changes that eyes can undergo, including the processing of low-quality images, making them more reliable than other methods. The approach consists of two steps: extracting visual characteristics from the photometric aspect of the eyes and their classification. Subsequently, the next section describes the materials and methods used to design and implement a cost-effective automotive electronic embedded system. This system aims to reduce accidents by monitoring drivers in critical situations, such as driving in states of fatigue and drowsiness or driving with inattention on highways.

3. MATERIAL AND METHODS

3.1. Material setup

In this project, we required equipment capable of processing video sequences in real-time while being compact enough for easy integration into a vehicle. There are several types of electronic cards able to make image processing, but the Raspberry Pi 4 Model B was chosen for its superior hardware performance, including a 64-bit quad core system-on-chip (SoC) processor at 1.5 GHz, 2 GB of RAM (expandable), and various features such as Wi-Fi, Bluetooth, USB 3.0 ports, and 40-pin GPIO connectors. Its small size (85×56×16 mm) and cost-effectiveness make it an ideal solution. The system is powered by a 5 V source, such as a car's cigarette lighter. Figure 3 shows the functional diagram of the on-board system used for detecting driving fatigue. This diagram illustrates how the Raspberry-Pi 4-B board, at the heart of the system, is connected to the various components, including a camera for driver monitoring and an alert module to report detected fatigue. This configuration demonstrates the integration of image processing and communications technologies to create a proactive safety feature in the vehicle.
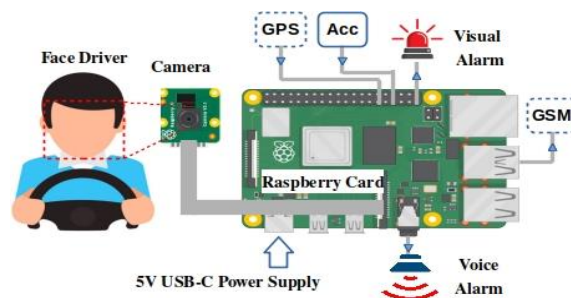

Figure 3. Functional system view

The device captures the driver's face in real-time using a camera as shown in the Figure 3. The Raspberry's microprocessor analyzes fatigue or drowsiness through an algorithm Written using a Python language and library OpenCV tools. When fatigue is detected, a visual alert is triggered, supplemented by an audible alarm if necessary. Advanced SOS measures, such as activating hazard lights for informing other road users or sending an emergency SMS with the vehicle's location, are implemented through the addition of NEO-6M GPS and GSM modules.

3.2. Software setup

As previously noted, image processing for face detection can be efficiently executed using the Python language, given the richness of its libraries in this field. A flow diagram, depicted in Figure 4, illustrates the overall operations of the system. Specifically, Figure 4(a) presents a flow diagram describing the system's comprehensive process. This process starts by capturing the driver's face in real time through a camera connected to the Raspberry Pi board. The captured images are then processed by a Python algorithm utilizing OpenCV libraries for detecting face and facial expressions indicative of fatigue or drowsiness, such as closing the eyes or yawning. Furthermore, this diagram elucidates the successive steps of acquiring visual data, analyzing it to identify signs of fatigue, and the immediate actions taken by the system in response to these signs, including activating alarms.

