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ENHANCING DRIVER ALERTNESS USING COMPUTER VISION DETECTION IN AUTONOMOUS VEHICLE

Chirag Vinalbhai Shah[1], Srinivas Naveen Reddy Dolu Surabhi[2] and Vishwanadham Mandala[3]

[1] Senior Software Engineer, GM

[2] Product Manager, GM

[3] Data Engineering Lead, Cummins, Inc

[1]Cshah221@gmail.com, [2] srinivas.csii@gmail.com and [3] vishwanadh.mandala@gmail.com

ABSTRACT

The focus of this paper is to detect drowsy drivers, aiming to accurately identify the state of the driver. Drowsy driving is a significant factor in traffic accidents, leading to fatalities and injuries. Detection methods can be categorized into two main groups: those that assess driver performance and those that evaluate the driver's state. Within the latter category, methods can be further divided into those utilizing physiological signals and those utilizing computer vision. This study utilizes video data of drivers captured by a camera, employing computer vision techniques to detect the driver's state. Driver head movements are used to determine a normal driver or a drowsy driver, by focusing on eye regions using image processing techniques. Artificial neural networks are used to classify the driver orientation. Physical drive tests achieved 99% accuracy in driver state recognition and 94% accuracy in eye state recognition, which are consistent with existing literature findings.

Index Terms: Drowsy driver detection, Simulation, Safety Driver Attention, Artificial Neural Networks, Traffic Accidents, Eye Closure Rate

INTRODUCTION

Driver fatigue is a significant concern in the road transport industry, with drowsiness being the most perilous consequence. Falling asleep while driving poses a grave threat to safety. Fatigue not only induces sleep but also diminishes reaction time, a crucial factor in ensuring safe driving. Additionally, it hampers vigilance, alertness, and concentration, thereby impairing the ability to engage in attention-demanding tasks like driving. Sleepiness also slows down the processing of information and may impact the quality of decision-making. A driver experiencing micro sleep can cause a collision with an object or vehicle or fail to realize they have drifted into the wrong lane. The outcomes of a drowsy driver are extremely hazardous, resulting in loss of life, injuries, and damage to vehicles. To mitigate the negative consequences caused by drowsy drivers, it is imperative to implement significant measures aimed at enhancing the working conditions of drivers. This will help minimize the potential risks associated with drowsiness while driving.

The Association for Safe International Road Travel reports that approximately 1.3 million individuals lose their lives in road crashes annually, equating to 3287 deaths per day [2]. The United States faces a similar situation, with statistics indicating that 57,000 people perish in road crashes each year, while 2.35 million sustain injuries or disabilities. The economic impact of road crashes in the United States amounts to $230.6 billion annually. Drowsy driving stands out as a leading cause of traffic accidents. The US National Highway Traffic Safety Administration estimates that around 100,000 traffic accidents occur each year due to driver drowsiness and fatigue [3,4]. Federal government data reveals that at least 1500 individuals lose their lives and 40,000 sustain injuries in drowsy driver crashes annually in the U.S. These figures are likely conservative, as detecting drowsiness in drivers is challenging unless witnessed or survived by someone who can attest to the driver's state [4]. A survey found that 37% of American adults admitted to having dozed off while driving at least once, with 27% reporting such an incident within the past year [5]. The National Transportation Safety Board in the United States has conducted multiple studies emphasizing the impact of sleepiness on accidents with large vehicles. Out of 147 single-vehicle accidents involving heavy trucks, 58% were found to be caused by drowsiness, as reported by the NTSB. The driver's capacity to drive is impacted by fatigue. As fatigue intensifies, the driver's response time lengthens and their capability to prevent accidents diminishes. Figure 1 illustrates a significant and positive relationship between the duration of driving and the occurrence of accidents caused by fatigue [6].

