

Tiredness Detection in Real Time Using Eye State Evaluation

Shruti Chigari¹, T Vijaykumar²

¹Student, Dept. of MCA, Bangalore Institute of Technology, Bengaluru, India

²Assoc Professor, Dept. of MCA, Bangalore Institute of Technology, Bengaluru, India.

Abstract: According to an earlier year's report on street collisions, the main factor in such fatal street mishaps is a result of careless behavior in addition to the sluggishness of the driver. This problem demonstrates the need for such a framework that can perceive the driver's sluggishness condition and gives the driver a ready signal before any mishaps occur. Thus, in light of the eye squint span, this proposed work has laid out tired recognition as well as a mishap evasion framework. First, the open and closed conditions of the eye are identified in relation to the eye viewpoint proportion (EAR). Furthermore, the flicker span or count is broken down while the progression eye condition from open to closed. Then, when the flicker span exceeds a specific cut-off point, it recognises the tired condition and sends an alarm message to the driver via the caution. On the yawning dataset, our created framework demonstrated an accuracy of 92.5 percent approx. (YawDD).

Keywords: eye squint location; Eye aspect ratio (EAR); sleepiness detection;

1. INTRODUCTION

"Sleepy" appears to be a simple word, yet it becomes more significant when someone is involved in a situation where profound fixation is a significant figure, for example, working in a synthetic manufacturing plant or operating a large vehicle, and so on. In such a case, if the individual deviates from his or her legitimate focus, an incredible disaster could happen. As has been observed, the majority of street crashes are caused by the carelessness of the driver while he or she is nodding off or sleepy while operating a motor vehicle. As stated by the 2018 research on roads mishaps in India released by the Ministry of Highway and Road Transportation, 4, 67,044 mishaps occurred both in states and Union Territories [1]. Furthermore, an examination within this report reveals that 78 percent of all street crashes they caused by driving negligence. Along these lines, there is a need to create a model that can prevent such tragic street collisions and save humanity's valuable existences. In this case, our proposed project meets these requirements. The numerous procedures that have been used to date to perceive the sluggish condition of the driver could be broadly classified into three groups, namely physiological, behaviour, and vehicle boundary-based strategies. Physiological and vehicle-based procedures are nosy in nature, whereas social-based procedures are non-interfering in nature. The term meddling refers to additional hardware that must be connected to the driver collection in order to bring the information needed to recognise the driver's condition. In this way, we considered the 'conduct'-based strategy in our proposed work. This strategy employs obvious signals to determine the driver's state of sluggishness. In our proposed structure, the detection of a driver's sluggish condition is primarily founded on flickering qualities of the eye using an eye viewpoint proportion boundary [17, 19, 20]. This entire paper is structured as follows: Section 2 exhaustively depicts the qualities and shortcomings already existing structures through a thorough investigation of writing review. Segment 3 thoroughly explains the proposed strategy. Section 4 also includes a discussion of the results and investigation. For example, Area 5 contains a thought about future projects and the completion of work proposed.

2. LITERATURE SURVEY

Despite the fact that numerous studies have been conducted to ascertain the level of exhaustion and sluggishness of the driver in light of physiological, social, and vehicle attributes. Among these are procedures, Forsman and colleagues. [2] planned a system that used various vehicle development such as flow position of vehicle on path, guiding wheel development, development include both brake and speed increase pedal, and so forth in the examination of driver's sleepiness level. These characteristics are mostly associated with the vehicle model, driving ability, and driver proximity. These methodologies do not perform well when there is an occurrence of miniature rests (driver nods off on wheel briefly) because it requires a large quantity of information in addition to time and effort to estimate these boundaries. Taking this into consideration, these strategies are occasionally meddling in nature, that is, outer supplies are mounted on the driver's assortment to catch these boundaries, diverting the driver from their normal driving. Few previous studies have also evaluated physiological trademarks like mind cue, pulse and nerve driving forces, and so on,

