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DEVELOPMENT OF VEHICLE DRIVER DROWSINESS DETECTION SYSTEM USING EYE ASPECT RATIO

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ABSTRACT

A countless number of people drive on the highway day and night. Taxi drivers, bus drivers, truck drivers, and people traveling long-distance suffer from lack of sleep. Due to which it becomes very dangerous to drive when feeling sleepy. The majority of accidents happen due to the drowsiness of the driver. The major aim of this research is to develop a system that alerts the driver if any type of drowsiness occurs. The proposed approach to detect driver's drowsiness is based on two levels: The face is detected from a video stream using facial landmark detection and the eye region is extracted. These facial landmarks are then used to compute the Eye Aspect Ratio (EAR) and are returned back to the driver. Numerous variety of images were considered for testing purposes. The obtained accuracy was found to be adequate. The proposed system will alert the driver when drowsiness is detected. Drowsiness detection is a safety technology that can prevent accidents that are caused by drivers who fell asleep while driving. To validate the proposed approach tests were conducted by using a variety of different images, such as the driver's face covered with a mask or glasses. The proposed approach uses EAR with adaptive thresholding to detect driver drowsiness in real-time. This is useful in situations when the drivers are used to the strenuous workload and drive continuously for long distances.

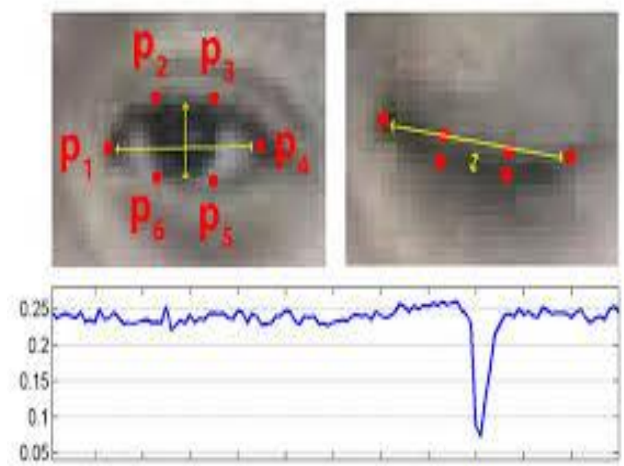
1. Introduction

The number of motor vehicles in developing countries has been gradually increased over the decade. Official investigation reports of traffic accidents point out that dangerous driving behavior, such as drunk and drowsy driving, accounts for a high proportion of accidents (Saito et. al. 2016). Most of the accidents related to driver drowsiness occur around 2:00-6:00 a.m. and 14:00-16:00, and it is often pointed out that night shifts make drivers particularly vulnerable (Chui et. al. 2016). Additionally, it is evident from the research that driver fatigue is also one of the major causes of road accidents. Different countries have different statistics for accidents that occurred due to driver fatigue. On average traffic, road accidents in the world claim 1.3 million lives and cause 50 million disabilities annually(Arimitsu et. al. 2007). Driver drowsiness is a serious hazard and major concern, which is identified as a direct or contributing cause in most road accidents. Since drowsiness can seriously slow down the reaction time and subsequently decrease driver's awareness and judgment (Lin et. al. 2008). The development of a Driver drowsiness detection system is capable of producing warning to the driver that can prevent road accidents and thus save lives. In general, the drowsiness detector system focuses on two important computer vision techniques, Facial landmark detection andEAR. The driver drowsiness detection is based on an algorithm, which starts with Detecting the face in the input video stream. Furthermore, facial landmark localization is applied to extract the eye regions from the face. Subsequently, the eye aspect ratio is computed to determine, if the eyes are closed or open. It further Generates the alarm if the eyes have been closed for a sufficiently long enough time.

Computer vision engineers and researchers have been trying to understand the human face since the very early days. The most obvious application of facial analysis is Face Recognition. However, to identify a person in an image one needs to find where in the image a face is located. Therefore, face detection locating a face in an image and returning a bounding rectangle/square that contains the face (Tereza and Jan2016). Facial landmark prediction is used in the system as the process of localizing key facial structures on a face, including the eyes, eyebrows, nose, mouth, and jawline. Specifically, in the context of drowsiness detection, we only needed the eye regions.

