[1] Sarita Kumari
[2] Harsha K
[3] Kehkeshan Jallal S
[4] Kusumika Krori Dutta
[5] Mohammad Hashim

Driver Drowsiness Detection Using Facial Landmarks: A Comprehensive Survey on Techniques, Algorithms, and Applications

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Abstract: - Driver fatigue and drowsiness are one of the leading causes of traffic accidents worldwide, which emphasises the importance of developing reliable and non-intrusive sleepiness detection technologies. To maintain safety, transport vehicle drivers need to be aware of the warning symptoms of fatigue, particularly while driving long distances at night. Detecting drowsiness is a simple task for human observers, but it remains a challenging task for computers. This paper examines several methods for detecting driver fatigue using facial landmarks, emphasizing the latest technological developments. The suggested system combines Python, SASS, Golang, and other technologies to offer a platform-neutral, device-independent solution. The technology can identify indicators of tiredness and notify the driver by letting the camera operate in the background, possibly averting deadly collisions with an accuracy of 97.3%.

Keywords: Head movement-based techniques, drowsiness detection, accident prevention, vehicular safety.

I. Introduction

Any nation's road network is essential to its economic development. India has the second-largest road network in the world, spanning 4,689,842 kilometers [1]. The increased vehicle traffic brought on by greater mobility and metropolitan connectivity has resulted in a rise in road accidents. In 2021, there were 501,754 traffic events in India, resulting in 151,113 fatalities [2]. Driver error accounts for 75% of road accidents, with driver fatigue being a major contributing factor.

Important factors can contribute to traffic accidents, as Fig.1 illustrates. Fatigue is one of the primary reasons of driver error, according to data from the Indian government's Ministry of Transport. Sometimes tired drivers find themselves behind the wheel after long, boring drives where driving requires minimal effort. Drowsiness while driving is characterized by decreased awareness and a tendency to nod off. This can lead to serious events as the driver may not be able to conduct an evasive maneuver, such as braking or swerving away from an impact. As Fig. 2 illustrates, most fatigue-related incidents end in fatalities. To prevent traffic accidents, increase driving safety, and save lives, real-time, non-intrusive driver sleepiness monitoring technologies are needed. When necessary, these systems can take over control of the vehicle and issue warnings to the driver. Technological advancements have resulted in the widespread availability of low-cost memory, fast on-board CPUs, night vision cameras, accelerometers, gyroscopes, and electro-mechanical actuators since Bosch developed the first driver aid system in 1978 [3]. The present study examines diverse methods for detecting tiredness and emphasizes the latest developments in head movement analysis for drowsiness identification. In 2022, there was a continued increase in the focus on drowsiness detection technologies, with more advanced algorithms and real-time applications being developed to enhance safety in various fields.

The section 2 of the paper deals with literature review followed by methodology in section 3 and result and conclusion in in section 4 and section 5 respectively.

II. Literature Review

The early and precise identification of sleepiness is essential for preventing road accidents caused by the driver weariness, which continues to be a serious concern. The literature has examined a wide range of techniques from physiological and behavioral approaches to vehicle-based techniques. In order to improve the accuracy and resilience this study synthesizes current methods while highlighting new developments, notably in the integration of machine learning and multimodal data. Behavioral Strategies: The main goal of behavioral techniques is to

[1] Electronics and Communication Engineering, Amity University Jharkhand, Ranchi, India. skumari@rnc.amity.edu
[2] Department of ECE, Nitte Meenakshi Institute of Technology, Bangalore, India. harsha.mkaramchandani@nmit.ac.in
[3] Department of ECE, Presidency University, Bangalore, India. kehkeshan@presidencyuniversity.in
[4] Department of EEE, M S Ramaiah Institute of Technology, Bangalore, India. kusumika@msrit.edu
[5] Computer Science and Engineering, Amity University Jharkhand, Ranchi, India. hashimmohammad1375@gmail.com

identify sleepiness by observing the motions of the driver's head, face, and eyes. These techniques frequently rely on visual information from cameras installed within the cars. Eyelid closure, blink frequency, and yawning detection are important markers. In their early research Bergasa et al. (2006) presented one of the earliest visual cue based real-time driver monitoring systems.

