Advanced Driver Drowsiness Detection System Using Machine Learning and Arduino

Jayaresmi J

Assistant Professor at LBS Institute of Technology for Women, and [6]Assistant Professor at LBS Institute of Technology for Women

Keywords: Accidents, Alert generation, Driver drowsiness, Prevention, Real time feedback, Timely Warnings

Correspondence to: jayaresmi@lbsitw.ac.in

Abstract Driver drowsiness is a critical issue in vehicle safety, with statistics showing it to be a significant factor in 10-40 percent of highway accidents. The consequences of falling asleep while driving is severe, leading to increased injury severity and a higher occurrence among sleep-deprived individuals. Drowsiness negatively impacts mental alertness, impairs judgment, and slows reaction time, posing a risk of human error that can result in death or injury. Previous techniques for detecting drowsiness, such as using sensitive electrodes directly attached to the driver's body, proved impractical and invasive.Machine learning alorithms and Arduino has been incorporated for dowsiness detection and alerting. The objective of the Drowsiness Detection System is to prevent accidents by identifying early signs of drowsiness and alerting the drivers. The system aims to enhance driver safety by providing real-time drowsiness feedback.

1. Introduction

About 20% of road accidents occur due to distraction of driver. Among that 30% is due to driver fatigue. Falling asleep while driving could cause fatal traffic Accidents. In order to reduce road accidents there is also a need to detect the causes such as drowsiness, fatigue and to alert the driver. This enables to choose an efficient method to reduce road accidents due to driver fatigue. Machine learning based drowsiness detection is a progressive application of artificial intelligence in increasing road safety and preventing accidents caused due to driver's drowsiness. This technology employs capturing of images on the driver's face and detecting drowsiness with the sequential eye monitoring. Real time monitoring by utilizing the captured images using the trained Machine Learnings models provide the most accurate outcome. This method widely stands out by the means of alert generation where the is a noise generation and a vibration to wake the driver and additional signal as a warning to the co-drivers on the road. In short words, this technology aims to develop a feasible and easy-to-use device for driver's safety and avoiding accidents. Detects and alerts driver drowsiness to both the driver, Passengers and nearby drivers on road.

2. Background

2.1 Drowsiness

Drowsiness presents a significant hazard to road safety, notably during specific time frames such as late at night or in the afternoon when the body's natural rhythm inclines towards sleepiness. The consequences of driving while drowsy can be severe, leading to accidents that may result in injuries or fatalities.

It is crucial to identify and address drowsiness early to prevent accidents. Since drivers often exhibit signs such as struggling to keep their eyes open, difficulty concentrating, and frequent yawning, implementing measures to detect these signs and alert drivers can be beneficial.

Additionally, understanding the demographic most susceptible to drowsy driving, such as young adults aged 18 to 30, allows for targeted interventions and awareness campaigns. By raising awareness about the dangers of driving while drowsy and promoting strategies to combat it, such as taking breaks, ensuring adequate rest, or switching drivers during long journeys, the likelihood of accidents can be reduced.

While other factors contributing to road accidents, such as drunk driving or mechanical failures, are more readily identifiable, addressing drowsiness requires proactive measures such as education, implementing monitoring systems in vehicles, and encouraging responsible driving habits. Ultimately, prioritizing road safety and tackling the issue of drowsy driving can help mitigate the risks associated with this perilous behavior.

2.2 Methods

Methods for drowsiness detection is vast and are mainly of subdivided into intrusive and non-intrusive. Various traditional methods include the use o physiological sensors like electroencephalography (EEG) and electromyography (EMG) which are considered which measure brain and muscle activity, respectively, to detect drowsiness. While providing direct indicators of the driver's physiological state, these sensors can be intrusive, uncomfortable, and may require expert calibration.
Machine learning based drowsiness detection is not only non-intrusive but accurate compared to the pre-existing traditional methods.

Machine learning models like Convolutional Neural Network (CNN) and Recurrent Neural Networks (RNN) collaboratively detects the eye blinking rates using continuous image capturing and declares drowsiness.

CNNs are specifically designed to process and extract features from images efficiently. In the context of drowsiness detection, CNNs are trained on large datasets containing images of individuals in both drowsy and alert states. These images are captured through onboard cameras or external monitoring devices in vehicles. The CNN learns to identify patterns and features associated with drowsiness, such as drooping eyelids. By iteratively adjusting its internal parameters through backpropagation, the CNN becomes adept at distinguishing between drowsy and alert states based on these visual cues.