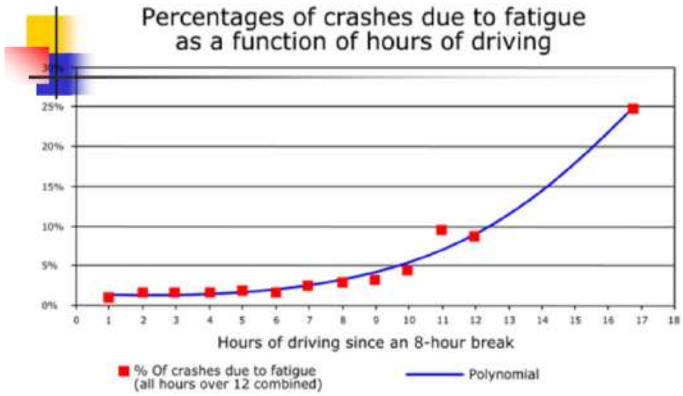


Fig 1: Crashes caused by fatigue as a percentage

The chart demonstrates a clear positive correlation between driving hours and crashes associated with fatigue [6]. Extensive data and statistics clearly highlight the gravity of Somnolent driving as a major concern. This article major focus is developing an accurate method for detecting drivers' alertness levels. The development of a reliable and user-friendly system to detect drowsiness has the potential to save lives and enhance overall quality of life. The proposed system assesses the safety driver's alertness by combining safety driver, vehicle, and environmental data. The vehicle needs to be able to handle intricate scenarios like approaching intersections, obeying traffic signals, and interacting with pedestrians and other vehicles in constantly changing driving conditions. A human supervisor must closely monitor these situations as variations in head movement may not always signal inattention automatically.

1.1. Driver Performance-Centric Methods

Detecting drowsiness in drivers involves using various methods such as lane tracking, monitoring the distance between vehicles, and installing sensors on components like the steering wheel and gas pedal. Pilutti, for instance, utilized vehicle lateral position and steering wheel position to create a model for detecting drowsiness. Some studies have also focused on analyzing driver steering wheel movements and grips as indicators of drowsiness. Car manufacturers like Nissan and Renault have implemented this technology, although its effectiveness is limited to motorway driving due to its reliance on road conditions. Additionally, these systems are heavily influenced by road quality and lighting, and they may not detect drowsiness until it has already impacted the vehicle's position.

1.2. Driver State-Focused Methods

When it comes to monitoring the condition of a safety driver, ensuring their focus and readiness to take control of the vehicle in emergency situations is crucial. Traditional Driver Monitoring Systems (DMS) typically gather data on safe driving behaviors, but a more advanced system goes beyond that by including vehicle, outside factors impacting vehicle data to give a holistic evaluation of the safety actions. This research delves into the detection of driver inattentiveness within the context of Autonomous Vehicles (AVs). The proposed method merges data from the driver and the vehicle itself to achieve a comprehensive assessment of the safety driver's vigilance level. By leveraging observations from the driver safety perspective. This way the system offers a way to gauge the driver alertness, facilitating timely interventions and alerts aimed at enhancing overall transportation safety.

Driver monitoring systems play a critical role in the realm of autonomous driving, ensuring that the safety driver remains attentive and ready to intervene when necessary. By continuously monitoring the safety driver's state, these systems can detect signs of inattention or drowsiness and alert the driver to refocus on the road. However, traditional DMS primarily focus on collecting data related to safe driving behaviors.

For validation of the proposed method, drive data is collected. An infrared camera is used to collect driver images, this data is used to detect eye movements. Alongside this, the vehicle's sensors gathered information regarding the surrounding environment, including both stationary objects and moving entities such as other vehicles and pedestrians. By combining data from these two sources, we were able to classify the attention of the safety driver into two main categories: consistent and inadequate. The system description diagram presented in Fig. 2 offers a simplified overview of our methodology.

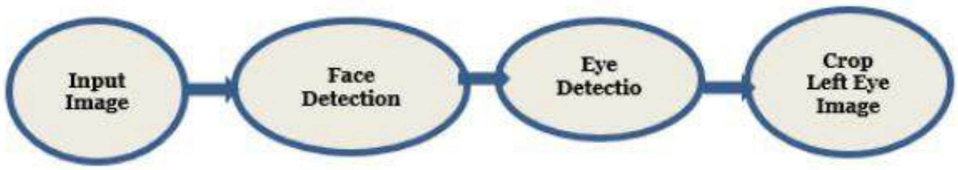


Fig 2: Driver eye state recognition

Our experiments revealed a concerning trend where safety drivers exhibited a decrease in their level of attentiveness as they grew more accustomed to the automated technology. This decline in attention, known as "automation complacency," aligns with existing research that suggests individuals tend to place more trust in automated systems, thereby reducing their overall vigilance.