to perceive the sleepiness condition of the driver. Simon et al. [3] investigate how a driver's sluggishness is detected using electromyography and other electric signals (EMG) electroencephalogram for muscle tone (EEG) [4] for cerebrum action, electrocardiography (ECG) for pulse, and electrooculogram (EOG) [5] for visual action. In this case, the investigation includes concluding that the degree of tiredness in light of physiological qualities is meddling in nature. Because of this nosy nature, a number of supplies with numerous sensors have been attached to various parts of the driver's body suitable for learning mental cues as well as nerve motivations, etc. As a result, these types of gear add weight to the driver, interfering with their smooth driving. As a result, it is critical that there be no actual connection between the ID framework and the driver. As a result, despite producing excellent results, these procedures are not industrially feasible. The PC vision strategies were introduced to resolve the issue revealed by physiological and nerve tests vehicle qualities-based sleepiness recognition methods discussed in the preceding sections. This method has recently gained popularity due to the low cost of execution, ease of design with the vehicle, and non-interfering nature. We discovered from the study of written works that the PC vision method mostly used the look in assurance of tiredness because it is simple to distinguish whether the driver is lethargic or a warning via the look [16, 18]. Bergasa and colleagues. [6], recurrence, plentifulness, term connected with opening and shutting of Both the mouth and the eye are important role in recognising proof of the driver's sluggishness state. Using this method, the system investigates the surrounding region and state of the iris in a specific time allotment to record these factors, for example, recurrence, abundance, term, and so on.

III. PRE-PROCESSING TECHNIQUE

The problem with technique was that it was extremely. In low lighting, it is difficult to capture the eye state., particularly during a bad weather pattern. As a result, as a pre-handling step, we used the Histogram levelling method in our proposed work, which distributes the force values throughout the casing. [7]. As a result, it reduces the impact of lopsided light scattering at each edge. Furthermore, as a pre-handling step, we used the Gamma Correction technique to improve the differentiation via a nonlinear change in the contribution and result planned values [8].

IV. PROPOSED METHODOLOGY

4.1. Summary of Proposed Work

In our proposed project, we first extracted the driver's frontal image from the video input stream. The face was then identified by drawing a bounding box around it. We used the dlib facial feature tracker's inbuilt face detection library, which is based on 68 facial landmarks, to create the bounding box [9]. Furthermore, we used the coordinates of predefined landmarks in dlib to localise the region of interest in the eye (ROI). Then by imposing a threshold value, we The eye aspect ratio (EAR) was calculated to determine whether the eyes were open or closed. Thus, the duration and number of frames involved in blinking determine the state of drowsiness, i.e. alert or drowsy. The flowchart in Figure 1 depicts step-by-step processing of proposed work