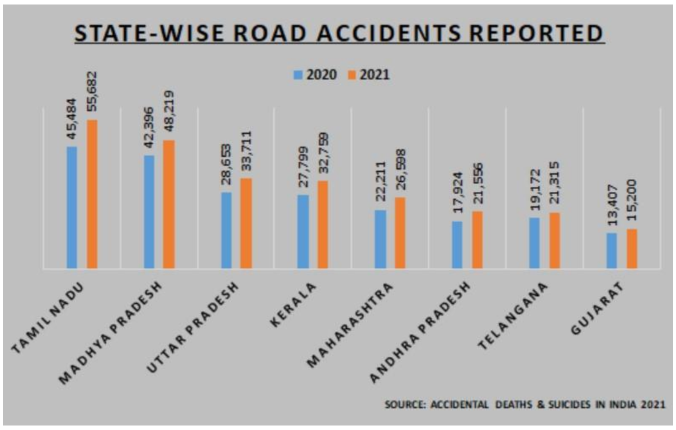

Fig 1: Road Accident Fatalities 2022

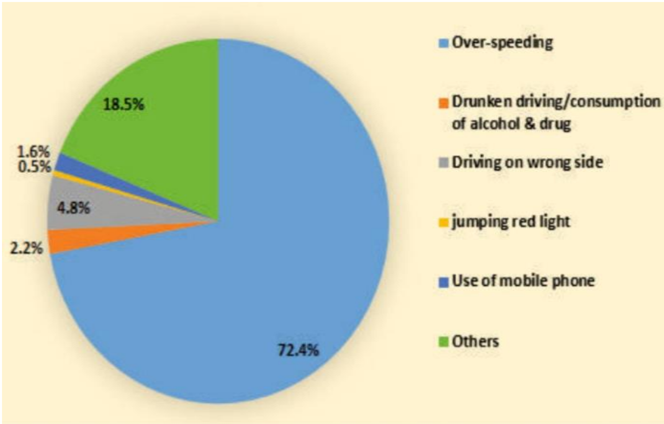

Fig 2: Causes of Accidents

This work has been expanded upon by more recent works, such Abtahi et al. (2022), which use deep learning models to improve real-time detection of minute facial changes.

In behavioral techniques, facial landmark detection has been the main focus. Using an ensemble of regression trees, Vahid Kazemi and Josephine Sullivan's model—which is included in the dlib library—achieved real-time facial landmark prediction by precisely estimating the motions of eye and face features. Parallel to this Nafis et al. have investigated the use of eyelid movement detection for tiredness recognition; nevertheless, more improvements are needed to ensure that these systems function completely reliably in a variety of scenarios, including head motions and changes in illumination.

By assessing internal indications of sleepiness, physiological monitoring approaches such as those that use heart rate variability (HRV) and electroencephalogram (EEG) data offer further levels of precision. HRV monitoring measures the autonomic nervous system activity which is being used more and more to identify signs of weariness. EEG-based methods, such those studied by Lal and Craig (2001), use alpha and theta wave detection to assess brain activity directly and determine when tiredness begins.

Vehicle-based methods keep an eye on how the driver interacts with the car, including lane positioning and steering behaviors. These techniques are usually employed as secondary markers of driver weariness since erratic steering or frequent lane changes may be signs of inattention. In order to achieve more accuracy in identifying driver weariness under real-world driving situations, Anderson et al. (2019) devised a model that combines steering wheel behavior with visual cues.

The dependability and precision of sleepiness detection systems are being transformed by advances in machine learning. While hand-crafted features were frequently used in traditional methods, deep learning is becoming a more important tool in current approaches for feature extraction and classification. Convolutional neural networks (CNNs) have been shown to be effective at automatically extracting characteristics from facial and ocular data in a study by Zhang et al. from 2024.

Furthermore, multimodal integration has become a potent instrument for enhancing system dependability. In order to construct more complete sleepiness detection models, recent research, including those of Liu et al. (2024), suggest merging visual data with physiological data (e.g., HRV and EEG) and vehicle-based metrics (e.g., steering and lane position). These methods decrease false positives and increase system resilience especially when one kind of data (visual, for example) is hidden or not available.

