IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Real-Time Driver Drowsiness Detection Using Eye Closure and Yawn Detection using Facial Landmarks

Ananya Bhavana D S [1] **Dr N. Sivakumar [2]**

[1] Research Scholar, Department of Computer Science, Jain (Deemed -to-be-University), Bangalore, Karnataka, India.

[2] Research Supervisor, Department of Computer Science, Jain (Deemed -to-be-University), Bangalore, Karnataka, India.

Abstract

Every year many people lose their lives due to road accidents. The cause for road accidents may be many reasons and one of the common reasons is the drowsiness of a driver. Micro drowsiness or fatigue can be a major cause to a huge accident. Thus, initial detection of fatigue before a critical situation may occur, is the ongoing research of this paper. A real-time eye-blink and yawn detection algorithm is proposed in this paper. The recent landmark detectors are trained on various datasets, with varying light and facial expressions and tested against robustness and intelligence with respect to a camera. The first step is to detect the facial region and capture video sequences using computer vision techniques. In the next step, the facial landmark detectors are used for locating the eyes and mouth region of the driver which are studied using the eye aspect ratio(EAR), which is a single scalar quantity to detect the eye and mouth opening in each frame. We show that the facial landmarks are detected precisely to show the level of eye and mouth opening. Finally, in collaboration, the driver state that is, asleep or awake, is determined and a warning alarm is played if sleep is detected. These various experiments prove a high accuracy against the proposed idea.

Keywords: driver drowsiness; fatigue; face-detection; facial landmark; Eye Aspect Ratio (EAR); eye-blink; yawn.

1. Introduction

One of the major causes of casualties considering people in road accidents is driver's drowsiness. Driving continuously for a long time, drivers easily get tired resulting into driver fatigue and drowsiness. Research studies say that most of the accidents occur due to driver drowsiness. Various countries have large statistics for accidents that occurred due to driver fatigue. Developing various technologies to detect driver drowsiness and thus reduce accidents is a major challenge in today's world. As indicated by the report by "Service of Road Transport and Highways" there were 4,552 mishaps detailed each year in India, that took lives of thousands of individuals as a result of tired drivers (Road Accidents in India 2016). For example, numerous vehicles are driven generally around evening time, for example, stacked trucks, the drivers of such vehicles who drive for such persistent extensive stretch become more prone to these sorts of circumstances. Distinguishing drowsiness of drivers is yet a progressing exploration to diminish the quantity of such miss-happenings and mishaps. Commonplace strategies used to recognize drowsy drivers are physiological based, vehicle based, and social based (S. Sangle, B. Rathore, R. Rathod, A. Yadav, and A. Yadav,2018) – (A. Kumar and R. Patra, 2018). Physiological techniques, for example, heartbeat, beat rate, and Electrocardiogram (T. Hwang, M. Kim, S. Hong, and K. S. Park,2016), (S. Junawane, S. Jagtap, P. Deshpande, and L. Soni,2017) and so on are utilized to recognize weariness level. Vehicle based techniques incorporate quickening agent example, increasing speed and controlling developments. Conduct methods (S. Sangle, B. Rathore, R. Rathod, A. Yadav, and A. Yadav,2018) – include yawn, Eye Closure, Eye Blinking, etc. (A. Kumar and R.Patra, 2018) .

To experience this overall issue, a solution that captures pictures in a progression, sends constant driver's information to the server, and decides fatigue utilizing EAR (Eye Aspect Ratio) and Yawn detection that has been proposed. The proposed framework prompts the driver to take a break or rest for a while. The techniques utilized are non-nosy in nature; subsequently, no extra expenses would be brought about over this proposal of drowsiness detection strategy. In this paper we propose a combined procedure to detect driver drowsiness, mixing the eye detection and yawn acknowledgment results for a more exact dynamic. The proposed strategy relies upon the facial identification of the driver captured by a camera installed in front of the driver. The other piece of elbowroom of our count is that it is liberated from the subject and subsequently can be conveniently used in checking systems.

The remaining part of the paper is sorted out as follows. In section 2, the literature review is presented. Section 3 presents the proposed approach to detect driver's drowsiness. Section 4 describes the performance evaluation with the discussion of the final experimental results. The conclusion of the paper is in Section 5.

2. Related Work

In order to detect drowsiness of drivers, a number of approaches have been proposed. This section summarizes the existing approaches to detect drowsiness.