Once trained, the CNN is deployed in real-time drowsiness detection systems, where it continuously analyzes incoming video frames from the onboard cameras. By processing each frame, the CNN can detect subtle signs of drowsiness in the driver, such as prolonged eye closures. When the CNN identifies patterns indicative of drowsiness, it can trigger timely alerts or interventions to mitigate the risks associated with drowsy driving. These interventions may include auditory warnings, visual alerts on the dashboard display, or even automated adjustments to the vehicle's driving assistance systems to ensure the safety of the driver and other road users.

On the other hand, RNNs are particularly well-suited for analyzing sequential data, making them valuable for processing time-series information such as physiological signals. In the context of drowsiness detection, RNNs can complement CNNs by analyzing temporal patterns extracted from image sequences captured over time.

For instance, RNNs can be employed to analyze the temporal evolution of eye movements captured in consecutive image frames. By treating each frame as a sequential data point, the RNN can learn to identify subtle changes over time that may indicate the onset of drowsiness, such as gradual drooping of eyelids.

Moreover, RNNs can also integrate additional contextual information, such as the driver's recent behavior or environmental factors, into the drowsiness detection process. By incorporating this context, the RNN can adapt its predictions dynamically based on the current driving conditions and the individual characteristics of the driver.

2.3 Materials and Functioning

The overview of the entire function is portrayed by the flowchart as shown in Fig.1. Image Sequence Input begins with a continuous stream of images captured by a camera where the sequence is concerned with sequential algorithm Recurrent Neural Network (RNN). Face Detection is where each frame is processed to detect faces using a face detection algorithm convolutional neural networks (CNNs). Once a face is detected, the region containing the face is isolated for further processing. This process is followed by eye detection that is within the detected face region, eyes are identified using another detection algorithm. This could involve locating eye landmarks or using predefined eye templates to recognize eye regions accurately shown in Fig. 2.

The state of each eye (open or closed) is continuously monitored over a series of frames. This is typically achieved by calculating the eye aspect ratio (EAR) for each eye based on the distances between key points around the eye, such as the corners of the eye and the midpoint of the eye. A condition is checked to determine if either or both eyes have been closed for a specified number of consecutive frames (n frames). If this condition is met, it indicates potential drowsiness. If the condition of closed eyes for n frames is satisfied, an alert is triggered to notify the individual or relevant personnel about the potential drowsiness. Id the condition is not met the cycle repeats to Image Sequence Input: After generating the alert, the system returns to processing the next frame in the image sequence, continuing the cycle of face detection, eye detection, and eye state tracking.

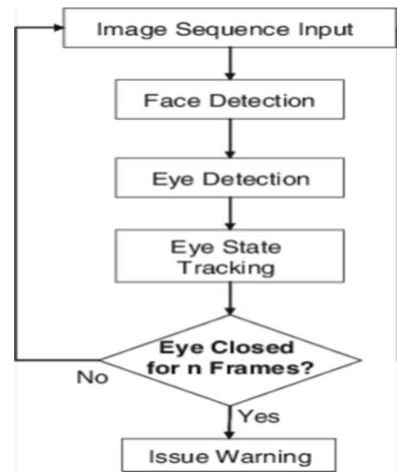


Fig. 1 Flow chart drowsiness detection and alerting

The Machine Learning models is trained using the standardized training chart as shown in Fig. 2. This face detection model contains 68 landmarks from 0 to 67 and plots a map for the model to locate the eyes and its dimension like height and length. This map is standardized and is open sourced for the usage in face detection

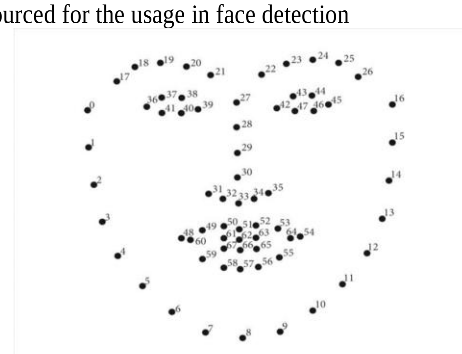


Fig. 2. Common training model for face detection

The camera captures the image of the driver continuously at a baud rate of 9600, frame by frame. The positions of the eyes are located by the model and the width between the eyelids are calculated using the Eye Aspect Ratio (EAR) as in Eq. (1)

$$EAR = \frac{\| p2 - p6 \| + \| p3 - p5 \|}{2\| p1 - p4 \|} \tag{1}$$

where the points p1, p2, p3, p4, p5 and p6 are the landmarks plotted on the eyes and shown in Fig. 3. These points are used to calculate the relative distances between the lids and hence the eye aspect ratio. The eye aspect ratio is 0 for a closed eye and is greater when open.