II. METHODOLOGY

The proposed method belongs to a group that focuses on the driver's state using computer vision. The percentage of eye closure (PERCLOS), also known as the eye closure rate, is a reliable measure for detecting drowsiness [31]. In this article, PERCLOS is utilized to determine whether the driver state in a video segment. Eye state estimation is carried in each frame, categorizing the eyes as open, semi-closed, or closed. The results from each frame are aggregated to assess the state of the driver.

Frames from the video feed undergo initial processing by the eye region extractor using an advanced Viola-Jones algorithm from MATLAB's Computer Vision System Toolbox. This algorithm identifies potential right and left eye regions along with the face. By applying decision rules, erroneous face candidates are filtered out, allowing for accurate face region detection. The recognized face section assists in pinpointing the exact eye regions from the previously identified candidates. Following this, the grayscale eye pictures are standardized to [12,18] dimensions and enhance contrast through histogram equalization before feeding into neural networks trained on respective subject eye region data. Output from these neural networks interprets the subject's eye state for each frame by digitizing and merging results from both eyes. The collective eye state representation (0 for open, 0.5 for semi-closed, 1 for closed eyes) is calculated as the "eye closure point per frame" across all frames in the video snippet. If this metric surpasses a specific threshold, it indicates drowsiness; conversely, falling below the threshold signifies an awake driver.

The accuracy of both eye state and drowsiness detection can be enhanced by merging the estimations for the right and left eyes. Our proposed algorithm makes a valuable contribution by utilizing this uncommon method to improve accuracy. While many studies focus solely on the open and closed states of the eyes, our research emphasizes the importance of the semi-closed state in identifying drowsiness.

In this method, the recorded driver video is used to extract 900 frames due to the 30 fps of the video database. These frames are then processed by the "Right and Left Eye Region Extractor" module, which identifies and isolates the right and left eye regions in each frame. The neural networks are trained using the using the extracted video data. The output of the neural network is analyzed using "drowsiness evaluator" subsystem, which categorizes the eye state as open, semi-closed, or closed. By calculating the average eye state point based on these outputs, we detect driver state. If average eye state point surpasses a set threshold, the driver is classified as drowsy. The testing procedure and functionality of each module are thoroughly explained in the chapter, providing a detailed overview of the system's operation.