In [8], detected real-time driver drowsiness using deep neural networks. They developed an Android application.

In [21], used EAR (Eye Aspect Ratio) as a standard measure to compute drowsiness of a person. They also detailed the types of systems used for detecting drowsiness of driver. For example, Active Systems (considered as reliable, but use special hardware that are expensive and intrusive like infrared cameras etc.) and Passive Systems (are inexpensive and rely on Standard cameras).

[16], used a camera fixed on the dashboard to capture and send images to Raspberry Pi server installed in the vehicle, to detect faces using Harr classifier and facial points using the Dlib Library.

[4], detected landmarks for every frame captured to compute the EAR (between height and width of eye) using the landmark points of face. After computing the EAR; (V. Varghese, A. Shenoy, S. Ks, and K. P. Remya,2018) determined the driver as drowsy if the EAR was less than the limit for 2 or 3 seconds (because the eye blink lasts approximately 100-400ms).

[5], used Mouth Opening Ratio as a parameter to detect yawning during drowsiness. There are several other research works that have been conducted to determine vision based drowsiness detection, fatigue detection, eye-tracking to detect driver fatigue.

In [2], 'Real-Time Driver Drowsiness Detection System Using Eye Aspect Ratio and Eye Closure Ratio' has showed the result of accuracy while using the Naïve Bayes and Support Vector machine classifier of approximately 80%.

[10], describes 'PORTABLE PREVENTION AND MONITORING OF DRIVER'S DROWSINESS FOCUSES TO EYELID MOVEMENT USING INTERNET OF THINGS' where they focus on eyelid movement with a high chance of an inaccurate prediction.

Another approach, [26] presented visual analysis of eye state and head pose (HP) for continuous monitoring of alertness of a vehicle driver. Most of the existing approaches to visually detect a non-alert driving method depend on eye closure or head nodding in particular angles to determine the driver drowsiness levels or distraction of the driver.

[24], utilizes the skin color detection for face detection, furthermore, making a classification based on thresholding, that will cause a particular range on the darker skin tones which may not predict correctly.

Another approach proposed a new method of analysing the facial expression of the driver through Hidden Markov Model (HMM) based dynamic modelling to detect drowsiness. Thus, with reference to the literature work we have a proposed a system that detects driver's drowsiness using EAR to detect eye closure and yawn which are detailed in the following section.

3. Proposed Approach to detect Driver's Drowsiness

In this segment, the proposed plan to detect driver drowsiness is presented. There are four stages to determine the driver's drowsiness, as it appears in figure 1. Initially, face region ought to be separated from the image that has been captured. Second, eye region is found in the face. Third, mouth ought to be recognized in the face region. These two undertakings work together with one another to improve the face identification results. At that point yawn and eye closure detections are applied to the extracted mouth and eye.

Next, the outcome is combined and a decision is drawn regarding the drowsiness of the driver. At last, if a sleepiness state is detected, an alarm is sent to the driver. In this way the face is captured in subsequent frames for a particular number of repetitions. In the accompanying 4 subsections, we clearly explain each progression in detail.

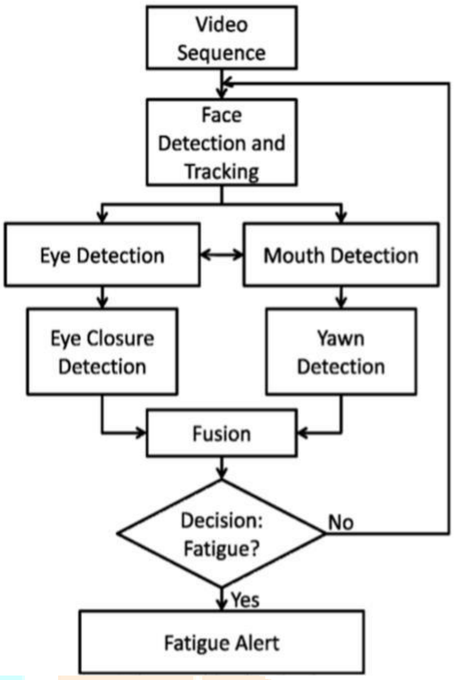


Figure 1: The proposed Drowsiness Detection system

The eye flicker is a quick shutting and opening of a natural eye. Every individual has a unique pattern of blinking. The pattern varies in the speed of shutting and re-opening, a level of pressing the eye and in a flicker term. The eye blink roughly lasts for about 100-400 milli seconds. We propose to use best in class facial milestone locators to capture the eyes and eyelid parts of the face. From the landmarks distinguished in Figure 2, we determine the eye aspect ratio (EAR) that is utilized as a gauge of the eye and mouth opening state. Since the per outline EAR may not really perceive the eye flickers effectively, a classifier that considers a bigger window of an edge is prepared.