Volume: 09 Issue: 02 | Feb - 2025 SJIF Rating: 8.448 ISSN: 2582-3930

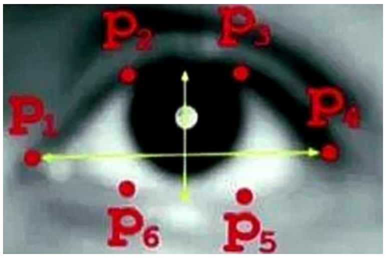


Fig. 3 Landmarks for Eye Aspect Ratio

The image Fig.4 shows the detection of the eyes interpreted by the Machine Learning model highlighted by the green lines. The green lines depict the identification of the eyes with reference to the face detection model in Fig.2. The green lines are live and changes based on the opening and closing of the eyelids. In Fig. 4, the eyes are visibly open with the eye aspect ratio approximately equal to 1. In Fig. 5 the width of the green lines reduces when representing the eyes are closed which leads to alert generation.

Fig. 4 Landmarks with eyes open

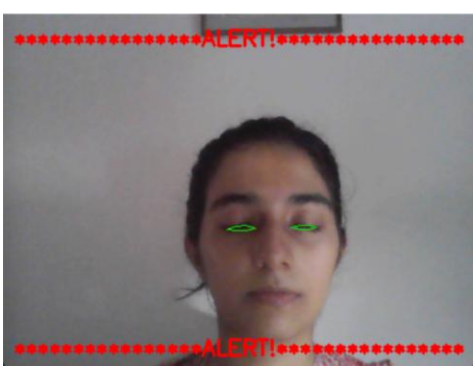


Fig. 5 Landmarks with eyes closed

A collection of 20 frames consecutively captured and continuously calculated with a low EAR of approximately zero is the cue to drowsiness. This rate lasts for the driver to have the eyes closed for about 4 seconds. The duration is set to 4 seconds with the study of road safety and repetitive experiments to prevent accidents. This set of collected data is not only implemented for detection but also updates and trains the model but in a controlled limit to prevent overfitting which is necessarily controlled to reduce the occurrence of confusion matrix. This simulation is facilitated by python environment.

Alert generation, the key step is extremely important to wake the driver from drowsiness. Different types of alert include auditory alerts, visual alerts. In this there are multiple alert generation not only for alerting the driver but also the co-drivers on the road.

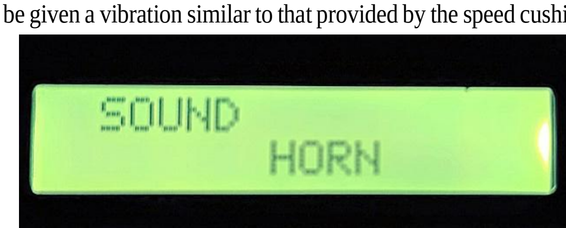
The alert generation beings with an alert warning "***ALERT!***" in the window in bright red color in a attempt to wake the driver up as shown in Fig.5 together with a beep alarming noise. This is purely generated through the inbuilt software and hardware of a system. In addition to this auditory alert, therein a collaboration with an external hardware system of coin vibrator and a Liquid Crystal Display (LCD). This extension is facilitated by a microcontroller Arduino UNO.

Arduino UNO is a microcontroller that works in c programming providing ample number of input and output pins. Arduino UNO is best fit for

this technology due to its capability to receive and transmit both analog and digital pulses through specified pins. It requires a voltage of approximately 5 volts for functioning which can be easily drawn from the software component. Arduino is simulated in the programming environment IDLE.

Fig. 5 Hardware components for alert generation

On receiving information from the model, the IDLE sends digital pulses indicating the driver is drowsy or not. If the driver is drowsy, the signal pulse of digital output 1 is send to the Arduino which a 5volts signal. On receiving the message, the Arduino activates the coin vibrator and the vibrator vibrates. Coin vibration motor of diameters 8mm to 12mm requiring a voltage of 3volts power is used. The coin vibrator is the small scale representation of a physical alert to the driver where the driver's seat is to be given a vibration similar to that provided by the speed cushions on road.



Simultaneously, there vehicle is equipped with an LCD display located in its exterior. This is used to provide a warning to the co-drivers on the road indicating the issue. The LCD display used is of the dimension 2x16 is the miniature of the running display to be placed on the vehicle. The LCD displays a message “SOUND HORN” to warn the drivers behind as shown in Fig. 6. This alerting method not only helps the co-drivers to be alert and prepared but also for their honks to act as an additional auditory alert system for the drowsy diver to wake up.

