

Blink and Yawn- Indicator of Driver Fatigue

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ABSTRACT

The project presents an innovative Python-based drowsiness recognition system designed to mitigate the risks associated with drowsy driving, a growing concern in road safety. Leveraging computer vision and machine learning techniques, including PERCLOS and Haar Cascades, the system detects signs of fatigue such as facial expressions, eyelid movement, and yawning. Upon recognition, the system activates alerts, tailored to user preferences, to engage the driver and prevent accidents. By addressing the critical issue of drowsy driving, the project exemplifies the potential of technology to enhance road safety and underscores the transformative impact of applied science on societal challenges.

Keywords: Open CV, Python, Drowsiness Detection, Eye Closure & Eye Blinking, Yawning, Fatigue

INTRODUCTION

Drowsy driving poses a significant threat to road safety in our contemporary society, particularly during long journeys undertaken by transportation professionals such as taxi drivers, bus drivers, and truck drivers. The escalating risk of accidents resulting from driver fatigue underscores the urgent need for effective solutions to mitigate this peril. In response, this project introduces an innovative Python-based drowsiness recognition system, leveraging advanced technologies such as computer vision and machine learning. Through the analysis of driver behaviour, including eyelid movements, facial expressions, and yawning, the system swiftly identifies signs of drowsiness. Upon detection, an alert mechanism is activated, customizable to user preferences, aiming to re-engage the driver's attention and prevent accidents. With a clear motivation to enhance road safety, prevent tragedies, and save lives, this project embodies the fusion of technology and human well-being, promising a safer future for all road users. In the following sections, we will explore the technical details of our drowsiness recognition system and the methodologies employed to ensure the safety of drivers during their journeys.

LITERATURE REVIEW

This paper aims to propose a drowsy driver warning system that detects the real-time driver's eye closure. In this system, if the driver's eye classifies as the close class for successive frames, it is a sign of drowsiness, and an alert will be sent to the driver early enough to avoid an accident. The proposed work of this article includes four contributions.[2]

The frames enter to preprocessing unit to detect the eyes and crop them. Then this unit applies the grayscale function and normalizes the histogram of the eye. The authors used low-resolution images to have real-time detection and histogram equalizer to overcome the bad illumination condition.

The authors proposed three neural networks regarding the parameter of fastness, high accuracy, and small dataset.

There is a proposed algorithm to evaluates the result of network detection; if it detects as a close eye, the system adds one to the counter, and if the number of the counter reaches more than 12 successive frames, that eye is close, send an alarm for the driver. Otherwise, it keeps the counter for the next frame, whenever an open eye categorizes, counter restart. In other words, the task of this counter is counting successive close frames for distinguishing blinking from falling sleep.



Collecting a new dataset that considers a new position of the eye, named oblique view of the driver.[3] For eye classification to the classes of open and close, three networks considered. The first network is the fully designed neural network, the second is a deep neural network withtransfer learning, and it uses a pre-trained VGG16 network, which uses the low-level features on the ImageNet dataset and high-level features to learn. The third network is similar to the second network, but it uses VGG19 with the same goal as the third network. The results show high accuracy and short computational time in the proposed methodology of this article.[6]

Road crashes and related forms of accidents are a common cause of injury and death among the human population. According to 2015 data from the World Health Organization, road traffic injuries resulted in approximately 1.25 million deaths worldwide, i.e. approximately every 25 seconds an individual will experience a fatal crash While the cost of traffic accidents in Europe is estimated at around 160 billion Euros, driver drowsiness accounts for approximately 100,000 accidents per year in the United States alone as reported by The American National Highway Traffic Safety Administration (NHTSA). In this paper, a novel approach towards real-time drowsiness detection is proposed. This approach is based on a deep learning method that can be implemented on Android applications with high accuracy. The main contribution of this work is the compression of heavy baseline model to a lightweight model. Moreover, minimal network structure is designed based on facial landmark key point detection to recognize whether the driver is drowsy.