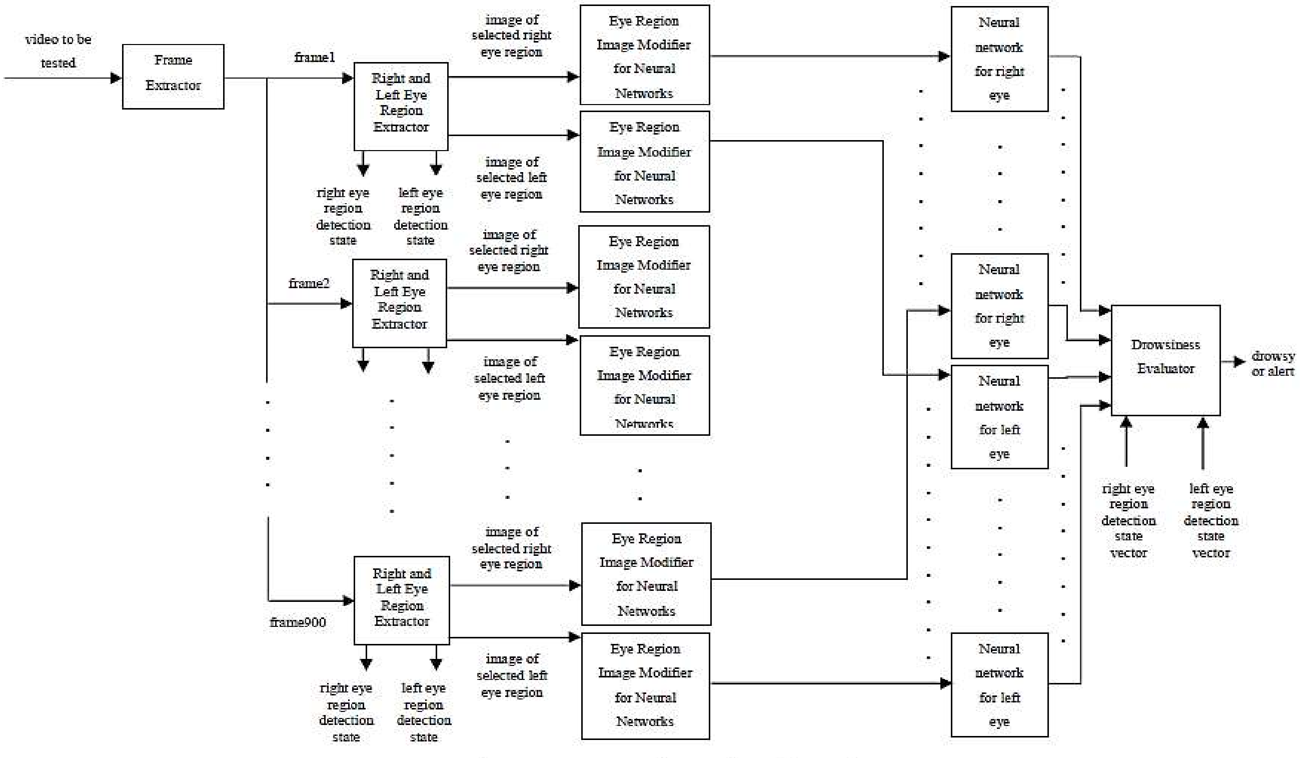


Fig 3: General procedure for testing

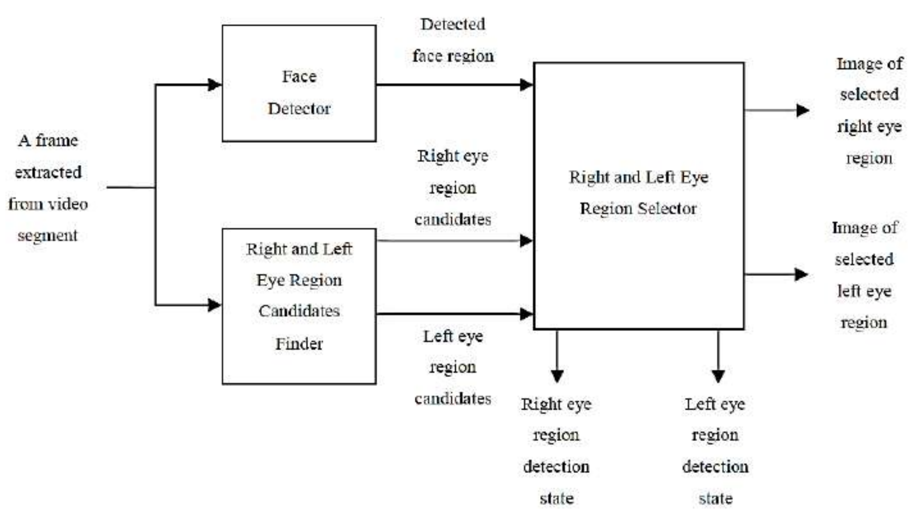


Fig 4: Analyzing the Eye Closure Rate for Driver Drowsiness Detection

2.1. Improving Drowsiness Detection in Drivers through Eye Closure Analysis

The detected eye regions vary in size, resulting in cropped images with different dimensions. To ensure consistency, neural networks require inputs of a fixed size. Therefore, it is essential to resize the eye region images for neural network input. Despite resizing, it is crucial to maintain key features during the process. Histogram equalization is a valuable technique for minimizing the impact of varying illumination levels across video segments. To assess its effectiveness, neural networks were trained using both the images. Histogram equalized images exhibited a 2% improvement in performance compared to those trained with regular gray-level images. This underscores the importance of utilizing histogram equalized images in this context.For optimal results, it is advisable to employ histogram equalization with gray-level eye region images, especially when dealing with varying illumination levels in video data. Figure 5 illustrates Eye Region Image Modifier module.