Paul Viola and Michael Jones established the integral picture idea which is now a fundamental method in real-time sleepiness detection systems. Their technique made it possible to quickly calculate picture features, which dramatically decreased the computing cost of feature detection.

Several obstacles still exist despite tremendous development. Improvements are still being made in real time processing capability and sensor accuracy. Head motions, poor illumination, and drivers wearing glasses are all problems for the visual detection systems in use today, especially the ones that just use cameras. Liu et al.'s study from 2023 for instance, showed that infrared (IR) cameras might help reduce the problem of reflections from glasses, although these systems are more expensive and need more calibration. The requirement for extensive and varied datasets presents another difficulty. The limited generalizability of many current models stems from their training on tiny, homogenous datasets. Although more varied datasets have been created recently, such the extensive NTHU Drowsy Driver Dataset (NTHU-DDD), data is still needed.

Furthermore, future research should focus on enhancing multimodal fusion techniques to ensure that systems can function reliably in a range of contexts. Accurate detection may be further improved by integrating more sensors such as wearable technology, accelerometers, and infrared cameras. These developments do, however, bring with them additional difficulties such as the need for more sophisticated data fusion techniques and an increase in processing load.

III. Systems For Determining Driver Drowsiness

In order to identify irregularities in the driving pattern, driver drowsiness detection systems (DDDS) continuously monitor a variety of parameters/features of the car [9], the driver, or the surrounding environment. According to the entity being observed, the DDDS can be categorized, as Fig. 3 illustrates.

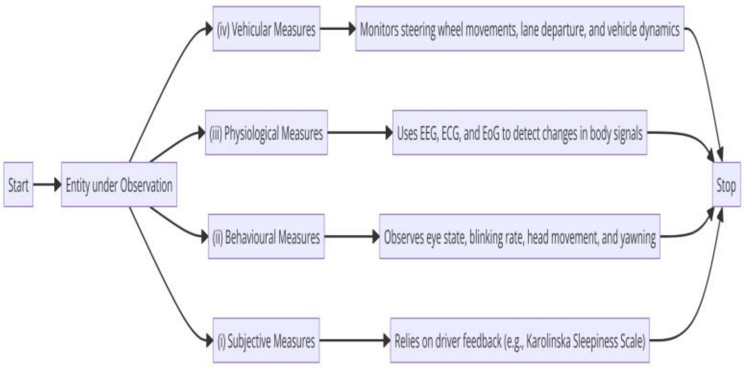

Fig. 3. Classification of Driver Drowsiness Detection Systems.

A. Appraisal Criteria

The driver’s feedback is used in subjective assessments to gauge the degree of tiredness. The nine-point Karolinska Sleepiness Scale (KSS)[10] measures tiredness using verbal descriptions (Table 1). These measurements are arbitrary, though, and they might not yield precise findings in real time.

Table I: Karolinska Sleepiness Scale (Kss)

Scale	Verbal Description
1	Extremely Alert
2	Very Alert
3	Alert
4	Fairly Alert
5	Neither Alert nor Sleepy
6	Some signs of sleepiness

Scale	Verbal Description
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very Sleepy, great effort to keep alert

B. Behavioral Measures

Behavioral tests use eye state, eye blinking rate, head movement, and yawning to identify driver fatigue. The overall procedure that behavioral measure-based systems adhere to is shown in Fig. 4.