The proposed model is able to achieve an accuracy of more than 80%.[13][14] Among works that focus on the analysis of the vehicle state and its relation to fatigue, the most common measures that are studied are steering wheel behaviours or lane departures [11–13]. In [14], other parameters of the car are used, such as the vehicle position or the steering wheel angle, and they perform data fusion on multiple measures to achieve a more reliable system. However, even if the diminishing performance over skill-based tasks by the driver can actually be a consequence of drowsiness, it appears at a later stage and it cannot be used to detect the early symptoms of fatigue [15].

There are many works that follow this approach, which use numerous and varied parameters and techniques for their detection. For example, in [17], the landmarks of the driver's face (that is, a group of points that locate the most important elements of the face: eyes, eyebrows, nose, mouth, and facial shape) are obtained, and then, using these landmarks, some parameters, such as the percentage of eye closure (PERCLOS), are calculated. Afterwards, these features are introduced on a support vector machine (SVM) that classifies whether the driver is tired or not. In [18], a combination of depth videos and deep learning is used for fatigue detection. In particular, it uses two CNNs: a spatial CNN, which detects object's positions, and a temporal CNN, which looks for information between two neighbouring frames. By using these two CNNs, the system is able to calculate motion vectors from one frame to another, which allows to detect yawns, even when the driver uses a hand to cover his or her mouth.[18]

This system will cover the driver's eyes using camera and by developing a algorithm we can detect symptoms of driver fatigue early enough to avoid unanticipated incidents. So need to detect driver fatigue in advance will be helpful and will give an alert warning which will be in form of sound and seat belt vibration who has frequency which variable between 100 to 300 HZs. The warning cannot be deactivated automatically it can be done by manually [22]

Sukrit et al. in [6] have used the most commonly used technique which is the Eye Aspect Ratio (EAR) and Eye Closure Ratio (ECR). Same accuracy for people wearing spectacles. Useful in conditions when drivers drive for longer distances. Adaptive thresholding varies greatly from person to person. So, in [6] Deng and Wu in [7] have used video Images that were used to detect Blinking, yawning and duration of eye closure. They drafted an identification technique for facial regions which is based on the Golden Ratio of 68 main points. There were not any publicly available image-based driver sleepiness recognition datasets. algorithm works with an accuracy reaching 95% when the Euclidean distance is within 20 pixels. Average accuracy regardless of environmental conditions is approximately 92%. The limitation is that it requires a highperformance machine with heavy processors and good RAM.[7]

In these algorithms, a counter starts counting during the time the eyes are closed and when it exceeds a certain threshold value, the alarm system is activated. When the eye is opened, the number in the counter decreases and the alarm system is disabled because it falls below the threshold value. In another study, a method that is close to the method described in this thesis has been proposed. In this study [6], eye and face detection are considered as an object detection approach. Eyes are labelled and trained as open and closed. Fatigue decision is determined by determining a threshold value, as mentioned in previous studies, and depending on whether the duration of eye closure exceeds this threshold value. This threshold value is determined as 40% of the frame rate of the image captured from the camera. For example, if camera is 30 FPS, the threshold value is 12. If blindfold is detected in at least 12 of the 30 frames, the alarm is activated.[17]



The ultimate aim of our work is to activate an alarm when the system detects that the driver is drowsy, which means that the alarm activation module will follow a binary behaviour (on/off, depending on the fatigue level of the driver). Because of this, only the "awake" and "drowsy" classes are used to train and test the system (60 awake videos, 62 drowsy videos).[9] The database provides the videos divided in 5 folds (or subsets of data), so in this work, we use 5-fold cross-validation to test the data. These videos were recorded with different cameras (web, mobile phone, etc.) which we have to specify the type of webcam used, resulting in a pool of videos with different qualities and resolution. This is very interesting to emulate real situations in a car, where there are light changes, but the results obtained can be moderate, as would correspond to this situation.[8]

Continuous advancements in computing technology and artificial intelligence in the past decade have led to improvements in driver monitoring systems. Numerous experimental studies have collected real driver drowsiness data and applied various artificial intelligence algorithms and feature combinations with the goal of significantly enhancing the performance of these systems in real-time. This paper presents an up-to-date review of the driver drowsiness detection systems implemented over the last decade. The paper illustrates and reviews recent systems using different measures to track and detect drowsiness. Each system falls under one of four possible categories, based on the information used. Each system presented in this paper is associated with a detailed description of the features, classification algorithms, and used datasets. In addition, an evaluation of these systems is presented, in terms of the final classification accuracy, sensitivity, and precision. Furthermore, the paper highlights the recent challenges in the area of driver drowsiness detection, discusses the practicality and reliability of each of the four system types, and presents some of the future trends in the field.[21]