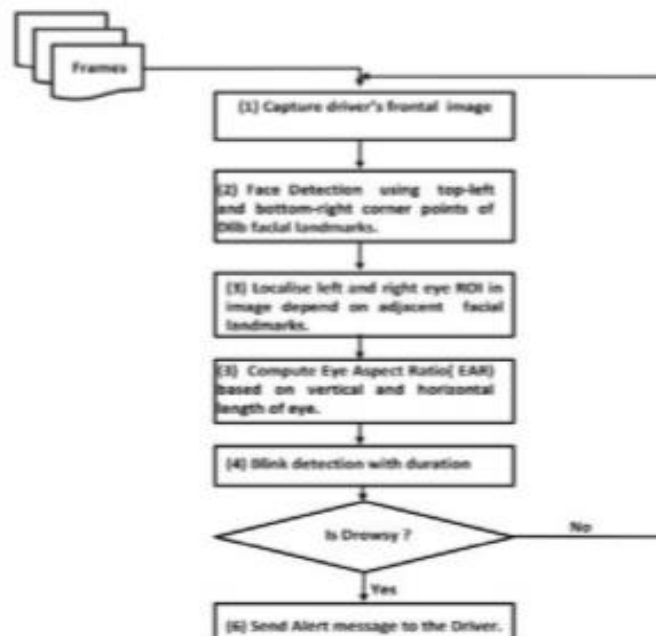


Fig. 1. Summary of proposed work



4.2. Face Detection

We consider the dlib facial element tracker database in our planned system to distinguish the driver's face from a picture. Because dlib libraries employ the Histogram of Oriented Gradient(HOG) Linear Support Vector Machine as a highlight descriptor (SVM) as a classifier. As a result, we will investigate face recognition using HOG here [10]. Before we begin discussing HOG, we should be aware of the angle. In this context, Angle is defined as a sudden change in pixel value when moving from left to right or through and through, i.e., from dark to white or the other way around. Moving from left to right produces a flat angle, while development from start to finish produces an upward slope. In HOG, there is a square or sliding window that contains 64 pixels by default. This sliding window is made up of a network of pixels with inclinations for shifts in greatness and pixel-related forces. Because HOG works with grayscale images. As a result, before applying the HOG, the image should be converted to grayscale. Furthermore, with the help of Figure 2 and conditions 1&2, the even as well as upward slope for each pixel accessible in block are registered as follows.

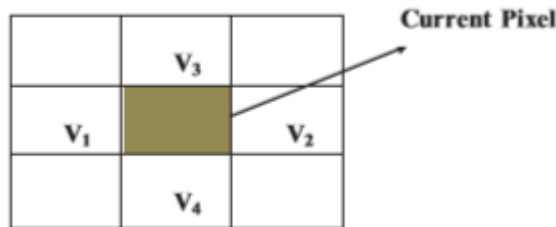


Fig. 2. Horizontal and Vertical Gradient Computation

$$\text{Horizontal Gradient (HG)} = V2 - V1 \quad (1)$$

$$\text{Vertical Gradient (VG)} = V4 - V3 \quad (2)$$

Where $V1$, $V2$, $V3$, and $V4$ are the pixel values in the current pixel's neighbouring pixels. After calculating both gradients, we use equations 3 and 4 to calculate the gradient magnitude and angle:

We obtained 64 gradient vectors for 64 pixels in a row in this manner and reduced them to 9 vectors. A Histogram plot of magnitudes and angles is used here to reduce the data into 9 vectors. As a result, we drag the sliding window across the entire image space and try to decipher the Histogram results. The interpretation of Histogram results yielded some HOG features that confirmed the face in the image. In our experiment, we used HOG to create an object of the built-in dlib face detector class and called the function detector with the grayscale image as an argument. Using the top-left and bottom-right pixel coordinates, draw a bounding box around the face. Figure 3 depicts the image containing the containing the as a result of our experiment described below



Fig. 3. Bounding box for face detection

4.3 Eye Detection

The different features associated with the face indicate drowsiness. Slow and fast blinking symptoms are present in the eyes, whereas yawning symptoms are present in the mouth. In addition to these characteristics, movement of the head detects drowsiness when it inclines downward or nods repeatedly. According to the various studies discussed above, blinking of the eyes is the most important feature in determining the state of drowsiness. We were able to eliminate the inbuilt landmarks for both eyes from the available 68 total landmarks after importing the Dlib facial shape predictor packages into our designed framework [9]. Both eyes' landmark point sequence numbers range from 37 to 48. In terms of our proposed work, these are the key data points that capture the feature. Following that, we obtained the coordinate values of all of these carefully selected landmarks, which ranged from 37 to 48 for each video frame. As a result, acquired coordinates include both eyes' periphery. This feature was chosen to display the blinking indication. Figures 4 and 5 show the method we used to extract this feature. We used Histogram equalisation and Gamma correction before extracting this feature to lessen the effect of light variation in each video frame.