Fig. 6. Message on LCD

When the Eye aspect ratio (EAR) increases meaning the eyelids are open and the driver is awake, the entire alerting system stops and the cycle continues. Every set of simulation and data images captured sequentially upgrades the model and trains it for better performance to provide maximum possible accuracy.

Conclusion

The evolution of machine learning-based drowsiness detection marks a pivotal advancement in enhancing road safety. The transition from traditional methods to sophisticated algorithms, encompassing attention mechanisms, reinforcement learning, and explainable AI, underscores a commitment to accuracy and real-time responsiveness. However, challenges such as ethical considerations and inter-individual variability remain pertinent. Looking ahead, the future scope is exciting, with prospects including integration with autonomous vehicles, personalized monitoring, and collaboration with healthcare systems. Navigating this dynamic landscape requires collaborative efforts among researchers, industry stakeholders, and regulators. Continuous monitoring, iterative improvements, and adherence to ethical practices will play a crucial role in shaping the trajectory of drowsiness detection. Ultimately, this technology holds the promise of not only contributing to safer roads but also advancing our understanding of driver well-being, fostering a comprehensive approach to road safety.

Acknowledgements

This work is supported by the Department of Electronics and Communication of LBS institute of Technology for Women, Poojappura, Kerala, India under the guidance of Prof. Jayareshmi J, Prof. Anusree L and Prof. Resmi R.

References

[1] Mohsen Babaeian, Nitish Bhardwaj, Bianca Esquivel, and Mohammad Mozumdar, Department of Electrical Engineering,California State University, Long Beach,1250 Bellflower Blvd, Long Beach, Real Time Driver Drowsiness Detection Using a Logistic-Regression-Based Machine Learning Algorithm CA 90840

[2] Priyanka Basavaraj Murdeshwar,Shruthi Tharanath Salian, Surekha ReddySharath D S, Dr. Driver Drowsiness Detection using Machine Learning Approach, ISSN: 2278-0181

[3] Prof. Swati Gade, Kshitija Kamble,Aishwarya Sheth, Sakshi Patil, Siddhi Potdar,5Computer Engineering Department, PDEA’S College of Engineering Manjari(bk), Pune-412307, India, Savitribai Phule Pune University, Driver Drowsiness Detection Using Machine Learning ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538

[4] Shikha Pachouly, Neha Bhondve, Ashutosh Dalvi, Vinit Dhande, Neerav Bhamare, Driver drowsiness detection using machine learning visual behaviour, Issue 6 June 2020, ISSN: 2320-2882

[5] Mittal, K. Kumar, S. Dhamija and M. Kaur, "Head movement-based driver drowsiness detection: A review of state-of-art techniques", 2016 IEEE International Conference on Engineering and Technology (ICETECH), pp. 903-908, 2016.

[6] T. Azim, M. A. Jaffar and A. M. Mirza, "Automatic Fatigue Detection of Drivers through Pupil Detection and Yawning Analysis", 2009 Fourth International Conference on Innovative Computing Information and Control (ICICIC)

[7] S. Arun, S. Kenneth and M. Murugappan, "Detecting Driver Drowsiness Based on Sensors: A Review", MDPI. Sensors, vol. 12

[8] Deep Review of Machine Learning Techniques on Detection of Drowsiness Using EEG Signal ,B. Venkata Phanikrishna, Allam Jaya Prakash & Chinara Suchismitha Pages 3104-3119

[9] D. Artanto, M. P. Sulistyanto, I. D. Pranowo, and E. E. Pramesta, “Drowsiness detection system based on eye-closure using a low-cost emg and esp8266,” in 2017 2nd International Conferences on Information Technology, Information Systems and Electrical Engineering (ICITISEE), IEEE, Nov. 2017, pp. 235–238.

[10] W. Han, Y. Yang, G. Bin Huang, O. Sourina, F. Klanner and C. Denk, "Driver Drowsiness Detection Based on Novel Eye Openness Recognition Method and Unsupervised Feature Learning", Proc. - 2015 IEEE Int. Conf. Syst. Man Cybern. SMC 2015, no. September, pp. 1470-1475, 2016.

[11] K. Singh and R. Kaur, Physical and Physiological Drowsiness Detection Methods, vol. 2, no. 9, pp. 35-43, 2013.

Author Information

JAYARESMI.J
Assistant Professor
ECE Department
LBSITW (APJAKTU), Thiruvanathapuram, Kerala, India.