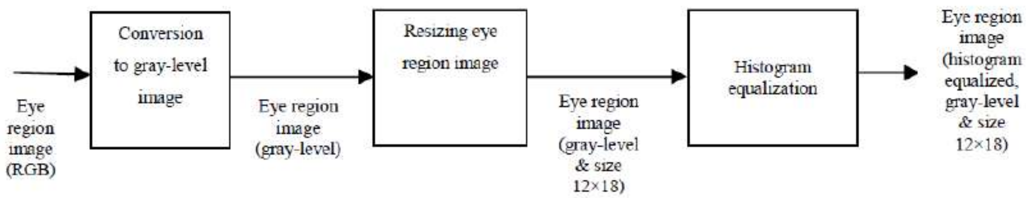


Fig 5: Eye Region Image Module

RESULTS

Twenty-five cases were assessed in total, of which ten were classified as requiring minimal attention and fifteen were classified as requiring regular attention. To address the shortcomings of the algorithm caused by the lack of eye movement monitoring, we established two regions of the safety driver's gaze. The area referred to as the Field of View (FV) (10-degree) region is where the safety driver focuses their visual attention to identify important details from their observations. The safety driver's peripheral vision (PV) encompasses a five-degree span and is responsible for the unconscious perception of environmental alterations. The unique attributes of each case are depicted in Figure 9, which includes three informative bars. Cases have been arranged according to safety driver attention and scenarios to facilitate interpretation. The initial bar presents the proportion of detected objects of each type within the given scene. Light grey segments represent pedestrians, whereas dark grey segments represent the proportion of vehicles. These two segments collectively constitute one hundred percent of the detected objects. The data that has been gathered enables the differentiation of two unique driving situations. Scenario I pertain to circumstances in which the proportion of detected objects identified as vehicles is between 95% and 100%, with any remaining percentage being ascribed to pedestrians. Therefore, a low rate of pedestrian observation is anticipated in this situation. Fifteen cases are classified within this category. In contrast, Scenario II exhibits a greater prevalence of pedestrians, comprising an estimated 5% to 45% of the objects that were observed. The ten remaining cases illustrate this scenario.