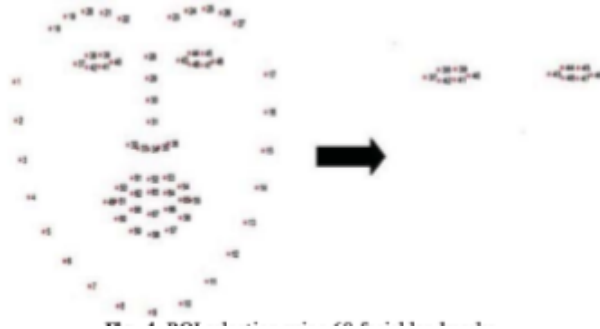


Fig. 4. ROI selection using 68 facial landmarks



Fig. 5. Facial landmarks detection and ROI selection

4.4 Eye Aspect Ratio (EAR)

The eye angle proportion (EAR) was calculated using the coordinates of the chosen milestones. During the tired state, the EAR contracts rapidly towards zero. EAR is the vertical to horizontal ratio of flat length of the eye. As shown in Figure 4, the 6 bordering tourist spots of the dlib bundle are important for limiting each eye, for example, either the left or right eye. These tourist attractions play an important role in calculating eye angle proportion.

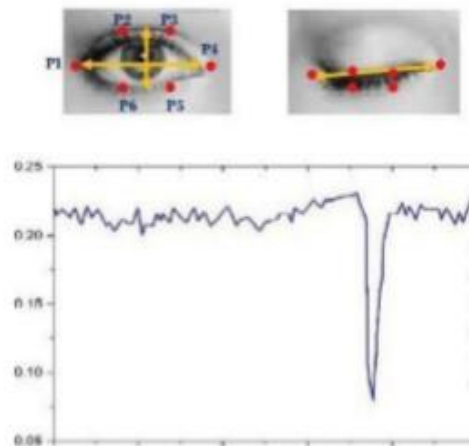


Fig. 6. Eye aspect ratio

According to convention, the six landmark points for an eye are denoted in Figure 6 by P1, P2, P3, P4, P5, and P6. First, we calculated the vertical Euclidian distance between the two points (P2, P6) (P3, P5). We also calculated the horizontal Euclidian distance between the points (P1, P4).

4.5 Blink Detection

As shown in Figure 7, the value of EAR varies depending on the state of the eye, for example, open or closed. Based on the analysis, we chose a limit of 0.35 for EAR to distinguish between the open and closed conditions of the eye. Time passed during the shutting condition of the eye is accepted as T in this case. The different condition of the driver based

on EAR esteem and slipping by time is highlighted in Table 1. Since it is widely accepted that the time elapsed time between two continuous casings is 100ms. As a result, the time spent closing one's eyes can be considered in relation to the number of casings.

Table 1: Driver's condition based on various conditions

Driver's State	Decision Parameter
Alert	EAR > 0.35
Normal Blink	EAR < 0.35 T < 300ms
Drowsy	EAR < 0.35 T >= 300ms & T < 900ms
Sleeping	EAR < 0.35 T > 900ms



Fig. 7. a. Eye aspect ratio for open eye, b. Eye aspect ratio for closed eye

V. RESULTS AND DISCUSSION

In our proposed work, we created a framework that can be easily deployed on a machine and is both powerful and solid to use. Because it is nosy, this created technique is profoundly appropriate in examination of physiological strategy-based framework, for example, EEG, EOG, and so on, because there is compelling reason to connect any additional gear with the group of drivers to identify the condition of tiredness [3]. In this case, two boundaries, such as EAR and time span (T), are used to pursue the choice of driver sleepiness. First, we contrast the EAR esteem and the pre-established limit esteem. In a nutshell, when the worth of the EAR is not exactly the edge, the condition of the eye changes from open to close. In this case, a flicker counter is used, and its value is increased. In fact, this counter keeps track of how much time has passed in the sluggish state. If the value of this counter is greater than exceeds a certain threshold, an alert message will be delivered to the driver to alert him to the situation. We have outlined Figure 8 to show the average driver squint. It is possible to recognise the starting and finishing points of the squint here. Furthermore, we can compute the time length for a flicker by subtracting the beginning and the end times. Further, we can compute the time length for a flicker by means of taking the distinction among start and end point of squint. A basic recipe for this is displayed in the situation