For every video frame, the eye and mouth landmarks are detected. The eye aspect ratio (EAR) between height and width of the eye and the aspect ratio of the mouth is computed.

a. Face Detection using Eye Aspect Ratio

Using dlib and OpenCV we can detect facial landmarks in an image. Our first step in detecting facial landmarks is to localize the face in an image and then detecting the eyes and the mouth region (ROI). Any region of the face can be detected using the 68 facial landmarks coordinates.

The indexes of the 68 coordinates can be visualized on the image based on which the ROI is selected.

Figure 2: Visualizing the 68-point facial landmark coordinates

In terms of driver drowsiness detection, we are interested in the eye and mouth regions out of the 68 coordinates.

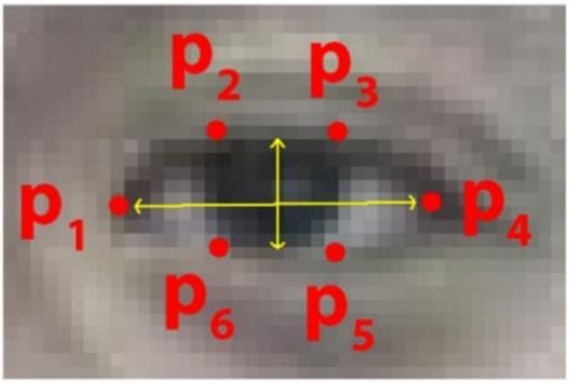


Figure 3: 6 facial landmarks associated with the eye

b. Eye Closure Detection

The EAR is given by the following equation as there is a correlation between the width and height of the coordinates.

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

where p1 to p6 are the 2D landmark locations. The EAR is mostly constant when an eye is open and is getting close to zero while closing an eye. It is partially person and head pose insensitive. EAR of the open eye has a little difference among people and it is completely invariant to a uniform scaling of the picture and in-plane pivot of the face. Since blinking is performed by the two eyes simultaneously, the average of both the EAR's of the two eyes is obtained. A case of an EAR signal over a video sequence is as seen below.

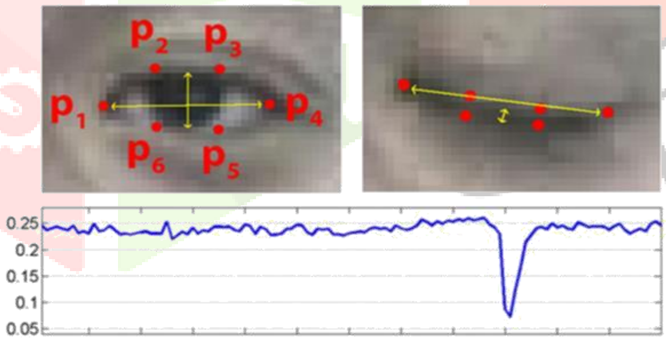


Figure 4: Top-left: Eye landmarks when the eye is open.

Top-right: Eye landmarks when the eye is closed.

Bottom: Plotting the eye aspect ratio over time. The dip in the eye aspect ratio depicts a blink

c. Yawn Detection

The yawn is recognized depending on the angle proportion of the mouth that has been extracted, where it is larger than a particular specified limit. The edge is chosen equivalent to .65 tentatively. Likewise, to make this stage more accurate, the mouth region is verified whether the map has a hole like structure, only if this kind of a structure obtained by the Convex Hull algorithm (mentioned in the section below) is seen, the yawning state is detected. The Euclidean distance between the upper and lower lip is computed and tested against the threshold value to determine the state of the driver (asleep or awake).

While detecting the driver mouth region, the distance between the camera and the person has to be kept in mind and the threshold value has to be selected accordingly. As the person moves away from the camera, the distance between the upper and the lower lip will decrease in the image captured by the camera. Thus, with reference to the distance between the person and the camera, a required threshold value will be selected.