Khan et al. [26] proposed a real-time DDD system based on eyelid closure. The system was implemented on hardware that used surveillance videos to detect whether the drivers' eyes were open or closed. The system started by detecting the face of the driver. Then, using an extended Sobel operator, the eyes were localized and filtered to detect the eyelids' curvature. After that, the curvature's concavity was measured. Based on the measured concavity value, the eyelid was classified as open (concave up) or closed (concave down). If the eyes were deemed closed for a certain period, a sound alarm is initiated. The system used three datasets. The authors generated two of them, and the third was acquired from.[27] The first dataset, which contained simple images, with a homogenous background, showed an accuracy of 95%. The second set, which included a complex benchmark image dataset, achieved an accuracy of 70%; the third one, which used two real-time surveillance videos, showed an accuracy that exceeded 95%.[28]

Blink frequency [25]	The number of times an eye closes over a specific period of time.
Maximum closure duration of the eyes [25]	The maximum time the eye was closed. However, it can be risky to delay detecting an extended eye closure that indicates a drowsy driver.
Percentage of eyelid closure (PERCLOS) [26]	The percentage of time (per minute) in which the eye is 80% closed or more.
Eye aspect ratio (EAR) [27]	EAR reflects the eye's openness degree. The EAR value drops down to zero when the eyes are closed. On the other hand, it remains approximately constant when the eye is open. Thus, the EAR detects the eye closure at that time.
Yawning frequency [28]	The number of times the mouth opens over a specific period of time.
Head pose [29]	Is a figure that describes the driver's head movements. It is determined by counting the video segments that show a large deviation of three Euler angles of head poses from their regular positions. These three angles are nodding, shaking, and tilting.

Some of the image-based measures.

Table 1. Some of the image-based measures



METHODOLOGY

Functional Necessities

A Utilitarian prerequisite is portrayed as one parcel or an component of a item, in the whole strategy of programming building that the conclusion client particularly requests as fundamental offices that the framework ought to offer.

- Recording the driver's conduct, the minute the trip starts.
- Persistent assessment of driver's facial highlights over the course of long trip.
- Raising an alert if driver feels tired.

Non-Functional Necessities

Non-functional necessities are fundamentally the quality limitations that the framework must fulfill concurring to the venture contract. These are too called non-behavioural prerequisites.

- Camera capturing the video ought to be of tall determination.
- Framework ought to work indeed in moo light conditions.
- Alert raised ought to be of tall volume to wake the driver up.

System Setup

Software Necessities

- Working Framework: Windows 10/8 (incl. 64-bit), Mac OS, Linux
- Language: Python 3
- IDE: Visual Studio Code

Hardware Necessities

- Processor: 64-bit, quad-core, 2.5 GHz least per center
- RAM: 4 GB or more
- Display:1024 x 768 or higher resolution monitors
- Camera: A webcam

Liberaries Utilized

1.<u>SciPy</u>: SciPy, which depends on NumPy, is utilized for calculating the Euclidean remove between the eyelids and lips for tiredness detection.

2.<u>NumPy</u>: NumPy gives back for multi-dimensional clusters and different cluster operations, which is pivotal for information manipulation.

3.<u>Dlib</u>: Dlib is an open-source C++ library that executes different machine learning calculations, counting those required for facial include analysis.

4.<u>OpenCV</u>: OpenCV is utilized for picture pre-processing some time recently advance calculations are connected to the pictures gotten from the webcam.

5.<u>Pygame</u>: Pygame is utilized for playing the caution sound to alarm the driver when tiredness is detected.

6.<u>Imutils</u>: The imutils library is utilized for checking and overseeing picture revolution and other image-related operations.