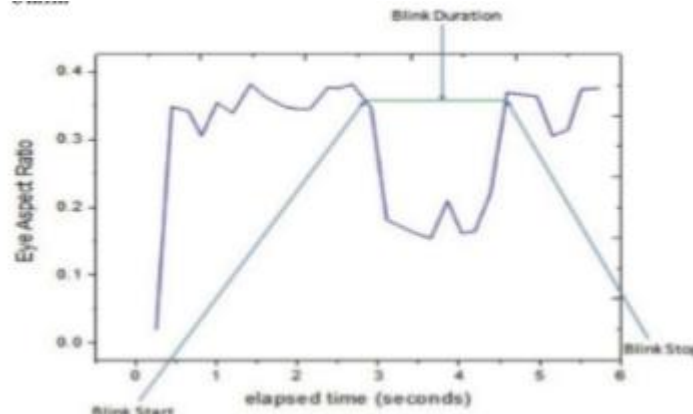


Fig. 8. Visualization of a typical blink

Our entire work is tested on the YawDD video dataset, which contains driver clasps with various facial prompts [11]. In the YawDD dataset, recordings are taken in two ways based on the location of the camera, for example, one underneath the front mirror and another over the driver's scramble. We considered the recordings taken from the camera present in the place of the driver's scramble for our proposed work. It includes approximately 29 recordings of male and female drivers with and without glasses. We discovered that eye flickering can be precisely identified or not during our investigation. With YawDD, we achieved a precision of approximately 92.5 percent in this perception. This perception outcome is depicted in Table 2 below. Based on our findings, we concluded that our intended framework performed admirably in the eye squint location alongside the flicker span. Regardless, it was not always providing dependable results when the driver wore the glasses. Here, we show a few edges from Figure 9 that we used in our examination work. We used Table 3 to demonstrate the relationship between our proposed work and previous work.



Figure 9: Handled outlines from YawDD dataset

Table 2: The procured outcome on YawDD

Video categories	Total tested videos	Accurately Identified videos
Female without glasses	07	07
Female with glasses	04	03
Male without glasses	04	04
Male with glasses	08	07

Table 3: Examination of Earlier and Proposed work

Previous Work	Features Used	Accuracy
[12]	ECG	90%
[13]	EEG	84%
[14]	Pupil	92%
[15]	Yawning	91.90%
Proposed Work	Eye blink pattern	92.5%

VI. CONCLUSION AND FUTURE WORKS

Despite this, our developed system performs better in detecting the driver's state of sleepiness. However, a few issues still exist that have a significant impact on the presentation of our planned framework, such as our framework failing to produce noticeable quality results in low perceivability conditions or at night. Furthermore, due to serious head development or head development very toward any path, our framework is incapable of recognising the driver's eyes. This designed framework is also incapable of recognising the driver's eyes when he or she is wearing sunglasses. Aside from these impediments, our framework has clearly distinguished eye squints and tiredness in adequate lighting. Even if the driver is wearing a power glass, the created framework can detect eye flicker. In the future, we may want to use some hearty programming, for example, CNN-face identifier, which can distinguish when the head is turned development is incredibly toward any path, but we should keep in mind to settle the time slipped by in acknowledgment of tiredness. Since then, we've dealt with the issue of determining the edge worth as a result of the various components



of each member's eye. Along these lines, one can standardise the information at this point to better suit this issue in the future and improve the overall precision of the framework. Furthermore, we may want to test a few different elements, such as mouth, hand or leg development, and head development, among others, in addition to eye flickering, to improve the precision and execution of our framework.

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