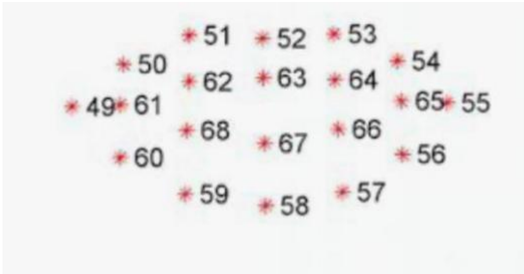


Figure 5: Facial Landmarks associated with the lip

We have used the **Convex Hull** algorithm for yawn detection to obtain the set of pixels included in the smallest convex polygon that surround all white pixels in the input. An example of this is as shown in the figure below:

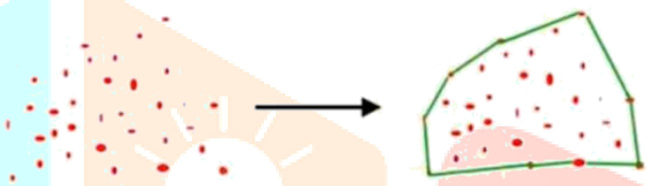


Figure 6: An example of the working of Convex Hull algorithm

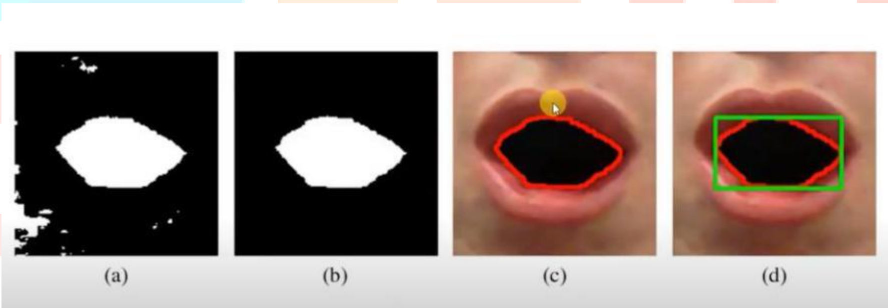


Figure 7: Convex Hull algorithm used in yawn detection

Classification:

The person is blinking if the EAR value drops very low. A very low EAR value may occur when a someone closes their eyes on purpose for a prolonged period of time or even performs a different facial expression, yawning, or even if the EAR encounters a random difference in the landmarks. Along these lines, we propose a classifier that takes a bigger window of frames into consideration. For the 30fps recordings, we tentatively found that ±6 edges can significantly affect a frame for blink recognition for a casing where an eye is shut most of the time when blinking. In this manner, for each case, a 13-dimensional feature is used by linking the EARs of its ±6 neighbouring frames. This is executed by a linear SVM classifier (called EAR SVM) prepared from sequences that are manually annotated. Positive models are gathered as ground-truth, while the negatives are those that are examined from parts of the recordings where no blink happens, with 5 frames dividing and 7 frames edge starting from the ground truth. While testing, a classifier is executed in a checking window style. A 13-dimensional element is figured and ordered by EAR SVM for each edge apart from the start and finishing of a video sequence.

d. Fusion and Decision making

There are three steps where fusion can be applied to in sleep recognition systems i.e., extraction of features, similarity checking stage, and the decision stage. In our module, we have applied fusion in the decision stage, in which the drowsiness of the driver is detected and an alarm is sent to the driver if either one of the following situations occur:

The yawning and eye closure are both detected simultaneously

Successive frames of eye closure is detected i.e., eye closure persists more than one second.
Consecutive yawning is detected and successive frames of one second.

We considered three drowsiness levels for our results.

‘Alert’ --- State 0, where the features are detected. In this state no yawning sign is detected and the eye closure is only for the blinking and lasts less than 1 second.

‘semi drowsy’ --- State 1, where yawning is detected, and the frequency of blinking is increased. ‘drowsy state’ --- State 2, where the eyes are mostly closed and yawning duration is increased.

4. Performance evaluation with Experimental Results and Discussion

The section presents the performance evaluation of the proposed approach by performing an empirical analysis of obtained results. First, the system collects the real-time data of the drivers depicted by Figures 4-a and 4-b. It then determines drowsiness of the drivers based on the EAR values that are computed based on the images captured of the user and its response from the server.