There are various approaches towards driver drowsiness detection. Mostly the standard methods are traditional and based on behavioral aspects whereas few work in intrusive manner and distract drivers. Apart from this, there are few methods that need expensive sensors to be deployed and few computationally intensive machine learning approaches. In nutshell, the driver drowsiness can be measured through three dimensions. They are vehicle based, physiological and behavioral measures. Despite the fact that the vehicle based measures (McDonald, A.D, et. al. 2012, Bhatt, P.P et al. 2017) are not intrusive, but might not be successive as far as the accuracy of the system is concerned. Because this type of approach depends completely on the driver's expertise and the nature of the road. The physiological measures are all about adding some sort of electronic device near to driver in order to monitor the driver's conditions. This further includes electrocardiography, electroencephalography, and few more sensors or smart devices like a wrist band and hand watches (Singh et. al. 2012, Mittal et. al. 2016, Kundinger et. al. 2020, Awais et. al. 2020). This aforementioned method is alsoknown as a sensor based approach. Even though the system based on sensors produce highly accurate outcomes, but are they are rarely adopted because of their practical limitations and issues, such as, battery life and power consumption.The last one, behavioral measure is a more practical and non-invasive approach. It contains image processing and computer vision techniques where the data is obtained from video or images by deploying the camera as an input medium. An enormous amount of research has already been conducted in this area. This is becoming a popular area of research due to the recently advanced algorithms. Additionally, this domain has also been extended by including the state of the art machine learning and deep learning algorithms for driver drowsiness detection (Ngxande, et. al 2017). However, our work is specific and only focuses on computer vision techniques for the system development.

The primary aim of this work was to come up with a non-intrusive, lightweight system for deployment in vehicles that is less computationally intensive than the rest of the other Machine Learning (ML) algorithms. EAR is an inexpensive and cost-effective image processing technique. In contrast to other traditional image processing methods for computing the blinks, EAR comprises a simple calculation based on the ratio of distances between facial landmarks of the eyes. Itcalculates the ratio of distances between the vertical eye landmarks and the distances between the horizontal eye landmarks. This can be further seen in Figure 1. Figure 1(a) shows open and closed eyes with landmarks pi automatically detected. The EAR is used to determine if the eyes are closed. If the eyes have been closed for a sufficiently long enough period, it is assumed that the user is at the risk of falling asleep and to generate an alarm to grab their attention. The horizontal x-axis indicates the time of the captured clip in Figure 1(b) graph. The vertical y-axis indicates is corresponding EAR value. It can be further observed from the figure that the value of EAR remains steady with minor fluctuations until it reaches the time frame where the eye gets close in the video. Thus, this affects the abrupt drop in the EAR value. The value of EAR reduces with a huge difference. This means that as the person closes or blinks the eye, EAR declines intensely towards zero.



time

Figure 1. Eye Aspect Ratio

2. Literature Review

In a bid to increase accurateness and accelerate drowsiness detection, several approaches have been already proposed in the literature. This section attempts to summarize previous methods and approaches to drowsiness detection. As indicated in the earlier section, this research area has excelled in three different directions for monitoring diver drowsiness. The first one is either using vehicle or road dynamics. The second one is through physiological measures subsequently the last one uses behavioral measures. The authors in (Arimitsu et. al. 2007), developed the driving simulator with the seat belt motor retractor, which was used in a commercial vehicle, to provide the vibration stimulus to the drivers. The limitation of this study was the variation of the portions, which were stimulated by the seat belt. Liang et. al. 2008, proposed a novel Brain Computer Interface (BCI) system that can acquire and analyze Electroencephalogram (EEG) signals in real-time to monitor human physiological as well as cognitive states, and in turn, provide warning signals to the users when needed. The accuracy of the BCI system is slightly less when compared to the existing systems to detect drowsiness. Lin et. al. 2010, proposed system consists of a wireless physiological signal-acquisition module and an embedded signal-processing module. In case, if defects in the EEG monitor then the detection of drowsiness may decrease. This approach is based on driving patterns, and it is highly dependent on vehicle characteristics, road conditions, and driving skills. To calculate driving patterns, deviation from a lateral or lane position or steering wheel movement should be calculated. Fagerberg 2004, Krajewski et. al. 2018, Rateb et. al. 2018 detected real-time driver drowsiness using deep Neural Networks (NN). They developed an Android application. Sagonas et. al. 2016 used EAR as a standard measure to compute the drowsiness of a person. They also provide comprehensive details regarding the types of systems used for detecting drowsiness of the driver. For example, Active Systems (considered as reliable, but use special hardware that is expensive and intrusive like infrared cameras, etc.) and Passive Systems (are inexpensive and rely on Standard cameras). Several other research works have been conducted to determine vision-based drowsiness detection (Patel et. al. 2018, Mehta et. al. 2019, Kumar et. al. 2018, Das et. al. 2017).