Moreover, Figure 4(b) specifically illustrates the alarm triggering mechanism when the system detects the absence of the driver's face or signs of drowsiness. This flowchart delineates how the system evaluates risk conditions based on the analysis of facial images and, upon detecting fatigue, how it initiates emergency measures such as visual and audible alarms to awaken the driver and alert passengers. It also emphasizes the importance of the system's reactivity to signs of fatigue, showcasing the sequence of actions triggered to minimize the risk of an accident and highlighting the system's capacity to actively intervene in the event of potential danger, thereby underlining the preventive nature of the developed system.
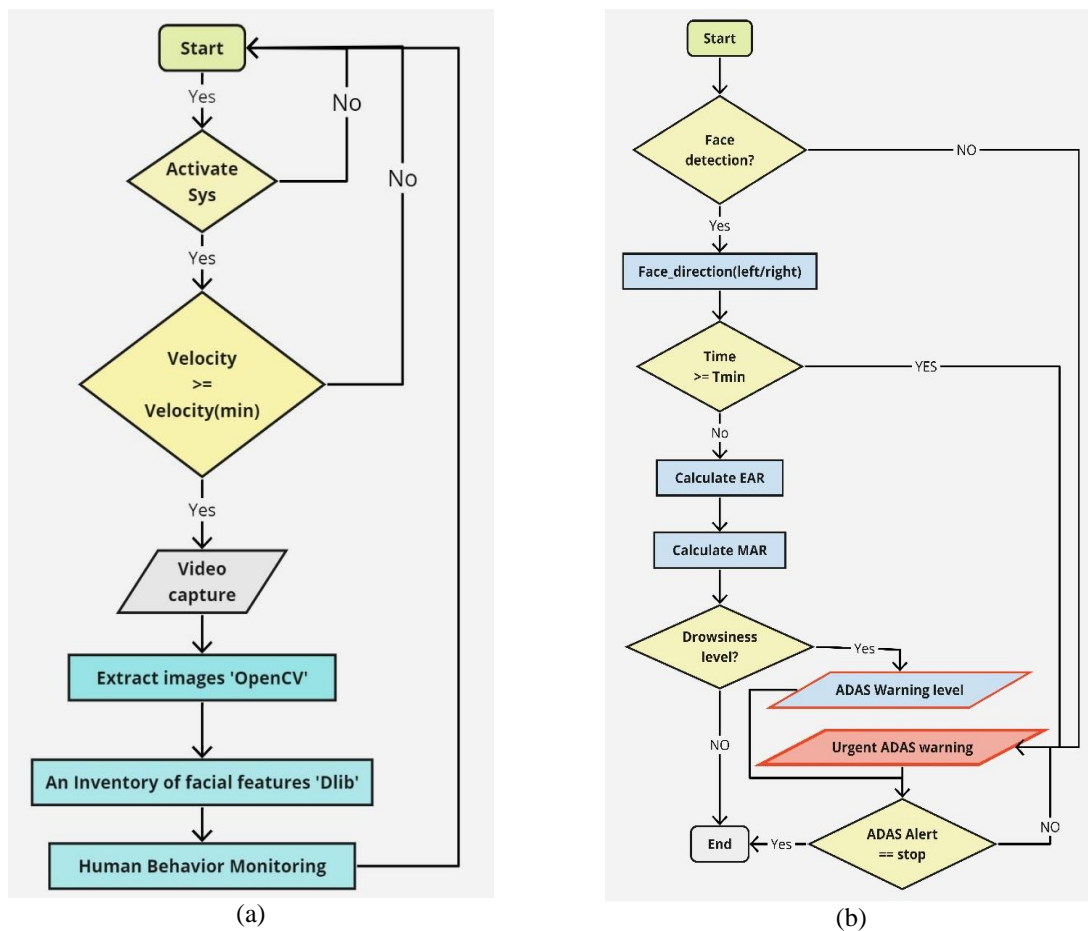

Figure 4. System algorithms flowchart: (a) overall system process and (b) driver behavior monitoring

A variety of Python tools and libraries are utilized in extracting facial features; such as eye condition. These libraries offer powerful capabilities for processing, manipulating, and analyzing images, as well as for creating machine learning applications in computer vision to extract facial features for detecting sleepiness in drivers. Among these libraries, notable ones include OpenCV, Dlib, Imutils, Scipy.spatial, and Pygame. OpenCV is renowned for its real-time image and video processing capabilities. It finds application in numerous fields, including facial recognition, video surveillance, and machine vision [16]. OpenCV boasts both low and high-level application programming interface (APIs) and facilitates parallel programming. According to its documentation, the library provides various functionalities, such as image manipulation (loading, saving, and copying), video acquisition, image processing, image analysis, and shape recognition. OpenCV is instrumental in capturing real-time video from video cameras, marking the initial data acquisition step. This stage aims to transform video recordings into images, which then form the foundation for subsequent analysis stages. Furthermore, OpenCV supports eye and face detection using the Viola-Jones (Haar cascade) method discussed in the first section. Figures 5(a) to 5(c) demonstrates the outcome of this process. Specifically, Figure 5(b) details the detection and analysis of the eye region to calculate the eye aspect ratio (EAR), a crucial metric for eye closure. Similarly, Figure 5(c) focuses on the mouth region to calculate the mouth aspect ratio (MAR), which is instrumental in detecting yawns, another fatigue indicator. Meanwhile, Figure 5(a) illustrates the facial feature points employed in drowsiness detection, with a focus on the eye region.