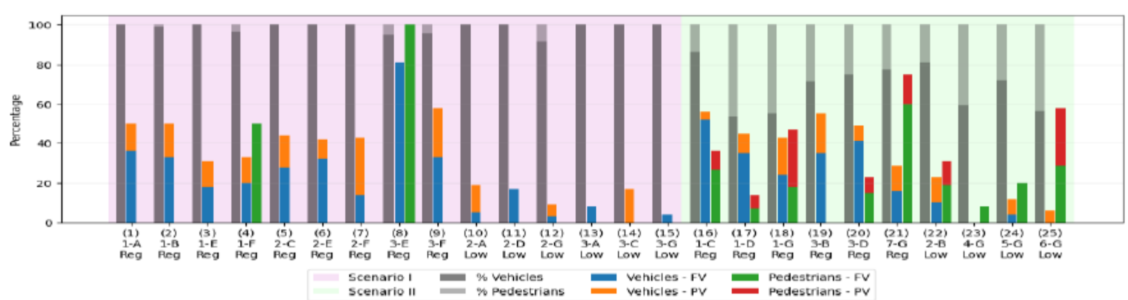


Fig. 6: Driver Case Studies

Second column gives surveillance capabilities information of the safety driver in detecting vehicles and pedestrians. The blue and orange segments in the graph represent the proportion of vehicles observed in the Field of View and Axillary regions. Percentage of pedestrians is indicated by green and red colors in the FV and PV regions. By sequentially utilizing the outputs, the system successfully classifies scenarios based on the level of attention required. Cases classified as receiving minimal attention indicate instances where a small number of vehicles and pedestrians are observed. In the first scenario, the data reveals that the proportion of observed vehicles never exceeds 20%, with minimal detection of pedestrians. Contrastingly, in the second scenario, pedestrians are observed more frequently than vehicles, suggesting a higher level of attention towards pedestrians. Moving to a more optimal situation represented in column 25, pedestrian observation falls below 25% while maintaining a balanced correlation between detected vehicles and pedestrians. Specifically, 50% of the identified pedestrians and vehicles are in the FV region, with the remaining 50% in the PV region. This visual representation aids in understanding the dynamics of attention allocation and observation parameters within the surveillance system.

Cases requiring regular attention exhibit a vehicle observation rate varying from 30% to 60% of the detected objects, while the observation rate for pedestrians falls within the range of 0% to 25%. In Scenario I, the paucity of pedestrians results in minimal or no observations on average. Nevertheless, this pattern is disrupted in two instances within this scenario: columns 4 and 8, where pedestrians were detected in significant proportions of 50% and 100%, respectively. After conducting a more thorough analysis, it was observed that the vehicle made a single detection associated with a pedestrian in case 8. This finding implies that the object detection system may have failed. Due to the lack of such detections, it is impossible to confirm the pedestrian's presence in this instance. In the same way, only one of the two pedestrian detections at the site explained fifty percent of the safety driver's observations in the column-4 scenario. The 71.56-second interval between these detections renders it improbable that they belonged to the same pedestrian, given that the vehicle was in motion throughout that duration. Notwithstanding these prospective detection failures, the classification of these cases remained accurate.

Figure 8 illustrates several instances of Scenario II along with the corresponding attention classification. For clarity regarding the examples, the metrics pertaining to each circumstance are presented in Table I.

TABLE I: Vehicle data showing FV and PV percentage

Attention	Veh. in FV	Veh. in PV	Ped. in FV	Ped. in PV
Low	0%	6%	29%	29%
Regular	16%	13%	60%	15%

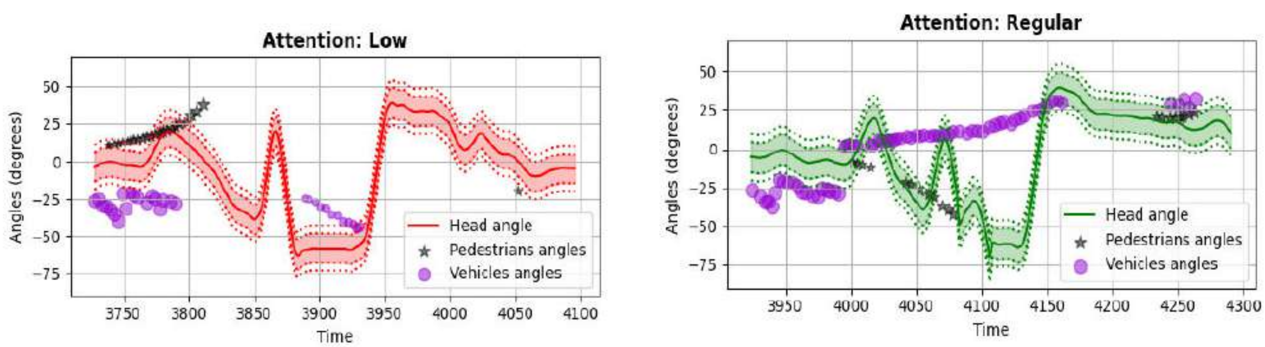
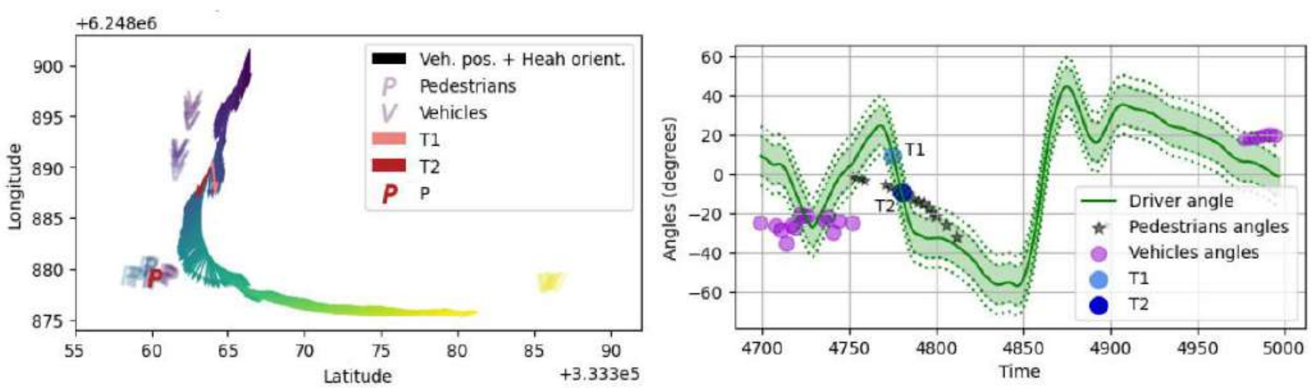