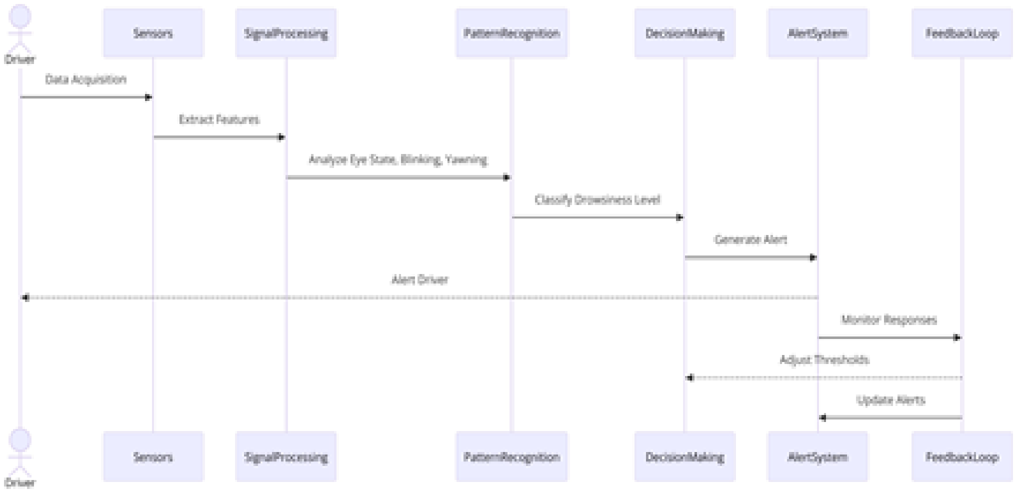

Fig. 4. General process followed by behavioral measure-based systems.

Table II: Driver Drowsiness Detection Systems Based On Behavioral Measures

Author	Year	Metric
G.M. Bhandari et al. [11]	2014	Yawn frequency
M. Saradadevi, P. Bajaj [12]	2008	Mouth and Yawning
C. Sun et al.[13]	2014	PERCLOS
J. Jo et al. [14]	2014	PERCLOS
M. Chutorian et al.[15]	2010	Head Movement
A.Tawari et al.[16]	2014	Facial features
M. Lew et al.[17]	2007	Blink rate, Yawn & Head motion

C. Physiological Measures

Physiological measures are intrusive techniques that need the driver to have electrodes in touch with their body in order to detect sleepiness. Fig. 5 illustrates the EEG, ECG, and EoG measurements that are part of this set.

Table III. Driver Drowsiness Detection Systems Based On Physiological Measures

Author	Year	Parameter
R.N.Khushaba et al.[18]	2011	EEG, ECG, EoG
Vicente et al.[19]	2016	Heart Rate Variability
Sampei et al.[20]	2015	Pupil movement, Blinking, EEG
Li, Ming-ai et al. [21]	2010	EEG
Yeo, Mervyn VM.et al.[22]	2008	EEG
C.L. Fu et al.[23]	2012	EEG

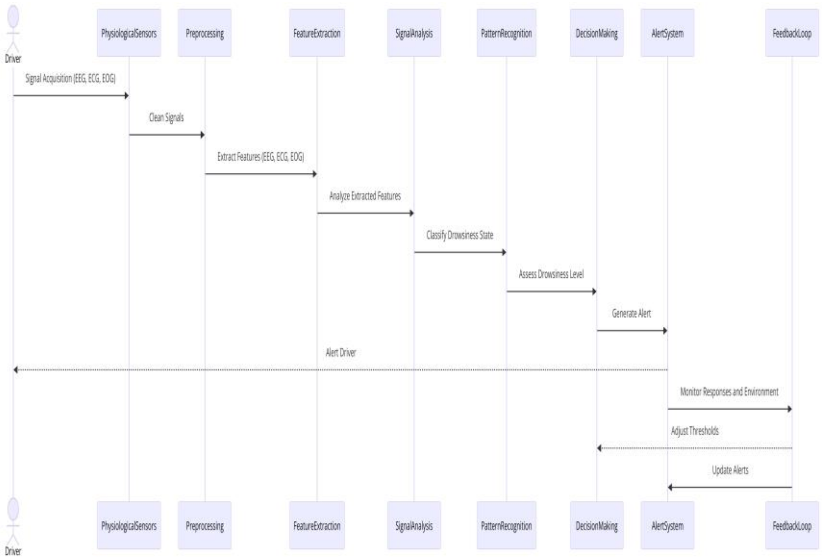

Fig. 5. General process followed by physiological measure-based systems.

D. Vehicular measurements

As seen in Fig. 6, vehicle measurements use parameters including steering wheel movement, lane departure, and acceleration pedal movement to identify anomalous driving behaviors.