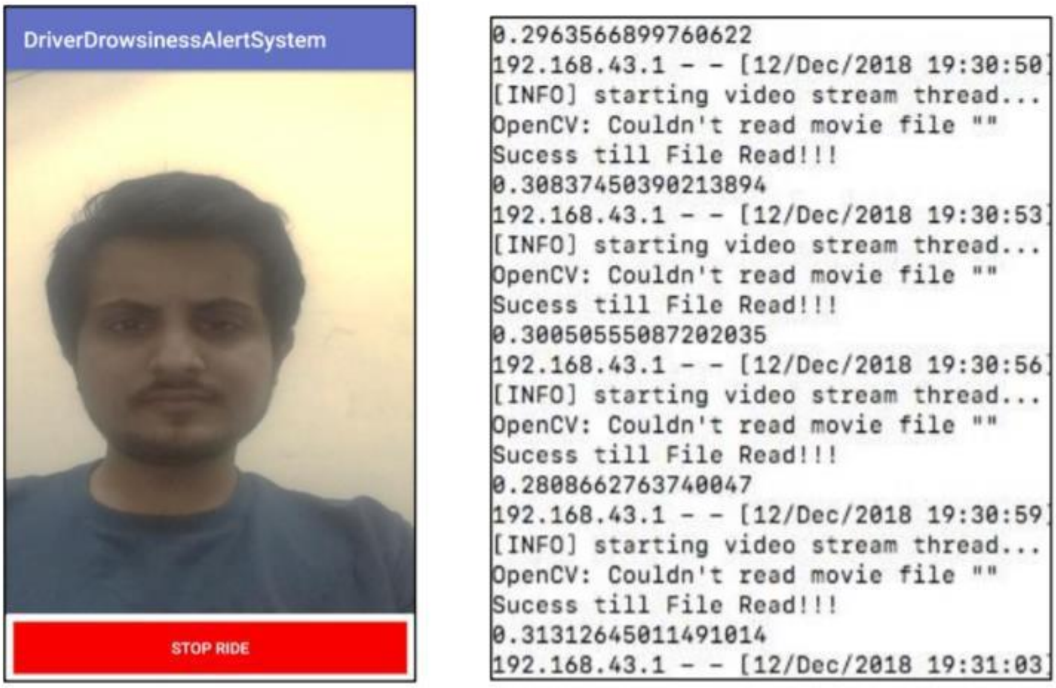
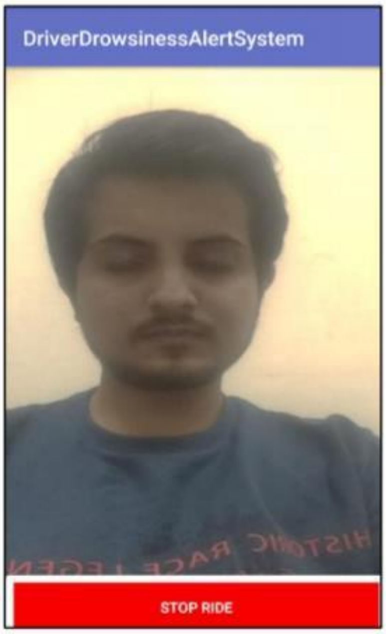