Fig. 7: Classification for each driver state

In a study, 29% of vehicle detections in the FV and PV regions contribute to safety and is combined during periods of regular attention. Additionally, 75% of pedestrian detections were recorded by the safety driver, with 60% in the FV region and 15% in the PV region. Vehicles only accounted for 22.22% of all objects detected, whereas pedestrians made up 16.67%. Notably, the PV region was responsible for the majority of pedestrian detections, making up 75% of the total. The safety driver's observations provide valuable insights into the distribution of vehicle and pedestrian detections in different regions, highlighting the significance of their presence in monitoring and ensuring the safety of the road.

The safety driver's attention was found to be lacking, with only 0% of vehicles in the FV region and 6% in the PV region being detected. Conversely, 29% pedestrians in both the FV and PV regions were observed. The respective percentages for the total objects detected are as follows: 3.64% for vehicles and 25.45% for pedestrians. An important discovery emerges from the examination of the safety drivers' focus throughout every lap, irrespective of the scenario in which it transpired. As indicated in Table II, in the initial circuit, every safety driver was categorized as maintaining consistent attention. Nevertheless, as the subsequent circuits progressed, a wider variety of patterns emerged. Two (29%) of the seven safety drivers maintained consistent attention for the duration of each cycle. In contrast, four safety drivers (57 percent) encountered variations in attention level, either from regular to low or from low to regular. A subset of participants (14%) exhibited a decline in attention that persisted consistently for the duration of the remaining circuits. The observed trend can be ascribed to an increase in safety drivers' self-assurance in operating their vehicles, potentially leading to a decline in overall attention levels.

The conduct is illustrated in Figure 9, where the lap times of the safety drivers are depicted at the base of the bars.



(a) Vehicle Position and driver orientation (b)Normal Driver

Fig. 8: Sequence Analysis of driver

Images from frontal and internal cameras show road and safety driver. Vehicle's data is on right side. Periods T1 and T2 indicated by red arrows, with pedestrian detection highlighted in red. T1 and T2 shown as blue points in angle plot.

TABLE II: Safety drivers' levels of attention on each lap driven..

Driver	Lap 1	Lap 2	Lap 3	Lap 4-7
A	Regular	Low	Low	-
B	Regular	Low	Regular	-
C	Regular	Regular	Low	-
D	Regular	Low	Regular	-
E	Regular	Regular	Regular	-
F	Regular	Regular	Regular	-
G	Regular	Low	Low	Low/Regular

To compress data, a data compression algorithm loses or discards some of the data. Image quality and size could be reasonably balanced by adjusting the com- pression level. The JPEG compression ratio is typically 10:1[8]. The JPEG method makes use of separately compressed 8 × 8-pixel image grids. Any matrices smaller than 8 x 8 don't have enough information, while any greater than 8 × 8 are either harder to work with conceptually or aren't supported by the hardware. As such, the quality of the compressed photos is low. For unaffected photos, every 8 x 8 grid should have the same error level to enable image to resave. Every square in the picture should decay approximately at the same rate because the flaws are dispersed uniformly throughout. In a modified image, the modified grid needs to have a larger error potential than the others. ELA. The difference between the two photos is calculated once the image is resaved with a 95 percent error rate [9]. This method checks to see if the pixels are at their local minima to see if there has been any change in the cells. This aids in identifying any instances of digital manipulation inside the database.