E. Factors Causing Drowsiness

The time of day, physical variables, work, and sleep all contribute to driver sleepiness [1]. Drunk driving and fatigue, from work are major causes of drowsiness, especially for transport vehicle drivers who operate their cars both during the day and at night. Most accidents happen when a driver is not paying attention. Whereas sleepiness is defined by a progressive withdrawal of attention from driving, driver distraction happens when an event captures the driver's attention [1]. It is impossible to quantify exhaustion and drowsiness precisely. Indirect metrics like the impact on driving performance, alterations in psychological states, and subjective assessments are used to measure them. Large corporations with installed driver assistance systems in their cars include Tesla, Mercedes-Benz, and others [24]. Samsung is also developing systems that use facial features to track a driver's attention [25], but these systems are only available in high-end automobiles and are out of the price range of most people. The number of automobiles with Android Auto has significantly increased. On the other hand, anyone can use our online application as long as they have a smartphone and a smartphone holder. The ideal setting for the application to function is created by the ease with which a smartphone holder can be affixed to the windshield, even in the absence of one. Because of this, even if there are superior solutions out there, this application is far less expensive.

IV. METHODOLOGY

A. Dataset

A video dataset, where the input is assumed to be a video and blinks are predicted in the video frames, is needed to assess the model's performance. Additionally, we must assess the blinks on photos where we can determine whether a blink is present or not to verify the model's accuracy.

B. Architecture

This implementation uses a combination of Golang and machine learning algorithms to facilitate the integration of Python on the backend with JavaScript and SASS on the frontend. The ML facial detection algorithm is run on the video frames that the camera has captured as input. The HAAR cascade frontal face detection method put out by Viola Jones [2] is used for detection. The face region is the only Region of Interest (ROI) in the final frames that are obtained following this phase; it has been cropped, scaled, and converted to grayscale. We then apply facial landmark detection to this region of interest. We only record the landmarks that correlate to the eye region for our implementation, which are located between landmarks 37 and 46 as shown in Fig. 7.

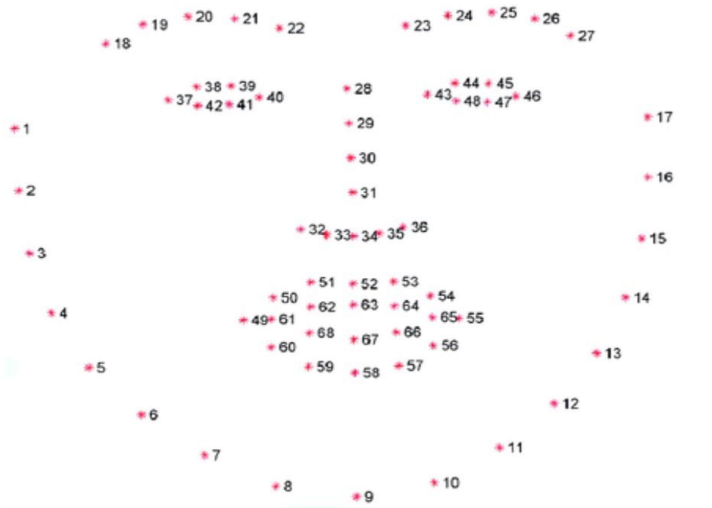

Fig. 6. Facial Landmarks (Landmarks 37-46)

Following that, the Eye Aspect Ratio (EAR) is calculated in relation to these landmarks. The alert will sound if this value falls below the ideal level for a specific amount of frames. Prior to being authorized, the user's credentials are kept in the database. The AI launcher receives this encoded video stream and forwards the video data to the AI module. In order to forecast drowsiness, the AI module decodes the video data and performs facial landmark and facial detection.

C. Facial Detection

We must first identify the faces from the images supplied by the video stream in order to apply the facial landmarks detection algorithm to the faces. To do this, we are utilizing OpenCV cascade classifiers, which are based on the methodology put forward by Paul Viola and Michael Jones [2]. Fig. 8 presents the block diagram illustrating how this technique is applied when the images are submitted to the Haar-cascade detector. Prior to sending the photos to the cascade classifier, which consists of the following four phases, they must first be cropped, scaled, and converted to grayscale.