Figure 5. Detection of key facial features by characteristic points of eye region and mouth region;
(a) detection of facial regions: eyes and mouth, (b) characteristic points of the eye region, and
(c) characteristic points of the mouth region

Dlib stands out with its graphics library that facilitates image processing [17]-[19]. The accuracy provided by Dlib, which employs the HOG method, surpasses that of OpenCV, which relies on the Haar cascade technique. In the design of this project, the Dlib library will be employed to detect faces and their characteristic points, marking the characterization step. This step aims to highlight significant facial expression features while eliminating redundant data. Dlib excels in estimating the location of 68 (x, y) coordinates that map facial points on a person's face, with these points stored in an indexed array. The implementation of the Dlib library specifically aims to identify the characteristic points of the eyes and the mouth to calculate the Euclidean distance, thereby determining the distance between two points. This calculation, when compared to a predetermined threshold, will enable the assessment of whether the driver is asleep, tired, or alert. In Dlib, 6 coordinate points (x, y) represent each eye, and 12 other points represent the mouth, as illustrated in Figure 5 [20]-[22]. It showcases these points that are identified from a pre-trained model [23]-[26], thereby underlining the project's emphasis on precision and effectiveness in monitoring driver alertness.

3.2.1. Eye aspect ratio

The EAR serves as a measure to describe and represent the characteristic points of the eyes. This measurement, indicating the ratio between the width and the height of the eye, is pivotal in determining the level of eye openness. The higher this value, the more open the eye is considered. Thus, it significantly aids in characterizing a base of examples (images) to discover a learning model that can predict the state of a new instance. The EAR value is calculated using (2):

$$EAR = \frac{Ae+Be}{2*Ce} \tag{2}$$

Where Ae is the distance between eye points (1) and (5) in the Figure 5(b), Be is the distance between points (2) and (4), and Ce is the distance between points (0) and (3). A specific threshold, termed the ocular

threshold (Te), is essential to assess whether the driver is asleep based on the EAR level. If the EAR value is below this threshold, the eye is considered closed. Typically, the threshold is set at Te=0.25.

3.2.2. Mouth aspect ratio

Yawning, as an indicator of fatigue due to its role in increasing oxygen intake and reducing carbon dioxide levels in the blood, is similarly measured by the MAR. This ratio elucidates the height to width ratio of the mouth, helping to ascertain whether the mouth is open (indicating yawning) or closed [22]. The MAR value is derived from (3):

$$MAR = \frac{Am+Bm}{2*Cm} \tag{3}$$

Where *Am* is the distance between mouth points (2) and (10), in the Figure 5(c), *Bm* between points (4) and (8), and *Cm* between points (0) and (6). A mouth threshold (Tm) defines whether the mouth is considered open in a yawning state based on the MAR value. If the MAR value exceeds this threshold, the mouth is deemed to be yawning. Generally, this threshold is Tm=0.5.

The Dlib library's official documentation showcases its features, including face extraction and feature point analysis. In this research, the Scipy.spatial sub-library is utilized for calculating Euclidean distances, facilitating complex geometric calculations required for measuring the eye-opening ratios EAR and MAR, and for detecting eye blinks. Moreover, the Imutils sub-library, with its "face_utils" function, provides utilities for processing facial features, such as detecting and extracting facial landmarks from images. This technique, in conjunction with the Dlib library, aids in detecting facial landmarks from input videos. Ultimately, using this module simplifies the extraction of facial features, such as key points e.g., eyes, nose, and mouth, from a face image. Additionally, the Pygame library, suitable for playing sounds, employed here to issue an audio alert.

4.   RESULTS AND DISCUSSIONS

After installing the Raspberry Pi operating system (Raspbian), OpenCV, and the necessary libraries, the system based on the Raspberry Pi 4 board and equipped with various sensors (camera, gyroscope, and GPS) and actuators (LED, speaker, and SOS system), as previously mentioned in section 2 was integrated into a vehicle for testing. These initial tests aimed to refine facial recognition under various conditions. Figure 6 comprehensively illustrates the system onboard implementation and driver behavior detection capabilities.