Dataflow Diagrams



Fig 1. Dataflow Diagram

Facial Point of Interest Marking

Dlib library is imported and utilized for the extraction offacial points of interest. Dlib employments a pre-trained confront detector, that is an advancement of the histogram of situated gradients. It comprises of two shape indicator model strained on the i-Bug 300-W dataset, that each localize 68and 5 point of interest focuses individually inside a confront picture[4]. In this approach, 68 facial points of interest have been used. In this strategy, frequencies of angle course of animage in localized districts are utilized to shape histograms. It is particularly reasonable for confront location; it can depict contour and edge highlights outstandingly in various objects. For recording the Facial Points of interest, the Facial Landmark Predictor was utilized by the framework to calculate lengths for the EAR values. The taking after figure speaks to the facial point of interest points of the Dlib library, which are utilized to compute EAR.



Fig 2. Facial Landmarks



Algorithm



Fig 3, Eye Co-ordinates

Here P1, P2, P3, P4, P5, P6 are the student arranges EAR isgenerally a consistent when eyes are open and is close about0.25. When EAR is less than 0.25 It is concluded that Personis drowsy. Eye Perspective Ratio(EAR) is calculated for both the eyes,

(|P2 - P6| + |P3 - P5|) -(1)

2(|P1 - P4|)

The numerator decides the separate between the upper and lower eyelids utilizing condition 1. The flat remove of the eye is spoken to by the denominator. EAR values are utilised to recognize driver languor in this system. The average of the EAR values of the cleared out and right eyes is obtained. The Eye Viewpoint Proportion is observed in our languor detection framework to see whether the esteem falls underneath the threshold esteem and does not climb over the limit esteem in the taking after outline. The person has closed their eyes and is languid, as shown by the previously mentioned circumstance. In contrast, if the EAR esteem rises once more, it implies that the individual is essentially squinting his eyes and is not lazy. The square design of our recommended method to recognize driver languor is appeared in Figure 5 (Proposed System).

EXISTING SYSTEM

A vehicular parameter-based technique relies on analysing data from steering wheel movements and lane detection systems. By employing algorithms, this approach can identify patterns such as frequent lane changes and the angles of steering wheel adjustments. These indicators serve as valuable metrics for predicting the likelihood of driver drowsiness.

Advantages:

Real-time analysis of driver behaviour. Non-intrusive, as it doesn't require additional sensors. Seamless integration with existing vehicle systems. Cost-effective implementation. Highly predictive of drowsiness.

Disadvantages:

Limited sensitivity to all instances of fatigue. Potential for false positives, causing driver annoyance. Effectiveness influenced by environmental factors. Lower accuracy compared to more comprehensive methods. Risk of driver adaptation affecting system reliability.





Fig 4. Existing System

PROPOSED SYSTEM

In today's fast-paced world, the demand for advanced safety and monitoring systems is ever increasing, particularly in situations where human vigilance is paramount. This innovative system represents a significant stride in ensuring the safety and alertness of individuals, particularly in scenarios where drowsiness can lead to severe consequences, such as accidents or reduced productivity. The core objective of this system is to analyse an image, typically a snapshot of a person's face, and perform a series of critical tasks to determine their state of drowsiness. These tasks include:

•Face Detection and Region of Interest Creation:

The system begins by identifying and isolating the person's face in the input image. The detected face serves as the region of interest (ROI) for subsequent analysis.

•Eye and Mouth Detection:

Within the ROI, the system employs advanced computer vision techniques to pinpoint the locations of the person's eyes and mouth. By monitoring these key facial features, the system can track changes in their status, specifically whether the eyes and mouth are open or closed.

•Drowsiness Score Calculation:

The system continuously assesses the status of the eyes and mouth. It assigns a drowsiness score based on specific criteria, considering factors like the duration of eye closures, the frequency of yawning, and other indicators of fatigue.

•Drowsiness Alert and Alarm Activation:

If the calculated drowsiness score surpasses a predefined threshold, the system promptly issues an alert to the individual. This alert can take the form of an audible alarm, a visual notification, or any other chosen alert mechanism. The purpose of this alert is to awaken the individual, ensuring they remain vigilant and preventing potential accidents.

Advantages:

- 1. Enhanced Safety: Detects drowsiness to prevent accidents.
- 2. Real-Time Monitoring: Continuously monitors for timely intervention.
- 3. Objective Assessment: Provides quantifiable alertness measure.
- 4. Timely Alerts: Issues immediate alerts upon drowsiness detection.
- 5. Versatile Applications: Applicable in various settings for accident prevention.