Figure 8(a): Results when eyes are open



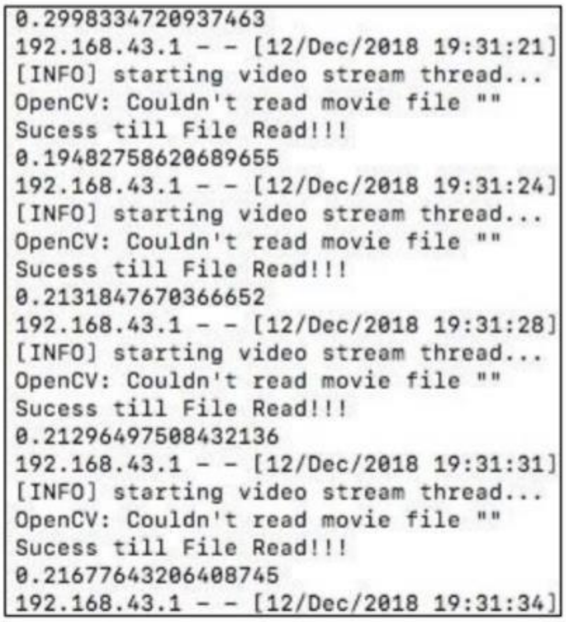


Figure 8(b): Results when eyes are closed

Two-way analysis has been performed in our work. Our first phase includes the results when the driver faces the camera. Data is collected from this phase, is further used in the second phase where detailed analysis of the results has been performed using machine learning classifiers to test the effectiveness of the proposed approach. Classifiers that were employed for empirical analysis were Naive Bayes, Support Vector Machine and Random Forest (K. Das and R. N. Behera,2017). To evaluate the performance of the classifiers, we compared the results obtained based on standard performance metrics. Naive Bayes Classifier is used to identify objects by applying Bayes Algorithm. Random Forest Classifier is an ensemble algorithm which generates a set of uncorrelated decision trees by randomly selecting the subset of training set and then aggregates them to arrive at a conclusion. SVM (Support Vector Machine) is a discriminative classifier that finds out a line that demarcates the classes. Table below shows the results obtained by using different classifiers.

Table-1: Results (in percentage) obtained after applying various classifiers

TPR: True Positive Rate, FPR: False Positive Rate, SVM: Support Vector Machine

S. No.	Classifier	TPR	FPR	Accuracy	Precision	Recall	F-Measure
1	Naïve Bayes	80	20.7	80	80.7	80	79.8
2	Random Forest	84	16.1	84	84	84	84
3	EAR SVM	96	4.1	96	96	96	96

From the table above, we can enumerate that the EAR SVM gives the best classification results with accuracy of 96%

5. Conclusion and Future Work

In this paper we introduced a combination based technique to screen driver drowsiness. Drowsiness may cause the late response while driving which causes the risk of a crash. By monitoring the behavioural characteristics of the driver and determining his awareness state, we can avoid possible threats in the case of drowsiness. We utilized a combination based technique to detect sleep while driving. Both yawn and eye closure discovery plans are utilized to make the framework accurate, while the calculations are straightforward and can be applied to business applications. The other advantage of our strategy is that it is autonomous of the subjects and there is no compelling reason to prepare the framework. Exploratory outcomes demonstrate the high effectiveness of our plan.

Best accuracy on two standard datasets was accomplished utilizing the robust landmark indicator followed by a basic eye blink identification dependent on the SVM. The calculation runs continuously, since the extra computational expenses for the eye blink recognition are negligible other than the ongoing landmark detectors.

The proposed SVM strategy utilizes the EAR thresholding. Then again, the thresholding is used as a solid classifier to recognize the eye state. We assume a fixed blink duration for all subjects and also assume a threshold distance between the upper and lower lip for the subject although every individuals blink and yawn last differently, which we see as a limitation. These results could be improved by using an adaptive approach.

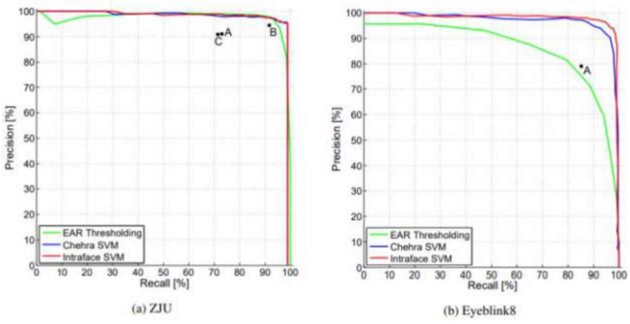


Figure 9: Precision of EAR SVM classifier against two standard datasets

The proposed framework works with the gathered informational indexes under various conditions. The facial landmarks are captured by the framework and machine learning calculations have been utilized for order. The framework gives best case precision of 96% for EAR SVM classifier.

The future work can incorporate combination of the proposed framework with universally utilized applications like Uber and Ola. The framework, whenever incorporated, can decrease the quantity of losses and wounds that happen normally because of these languid conditions of the drivers. This trial can run as a piece of pilot plan for example for a couple of days/months in various locales of the reality where such occurrences happen routinely.

REFERENCES

[1] “Road Accidents in India 2016,” 2016.

[2] Mehta.S, Dadhich.S, Gumber.S, Bhatt.A.J, “Real-Time Driver Drowsiness Detection System Using Eye Aspect Ratio and Eye Closure Ratio”, 2019.

[3] Sangle.S, Rathore.B, Rathod, Yadav.A, “Real Time Drowsiness Detection System,”, 2018.

[4] Varghese.V, Shenoy.A, Ks.S, and Remya.K.P, “Ear Based Driver Drowsiness Detection System,”, 2018

[5] Kumar.A and Patra.R, “Driver drowsiness monitoring system using visual behaviour and machine learning,”, 2018.