The current research area is advancing due to recent technological developments in the domain of image processing and machine learning (Vurul et. al. 2009). The development of a drowsiness detection system that indulges more accurate and reliable results becomes a challenging task due to robust and computationally intensive algorithms. Recently, a lot of work is done using advanced machine learning and deep learning models (Dua et. al. 2020, Park et. al. 2016, Chirra et. al. 2019). As Deep learning algorithms are producing state of the art results, more accurate outcomes can be achieved. As far as these algorithms are concerned, there are few limitations. For using these advanced algorithms, computational resources must be exceptional. Apart from this, in order to train a deep learning model, for example, Cable News Network (CNN), it is essential to have a large Dataset. On contrary, EAR produces reasonable accuracy and is less computationally intensive. Therefore, our proposed system uses Adaptive EAR thresholding in order to identify and monitor the eye blinks and drowsiness.

3. Research Methodology

This section details the proposed approach to detect driver's drowsiness that works on two levels. The face is detected from a video stream using facial landmark detection and extract the eye regions. These facial landmarks are then used to compute the EAR and are returned back to the driver. In our context, the EAR value received at the application's end would be compared with the threshold value taken as 0.3. If the EAR value is less than the threshold value, then this would indicate a state of fatigue. In case of Drowsiness, the driver and the passengers would be alerted by an alarm. The subsequent section details the working of each module as summarized in Figure 2.

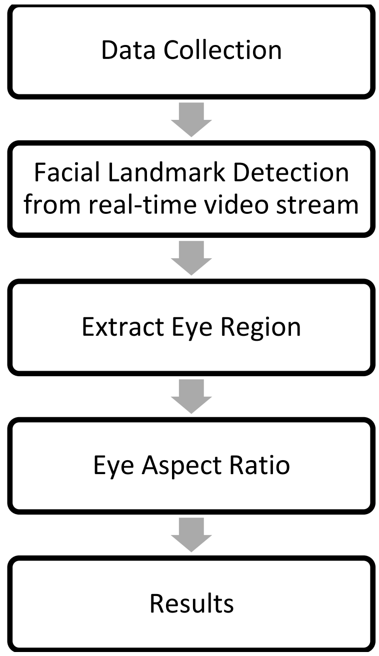


Figure 2. Flow of Methodology

Data Collection and Preprocessing: The data for this research study is recorded directly from a machine webcam using OpenCV. From webcam video stream face is being detected continuously. Facial landmarks are used to localize and represent silent regions of the face, such as eyes, eyebrows, nose, mouth, jawline. Facial landmarks have been successfully implemented for face alignment, head pose estimation, face swapping, blink detection. Detecting facial landmarks is therefore a two-step process: Step-1 is to Localize the face in the image. And, step-2Detects the key facial structures on the face Region of Interest (ROI).

Experimental Setup: Face detection i.e. Step-1 can be achieved in several ways. OpenCV's built-in Haar cascades can be used. Pre-trained (Histogram of Oriented Gradients (HOG) + Linear Support Vector Machine (LSVM) object detector specifically for the task of face detection can be applied. Or deep learning-based algorithms for face localization can also be used. In either case, the algorithm used to detect the face in the image doesn't matter. Instead, important is that through some method/algorithm the face bounding box (i.e. the (x, y)-coordinates of the face in the image) can be obtained. Given the face region then Step-2 can be applied i.e. detecting key facial structures in the face region. There are a variety of facial landmark detectors, but all methods essentially try to localize and label the following facial regions: mouth, right eyebrow, left eyebrow, right eye, left eye, nose, jaw. This method starts with a training set of labeled facial landmarks on an image. These images are manually labeled, specifying specific (x,y)-coordinates of regions surrounding each facial structure. Subsequently, the probability on the *distance* between pairs of input pixels. The pre-trained facial landmark detector inside the dlib library is used to estimate the location of 68 (x,y)-

coordinates that map to facial structures on the face. The indexes of the 68 coordinates can be seen in Figure 3. Table I indicates the coordinates related to both eyes.