Disadvantages:

- 1. False Positives: Risk of unnecessary alerts due to non-drowsiness factors.
- 2. Environmental Factors: Accuracy affected by lighting, camera quality, etc.



- 3. Privacy Concerns: Raises issues about personal data usage.
- 4. Technical Challenges: Requires complex algorithm development and integration.
- 5. User Acceptance: Success hinges on overcoming resistance to constant monitoring.



Fig 5. Proposed System



RESULT AND ANALYSIS



Fig 6.Yawn Detection Ratio



Fig 7.Yawn Detection



Fig 8.Eye Aspect Ratio





Fig 9.Eye Detection

CONCLUSION

In conclusion, the real-time drowsiness detection system, utilizing facial feature analysis from input images, emerges as a crucial advancement in safety and alertness monitoring. It effectively addresses the pressing need for heightened safety in situations vulnerable to drowsiness-induced accidents or decreased productivity. Through continuous monitoring of eye and mouth status and generating a drowsiness score, it offers an objective measure of individual alertness. Its capacity to deliver timely alerts, such as alarms, acts proactively to avert accidents, proving invaluable in contexts like drowsy driving and industrial safety. With ongoing technological progress, the system holds promise for further enhancements and wider applications, solidifying its pivotal role in safeguarding lives and bolstering overall safety.

REFERENCES

- [1] Distance, D'Orazio.T, Guaragnella.C and Leo.M, —A visual approach for driver inattention detection, IPattern Recogn., vol. 40, no. 8, 2007, pp. 2341–2355.
- [2] S. Singh, N. P. papanikolopoulos, "Monitoring Driver Fatigue using Facial Analysis Techniques", IEEE Conference on Intelligent Transportation System, pp 314-318
- [3] Bradski.G, Kaehler.A, -Learning OpenCV, O'Reilly, 2008.
- [4] R. Ahmad, and J. N. Borole, "Drowsy Driver Identification Using Eye Blink Detection," IJISET International Journal of Computer Science and Information Technologies, vol. 6, no. 1, pp. 270-274, Jan. 2015.
- [5] Agarwal, V. Murali, N. V., and Chandramouli C. 2009. "A cost-effective ultrasonic sensor-based driver assistance system for congested traffic conditions," EEE transactions on intelligent transportation systems (10:3), pp 486-498
- [6] S. Mehta, S. Dadhich, S. Gumber, and A. J. Bhatt, "Real-Time Driver Drowsiness Detection System Using Eye Aspect Ratio and Eye Closure Ratio Fatigue Detection Non-Intrusive Methods Driver monitoring system," (2019).
- [7] W. Deng and R. Wu, "Real-Time Driver-Drowsiness Detection System Using Facial Features," IEEE Access, vol. 7, pp. 118727–118738, (2019).
- [8] N. Dalal and B. Triggs, "Histograms of Oriented Gradients for Human Detection", IEEE conf. on CVPR, 2005.
- [9] Narayan, Vipul, and A. K. Daniel. "Design consideration and issues in wireless sensor network deployment." (2020): 101-109.
- [10] Choudhary, Shubham, et al. "Fuzzy approach-based stable energy-efficient AODV routing protocol in mobile ad hoc networks." Software Defined
- [11] Narayan, Vipul, and A. K. Daniel. "RBCHS: Region-based cluster head selection protocol in wireless sensor network." Proceedings of Integrated Intelligence Enable Networks and Computing: IIENC 2020. Springer Singapore, 2021.
- [12] Narayan, Vipul, and A. K. Daniel. "CHOP: Maximum coverage optimization and resolve hole healing problem using sleep and wake-up technique for WSN." ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal 11.2 (2022): 159-178.