[6] Hwang T, Kim M, Hong S, and Park K S, “Driver drowsiness detection using the in-ear EEG,” ,2016.

[7] Junawane.S, Jagtap.S, Deshpande.P, and Soni.L, “Driver Drowsiness Detection Techniques : A Survey,” , 2017.

[8] Jabbar.R, Al-Khalifa.K, Kharbeche.M, Alhajyaseen.W, “Real-time Driver Drowsiness Detection for Android Application Using Deep Neural Networks Techniques,”, 2018.

[9] Soukupova.J and Cech.J, “Real-time eye blink detection using facial landmarks,” , 2016.

[10] García .I, Bronte .S, Bergasa .L .M, Almazán .J, and Yebes .J, “Vision-based drowsiness detector for real driving conditions,”, 2012.

[11] Nagargoje S.S and Shilvant D.S, “Drowsiness Detection System for Car Assisted Driver Using Image Processing,”, 2015.

[12] Podder S and Roy S, “Driver’s drowsiness detection using eye status to improve the road safety,” , 2013.

[13] Omidi.F and Nasleseraji.G, “Non-intrusive Methods used to Determine the Driver Drowsiness: Narrative Review Articles,”, 2016.

[14] Gopal A and Vineeth V, “Driver Drowsiness Detection System,”, 2017.

[15] Srijayathi K and Vedachary M, “Implementation of the Driver Drowsiness Detection System,”, 2013.

[16] Chellappa A, Reddy M S, Ezhilarasie R, Kanimozhi Suguna S, and Umamakeswari A, “Fatigue detection using Raspberry Pi 3,”, 2018.

[17] Singh .H, Bhatia.J.S, and Kaur>J, “Eye tracking based driver fatigue monitoring and warning system,”, 2011.

[18] Fuletra.J.D, “A Survey on Driver’s Drowsiness Detection Techniques,”, 2013.

[19] Patel.K.C, Khan.S.A, and Patil.N.V, “Real-Time Driver Drowsiness Detection System Based on Visual Information,”, 2018.

[20] Das.K and Behera.R.N, “A Survey on Machine Learning: Concept, Algorithms and Applications,”, 2017.

[21] Soukupova.T and Jan´ Cechˇ, “Real-Time Eye Blink Detection using Facial Landmarks”, 2016.

[22] Asthana.A, Zafeoriou.S, Cheng.S, and Pantic.M. Incremental face alignment in the wild, 2014.

[23] Bergasa.M.L, Nuevo.J, Sotelo.M.A, Real-time system for monitoring driver vigilance, 2004.

[24] Chau.M and Betke.M, Real time eye tracking and blink detection with USB cameras, May 2005.

[25] Danisman .T, Bilasco.I, Djeraba.C, and Ihaddadene.N, drowsy driver detection system using eye blink patterns, Oct 2010.

[26] Dinh.H, Jovanov.E, and Adhami.R, Eye blink detection using intensity vertical projection, 2012.

[27] Divjak.M and Bischof.H, eye blink based fatigue detection for prevention of computer vision syndrome, 2009.

[28] Drutarovsky.T and Fogelton.A, Eye blink detection using variance of motion vectors, 2014.

[29] Lee.W.H, Lee.E.C, and Park.K.C. Blink detection robust to various facial poses, 2010.

[30] Pan.G, Sun.L, Wu.Z, and Lao.S, eyeblink-based anti-spoofing in face recognition from a generic webcamera, 2007.

[31] Ren.S, Cao.Z, Wei.Y, and Sun.J, Face alignment at 3000 fps via regressing local binary features, 2014.

[32] Sahayadhas.A, Sundaraj.K, and Murugappan.M, detecting driver drowsiness based on sensors, 2012.

[33] Sukno.F, Pavani.S.K, Butakoff.C, Automatic assessment of eye blinking patterns through statistical shape models, 2009.

[34] Torricelli.D, Goffredo.M, Conforto.S, and Schmid.M. An adaptive blink detector to initialize and update a view-basedremote eye gaze tracking system in a natural scenario, 2009.

[35] Xiong.X and De la Torre.F, Supervised descent methods and its applications to face alignment, 2013.

[36] Yan.Z, Hu.L, Chen.H, and Lu.F, Computer vision syndrome, 2008.

[37] Yang.F, Yu.X, Huang.J, Yang.P, and Metaxas.D, Robust eyelid tracking for fatigue detection, 2012.