The Figure 6(a) depicts the initial setup of the system in the vehicle, showcasing the Raspberry Pi with its connected components, prepared for real-world testing. Figure 6(b) captures a moment when the system successfully distinguishes the driver from passengers, thereby demonstrating its capability to accurately identify the vehicle's operator. Subsequently, Figures 6(c) and 6(d) display the system assessing the driver's head orientation (left and right). These observations highlight the system's ability to detect potential inattention when the driver's gaze deviates from the road, prompting a visual alert. Figure 6(e) presents the user interface issuing a fatigue alert, based on the EAR calculation, which assesses the frequency of eye blinking to evaluate the driver's alertness. If this posture persists for more than 3 seconds and the vehicle's speed exceeds a certain threshold (e.g., 60 km/h), a visual and an audible alarm are activated to caution the driver. In Figure 6(f), the system detects drowsiness through the analysis of the MAR, monitoring yawns or other mouth movements indicative of fatigue. Particularly noteworthy is Figure 6(g), which underscores the system's effectiveness under nighttime driving conditions by demonstrating its capability to identify drowsiness even in low-light scenarios, vital for enhancing driving safety during the night. Each of these instances attests to the system's advanced and responsive nature in various driving scenarios, underscoring its potential to augment driver safety by alerting to varying degrees of inattention and fatigue as like in the Figure 7.

Figures 7(a) and 7(b) depict a critical situation where the vehicle is in motion, yet the driver's face is not detected, suggesting unconsciousness or severe distraction. In such cases, the system triggers an emergency advanced driver-assistance systems (ADAS) warning, as described previously in section 2. This function is crucial for initiating immediate corrective measures to avert potential accidents due to driver incapacitation. Conversely, Figures 7(c) and 7(d) illustrate situations where the vehicle is stationary, and no face is detected. Here, the absence of detection does not immediately necessitate an emergency alert; instead, the system diligently attempts to locate the driver's face, ensuring readiness for when the vehicle commences movement. This proactive approach by the system highlights its sophistication and its pivotal role in continuously safeguarding driver awareness and safety. Each scenario in Figure 7 emphasizes the system's adaptability to various conditions and its essential role in monitoring driver consciousness to improve road

safety. It is also crucial to note that the camera is capable of capturing faces within a 140-degree angle, significantly ensuring that the driver's face remains within the field of view under most circumstances, thus allowing for reliable monitoring and prompt system responses to various driver states. In Table 1, we detail various scenarios and describe how the final system responds by generating alerts for different driver states.
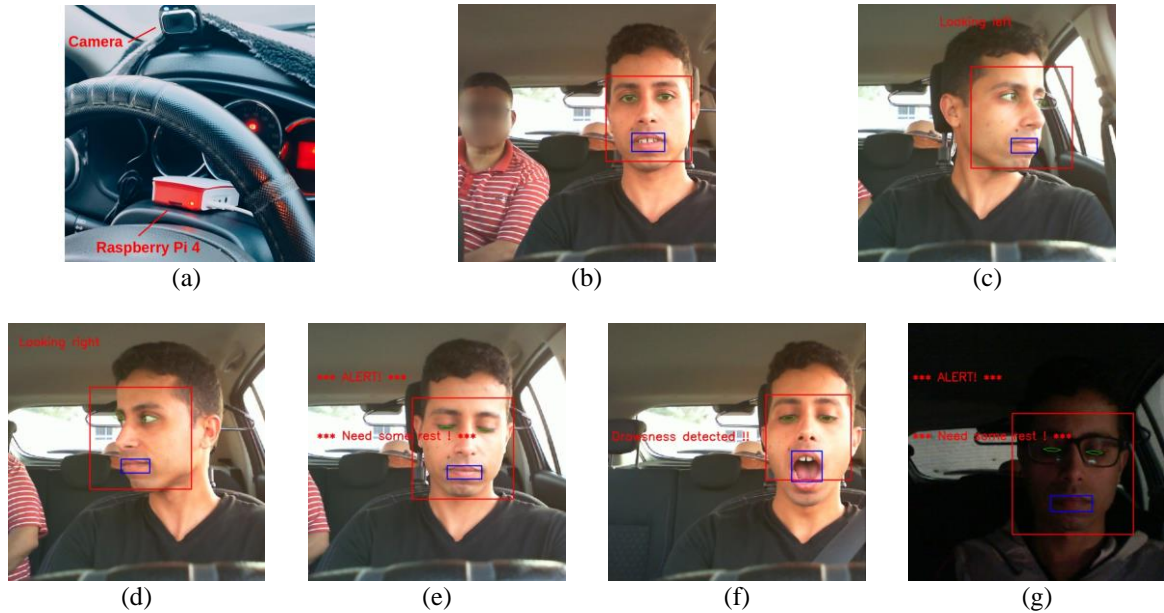

Figure 6. Implementation and results of different driver behavior detection: (a) driver monitoring setup with Raspberry Pi and camera, (b) normal driving detected, (c) driver looking to the right, (d) driver looking to the left, (e) yawning detected, (f) mouth open, possible drowsiness detected, and (g) night driving detected