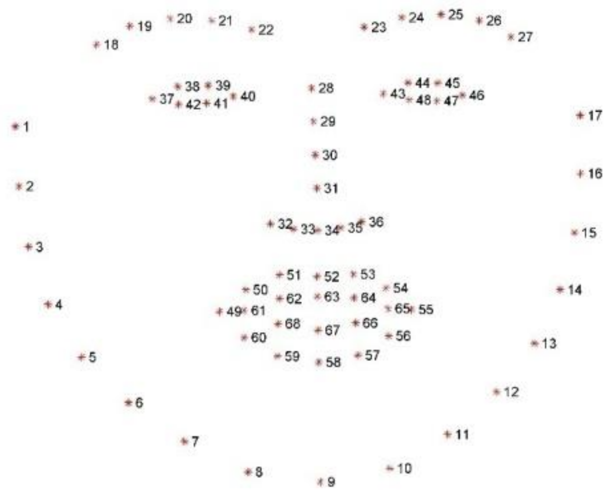


Figure 3. Visualizing the 68 facial landmark coordinates

Table 1. Facial Landmarks [15]

Part	Landmark Points
Left Eye	[37-42]
Right Eye	[43-48]

The AER involves a very simple calculation based on the ratio of distances between facial landmarks of the eyes. This method for eye blink detection is fast, efficient, and easy to implement. Each eye is represented by 6 *(x,y)*-coordinates, starting at the leftcorner of the eye (Figure 4):

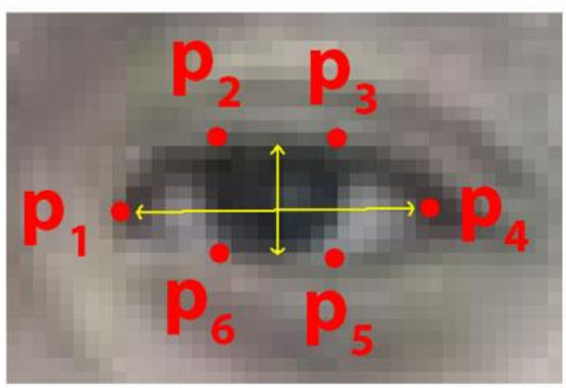


Figure 4. The 6 facial landmarks associated with the eye

Based on the work by Patel et. al. 2018. EAR is defined as the ratio of height and width of the eye and was computed using Equation (1).

$$\mathrm{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|} \tag{1}$$

The numerator computes the height of the eye i.e. the distance between the vertical eye landmarks. The denominator computed the width of the eye i.e. the distance between horizontal eye landmarks. Where p_1, p_2, p_3, p_4, p_5,p_6 are 2D facial landmark locations.

In our drowsiness detector case, the EAR is monitored to check if the value falls below the threshold value, and also it does not increase again above the threshold value in the next frame. The above condition implies that the person has closed his/her eyes and is in a drowsy state. On the contrary, if the EAR value increases again, it implies that the person has just blinked the eye and there is no case of drowsiness. As you can see in Figure 5 , left eye and right eye are detected with spectacles using facial landmark detection.

Figure 5 shows that initially an image is taken from the video stream. Moreover, the face is detected and the eyes are being focused. Later on, EAR is calculated, finally it is identified that either eyes are closed or not, and based upon that it is decided that there is any sort of drowsiness or not.