- [13] Narayan, Vipul, and A. K. Daniel. "CHHP: coverage optimization and hole healing protocol using sleep and wakeup concept for wireless sensor network." International Journal of System Assurance Engineering and Management 13.Suppl 1 (2022): 546-556.
- [14] Narayan, Vipul, and A. K. Daniel. "IOT based sensor monitoring system for smart complex and shopping malls." Mobile Networks and Management: 11th EAI International Conference, MONAMI 2021, Virtual Event, October 27-29, 2021, Proceedings. Cham: Springer International Publishing, 2022. Journal of Pharmaceutical Negative Results | Volume 14 | Special Issue 1 | 2023 1178
- [15] Narayan, Vipul, and A. K. Daniel. "Energy Efficient Protocol for Lifetime Prediction of Wireless Sensor Network using Multivariate Polynomial Regression Model." Journal of Scientific & Industrial Research 81.12 (2022): 1297-1309.
- [16] Awasthi, Shashank, et al. "A Comparative Study of Various CAPTCHA Methods for Securing Web Pages." 2019 International Conference on Automation, Computational and Technology Management (ICACTM). IEEE, 2019.
- [17] R. Ahmed, K. E. Emon, M. F. Hossain, (2014). Robust driver fatigue recognition using image processing. 2014 International Conference on Informatics, Electronics& Vision (ICIEV), pp. 1-6.
- [18] Narayan, Vipul, et al. "E-Commerce recommendation method based on collaborative filtering technology." International Journal of Current Engineering and Technology 7.3 (2017): 974-982.
- [19] Narayan, Vipul, et al. "To Implement a Web Page using Thread in Java." (2017).
- [20] Srivastava, Swapnita, and P. K. Singh. "HCIP: Hybrid Short Long History Table-based Cache Instruction Prefetcher." International Journal of NextGeneration Computing 13.3 (2022).
- [21] Srivastava, Swapnita, and P. K. Singh. "Proof of Optimality based on Greedy Algorithm or Offline Cache Replacement Algorithm." International Journal of Next-Generation Computing 13.3 (2022).
- [22] Hardeep Singh, Mr. J.S Bhatia, Mrs. Jasbir Kaur, "Eye Tracking based Driver Fatigue Monitoring and Warning System", 2011.
- [23] Srivastava, Swapnita, and Shilpi Sharma. "Analysis of cyber related issues by implementing data mining Algorithm." 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence). IEEE, 2019.
- [24] Narayan, Vipul, and A. K. Daniel. "Multi-tier cluster based smart farming using wireless sensor network." 2020 5th international conference on computing, communication and security (ICCCS). IEEE, 2020
- [25] Bamidele A., Kamardin K., Syazarin N., Mohd S., Shafi I., Azizan A., Aini N., Mad H. Non-intrusive driver drowsiness detection based on face and eye tracking. Int J. Adv. Comput. Sci. Appl. 2019;10:549–569. doi: 10.14569/IJACSA.2019.0100775. [CrossRef] [Google Scholar]
- [26] Lin S.T., Tan Y.Y., Chua P.Y., Tey L.K., Ang C.H. Perclos threshold for drowsiness detection during real driving. J. Vis. 2012;12:546. doi: 10.1167/12.9.546. [CrossRef] [Google Scholar]
- [27] Rosebrock A. Eyeblink Detection with OpenCV, Python, and dlib. [(accessed on 20 September 2021)]. Available online:<u>https://www.pyimagesearch.com/2017/04/24/eye-blink-detection-opencv-</u> pythondlib/ mizu4CFOAAAAAdAAAABAK
- [28] Moujahid A., Dornaika F., Arganda-Carreras I., Reta J. Efficient and compact face descriptor for driver drowsiness detection. Expert Syst. Appl. 2021;168:114334. doi: 10.1016/j.eswa.2020.114334. [CrossRef] [Google Scholar].
- [29] Popieul J.C., Simon P., Loslever P. Using driver's head movements evolution as a drowsiness indicator; Proceedings of the IEEE IV2003 Intelligent Vehicles Symposium; Columbus, OH, USA. 9–11 June 2003; pp. 616–621. [Google Scholar]
- [30] Tayab Khan M., Anwar H., Ullah F., Ur Rehman A., Ullah R., Iqbal A., Lee B.-H. Kwak K.S. Smart real-time video surveillance platform for drowsiness detection based on eyelid closure. Wirel. Commun. Mob. Comput. 2019;2019:1–9. doi: 10.1155/2019/2036818. [CrossRef] [Google Scholar]