Figure 7. Other situation of driving behavior detection: (a) in-motion no face detected, triggering emergency ADAS warning, (b) moving driver unresponsive, activating emergency ADAS alert, (c) stationary no face detected, no alarm, and (d) stopped driver absent, no alarm

Table 1. Various alertness level for different drowsiness degrees

EAR test	MAR test	Face direction test	Alert type
True	True	True	No alert
True	False	True	Tiredness alert
False	True	True	Cautionary alert
True	True	False	Warning alert
True	False	False	Warning alert
False	True	False	Warning alert
False	False	True	Warning alert
False	False	False	Emergency alert

Notably, the system categorizes drowsiness into four distinct levels of alert, each corresponding to a different degree of drowsiness severity: fatigue alert, cautionary alert, warning alert, and emergency alert.

These categories help in tailoring the system's response to the specific needs posed by the driver's condition, ensuring both safety and appropriateness of the alert issued. The alert levels are defined as follows:

− Fatigue alert: this level is triggered when the system detects signs of mild drowsiness in the driver. It serves as an early indication that the driver may need to take a rest or a break, helping to prevent the escalation of fatigue to more dangerous levels.
− Cautionary alert: it is activated at a moderate level of drowsiness. It indicates that the risks associated with continued driving while fatigued are increasing and that the driver should consider stopping.
− Warning alert: it is issued when the system identifies severe drowsiness, this alert level represents a heightened danger to safety. It serves as a pronounced caution to the driver, urging them to take immediate action to have a rest before continuing to drive.
− Emergency alert: this is the most critical level of alert; it is generated in cases of extreme drowsiness or unconsciousness. The system's emergency response could involve activating additional safety measures or alerts to prompt immediate driver or passenger intervention.

The structured approach to categorizing driver drowsiness and issuing corresponding alerts plays a pivotal role in enhancing road safety. By precisely assessing the severity of the driver's condition and responding with a tailored alert level, the system endeavors to reduce the risks associated with drowsy driving, thereby potentially saving lives, and preventing accidents. This sophisticated response mechanism in Table 1 facilitates a more effective and context-aware strategy for managing driver alertness, ultimately contributing to the safety of all road users.

For each distinct scenario, the algorithm evaluates the driver's drowsiness based on tests like EAR, MAR, and gaze direction, subsequently determining the most suitable alert level to issue. Despite its promising outcomes, our drowsiness detection system encounters certain limitations. Primarily, the accuracy of detection is significantly influenced by the vehicle's interior lighting conditions. In dimly lit environments, standard cameras might not accurately capture the driver's eyes, potentially leading to incorrect assessments. Therefore, the use of a camera equipped with a night vision mode is advised to overcome this challenge.

Additionally, the system exhibits noticeable delays in processing the algorithms, particularly when integrating other SOS alert functionalities. Given that the Python algorithms operate within the Raspbian operating system on the Raspberry Pi board, this delay is largely attributed to the extensive sequential processing demanded by the board's microprocessor. Addressing this issue could involve opting for a board with superior specifications, such as the Raspberry Pi 5, or transitioning to parallel processing technologies like field programmable gate array (FPGA). FPGA technology marks a novel research avenue in image processing due to its capability to execute algorithms in a hardware description format with parallel processing capabilities [27]. Such advancements are expected to significantly enhance real-time performance within the ADAS framework, thereby offering a more responsive and efficient system for monitoring driver alertness and ensuring road safety.

5. CONCLUSION

The ADAS systems using artificial intelligence represent a significant advance in the field of road safety and public health. The results of this study demonstrate the effectiveness of algorithm models integrated into an embedded system such as the Raspberry Pi card to ensure continuous monitoring of driver behavior and precise recognition of signs of drowsiness, thus offering promising prospects for the development early detection systems. These technological advances could help reduce accidents related to fatigue while driving, thereby improving the safety of drivers and passengers. However, challenges remain, particularly regarding the adaptability of the models to various driving contexts and the handling of false positives. Future research should focus on continued algorithm optimization, real-time data integration, and large-scale validation across diverse populations. In conclusion, the use of artificial intelligence for driver behavior monitoring has considerable potential to improve road safety. However, it is imperative to continue research and development efforts in order to guarantee the reliability, precision, and generalization of these systems in varied conditions, thus contributing to creating a safer road environment and preventing accidents linked to traffic, fatigue or inattention while driving.

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