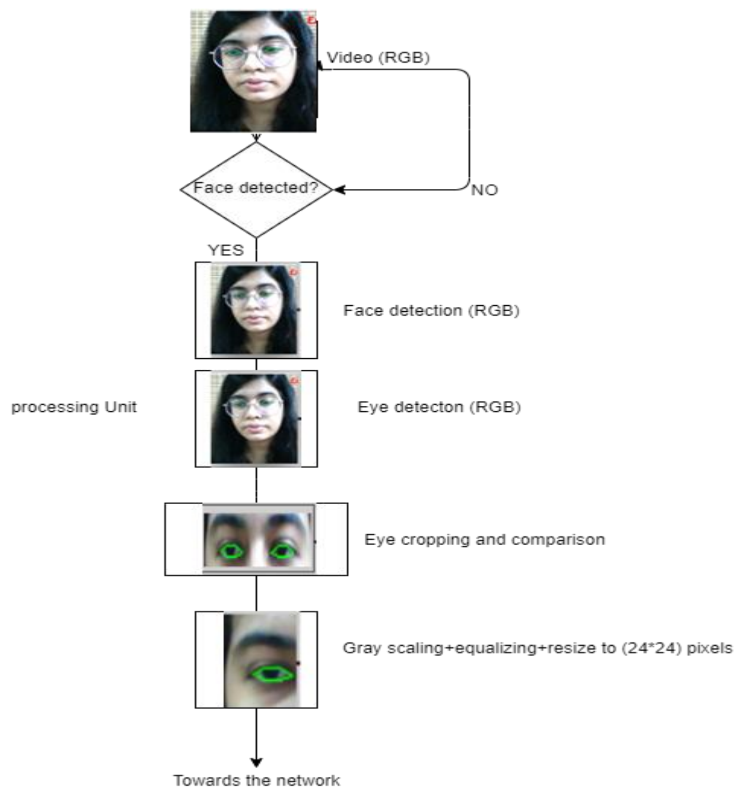


Figure 5. Flow of algorithm

Results

This section presents the results on the detection of visual indicators of drowsiness.If the EAR falls below the threshold as specified as EYE_AR_THRESHof 0.3, the counter starts counting the number of frames the person has closed their eyes.The value of the threshold was chosen by the heuristic search. Several numbers of trials and error attempts were executed to obtain the optimal value of threshold where 0.3 was producing a satisfactory outcome. Similarly, the number of frames is chosen. Moreover, after counting the number of frames, if the number of frames the person has closed their eyes in, exceeds than 48 digit value, meaning that if a person has closed their eyes for 48 consecutive frames, the alarm will be generated. As the results show, a drowsiness detector can detect when someone at risk of dozing off and then plays a loud alarm to grab their attention.

Figure 6(a-b) demonstrates the detection of eyes under normal conditions eye aspect ratio and generating an alarm when eyes are closed.

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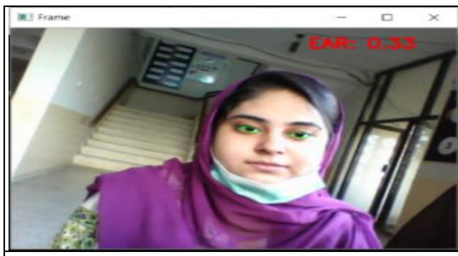

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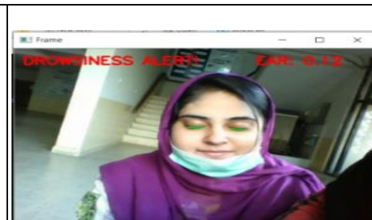

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<td>Figure 6(a). Detecting Eyes</td>
<td>Figure 6(b.) Detecting Eyes and Generating Alert</td>
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Figure 7(a-b) demonstrates the detection of eyes while wearing a mask, using EAR and generating an alarm when eyes are closed.

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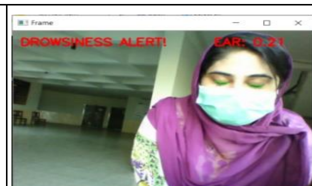

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<td>Figure 7(a). Detecting Eyes while driver is wearing mask</td>
<td>Figure 7(b). Detecting Eyes with mask and Generating Alert</td>
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Figure 8(a-b) demonstrates the detection of eyes while wearing a mask and glasses, using EAR and generating an alarm when eyes are closed.