The data retrieved from the vehicle during two instances is shown in Figures 8a and 8b. The images display the truck's frontal camera view in the upper-left corner, aiding in identifying both the vehicle and the pedestrian. One of the vehicle's three front-mounted cameras is used to detect objects. In the lower-left image, the infrared camera captures the safety driver, emphasizing key features mentioned in Section III-B (marked by red points) and orientation angles indicated by three colored lines near the safety driver's position. Additionally, important algorithm data is presented in the upper-left corner. A red arrow signifies the safety driver's head orientation, a green path represents the vehicle's trajectory, and a yellow-purple marker indicates the pedestrian detected in the lidar data on the right side. Moreover, an additional object is identified by the vehicle in Fig. 10a, corresponding to a stationary vehicle in this specific scenario.

Figure 8b displays the dataset visualized, showing the correlation between the safety driver's head orientation and the vehicle's position. In Figure 8a, vehicles and pedestrians are marked with "V" and "P" respectively. Individual pedestrians detected by the camera make up the pedestrian group, while each distinct vehicle forms a separate group. The pedestrian identified at T2 is highlighted in red. The intersection of head orientation and pedestrian bearing angle relative to the vehicle is depicted in Figure 8b. Despite both scenarios occurring during the blue points, the driver first noticed parked vehicles before the pedestrian, emphasizing the driver's attentiveness. The safety driver focused on most objects in the scene, with the pedestrian coming into view shortly after T1, indicating a high attention span. Therefore, this case is classified as requiring routine attention.

CONCLUSION

The article uses eye closure rate as a drowsiness indicator, extracting video data into frames analyzed by an eye region extractor. After resizing and equalizing the gray scaled eye regions, neural networks process each left and right eye image separately, trained on the subject's eye region data. The digitized outputs from both networks are combined to determine the subject's eye state. Frames are then categorized as open, semi-closed, closed, or deemed with "no valid estimation" based on the averaged eye state points. This average is calculated from frames where valid estimations were made. Segments with an average eye state point above the threshold indicate drowsiness, while those below are classified as alert. This innovative approach efficiently assesses drowsiness levels by analyzing visual cues, providing a reliable method for early detection and alerting individuals when they may be at risk of falling asleep. Through this technology, potential accidents due to drowsiness can be minimized, enhancing safety in various settings such as driving or operating heavy machinery.

Our method has achieved an impressive 99.1% accuracy in detecting drowsiness, showcasing its efficacy. This success stems from a strategic balance between input size and the computational resources demanded by the neural network. By converting eye region images to 12x18 grayscale and resizing them, we reduce the number of neurons required for processing, thus optimizing efficiency. Additionally, applying histogram equalization enhances eye state detection by mitigating the impact of lighting variations. we also incorporated merging the outputs of separate neural networks dedicated to the right and left eyes. This fusion technique involves eliminating frames where the neural networks produce conflicting results, further refining the accuracy of eye state detection. By leveraging these methodologies, we not only achieve high precision in drowsiness detection but also streamline the computational demands of the neural network, offering a well-rounded solution.

To enhance data collection from the vehicle's surroundings, we plan to refine processing techniques and expand our dataset. This will involve integrating map data into our system to provide additional information for better understanding the environment. The inclusion of cartographic data will allow us to differentiate between pedestrians on sidewalks and those on the road. It will also enable us to identify right-of-way, determine vehicle travel directions, and consider other important factors. By implementing this system, we aim to improve overall driving safety by generating alerts for safety drivers when their situational awareness is inadequate. Expanding our dataset and incorporating map data will significantly enhance the accuracy and relevance of the information obtained from the vehicle's surroundings. This approach will not only improve our understanding of the environment but also contribute to the development of more effective safety measures for autonomous driving.

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