Figure 8(a). Detecting Eyes wearing mask & glasses

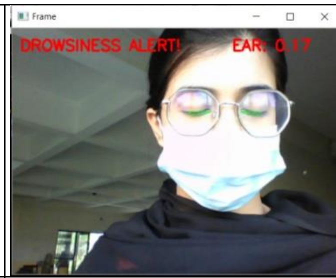

Figure 8(b). Detecting Eyes with mask & glasses and Generating Alert

Figure 9(a-b) demonstrates the detection of eyes while wearing glasses and driver with hairs on face, using EAR and generating an alarm when eyes are closed.

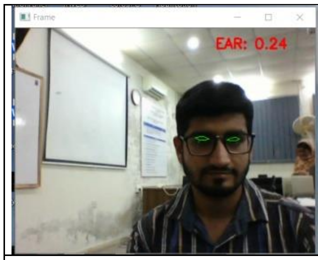

Figure 9(a). Detecting Eyes wearing glasses, hairs on face

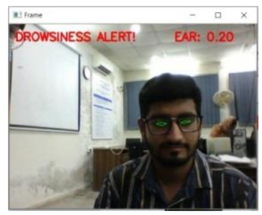

Figure 9(b). Detecting Eyes with glasses while driver has hairs on face and Generating Alert

Figures 10(a-b-c)-11(a-b) demonstrates the detection of eyes while the driver is distracted to left or right, but it is not generating an alert, but when the driver is nodding in front and eyes are closed, an alert is being generated.

In our work, observations and few more images are obtained by the laptop's webcam which is similar to the driver facing the camera. Table 2 demonstrates the results obtained by placing additional objects like the mask, glasses. The average percentage of strikes is 89.28%. Table 3 demonstrates the results obtained by considering the hair covering the driver's face. The drivers were women and men, the average percentage of strikes was 84.16%. Table 4 demonstrates the results of the detection, considering the normal operation of the system in which the responses are obtained from drivers under normal conditions described above. And the level of total strikes on detection represents an average percentage of 30%.

Figure 10(a). Detecting Eyes when driver is distracted to left

Figure 10(b). Detecting Eyes when driver is distracted to right

Figure 10(c) Generating Alert when driver is nodded to front

Figure 11(a). Display of Straight Head for Close Eye (the First Row) and Open Eye (the Second Row)

Figure 11(b). Illustration of Some Closed Left Eye (the First Row), Closed Right Eye (the Second Row), Open Left Eye (the Third Row) and Open Right Eye (the Fourth Row)

Table 2. Detection levels for different drowsinessparameterunder Special Conditions

Test	Observations (Nos.)	Strikes (Nos.)	Strikes (%)
Driver without glasses	140	129	92.14
Driver with glasses		131	93.57
Driver with mask		125	89.28
Driver with mask and glasses		115	82.14

Table 3. Detection levels for different drowsiness parameter considering the hair covering

Test	Observations (Nos.)	Strikes (Nos.)	Strikes (%)
Driver with Beard/hairs on the face	60	49	81.66
Driver without Beard/hairs on the face		52	86.66

Table 4. Detection levels for drowsiness parameter under normal conditions

Test	Observations (Nos.)	Strikes (Nos.)	Strikes (%)
Front Nodding	50	45	90.00
Distraction to right		00	No Alert
Distraction to left			

Conclusion

In this work, a prototype of a real-time system that monitors and detects the loss of attention of vehicle drivers is proposed. The primary aim of our research work is to propose a reasonable, inexpensive non-intrusive system for driver drowsiness detection using a less computationally intensive approach. In our proposed implementation, the face of the driver is detected by capturing facial landmarks and a warning is given to the driver to avoid real-time crashes. Our developed system uses EAR with adaptive thresholding to detect driver drowsiness in real-time. This is useful in situations when the drivers are used to the strenuous workload and drive continuously for long distances. The proposed system works with the collected data sets under different conditions. The facial landmarks captured by the system are stored and ML algorithms have been employed for classification.

Future Work

The future work can include the integration of the proposed system with globally used applications like Uber and Careem. The system, if integrated, can reduce the number of casualties and injuries that happen regularly due to these drowsy states of the drivers. This experiment can run as a part of a pilot plan i.e. for a few days/months in different regions of the world where such incidents occur regularly. Thus, our proposed approach also can be extended for different types of users such as bike riders or in different domains like railways, airlines.

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