1. Cascading classifiers
2. AdaBoost training
3. Creating integral images
4. Haar feature selection

This system achieves a high judgment rate by processing images very quickly [2]. At the end of this algorithm, we get the face region.

D. Facial Landmarks

The eye corners, nose tip, mouth corners, and other prominent facial points are examples of facial landmarks, also known as facial feature points, that are discernible marks in facial photographs that make up intriguing portions of the images [26]. An ensemble of regression trees is used in facial landmark identification to determine landmark locations based only on pixel intensities [3]. The landmarks that correspond to 37–46 is identified in this specific implementation, which is close to the ocular region.

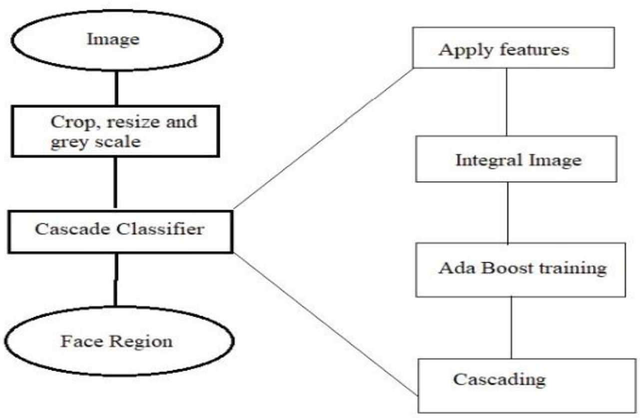

Fig. 7. Block Diagram of Facial Detection

E. Eye Aspect Ratio

Active techniques for detecting eye blinks frequently rely on specialized hardware, like illuminators and infrared cameras [4]. We can reduce the expense of external gear by using facial landmarks; for example, we can tell if someone's eyes are open or closed using simply a smartphone's camera. The Eye Aspect Ratio (EAR) can be calculated using the following formula, which was put out by T. Soukupova and J. Cech [27], once the spots close to the eye region have been identified:

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

To determine how frequently the eyes blink, it is essential to accurately identify their form [28]. The width is measured by measuring the distance between p1 and p4, and the height of the eye is measured by measuring the distance between the other points. Although it fluctuates, the eye aspect ratio

should always be higher than a certain value. The threshold is chosen at 0.25 for this project, per T. Soukupova and J. Cech's suggestion [27]. The warning will sound if the EAR value stays below 0.25 for more than seven frames in a row. This model can be applied practically using the facial detection and facial landmarks detection discussed in the previous sections. Fig. 8 shows a real-time evaluation of the eye aspect ratio in a live video camera. Since the value is above 0.25, the alarm would not ring.

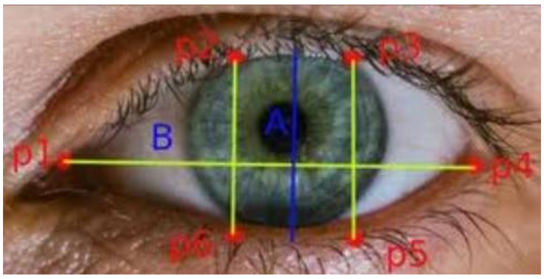

Fig. 8. Evaluation of Eye Aspect Ratio

F. Encoding

Data can be delivered over the internet using streaming, which eliminates the need for the user to download the entire file. A method known as "live streaming" sends the stream live across the internet. Video encoding entails reducing the size of video data in order to transfer it more quickly to the destination device, where it is decoded. Video encoding is required because uncompressed video files are too large to transmit over the internet and because video must be in a format that is compatible with all types of consumer devices. The server receives the live video stream from the smartphone camera and uses a streaming protocol to divide it up into manageable chunks. Next, an encoding standard is used to encode the video standard.

V. Results And Discussion

The study's video dataset originates from a model presented by Isha Gupta et al. [17], which enables the system to predict sleepiness by monitoring changes in the blink counter and eye aspect ratio (EAR) over time. To evaluate the accuracy of blink detection, a total of 323 photos were gathered, showing people in "eye-closed" and "neutral" states. Isha Gupta et al. reported that the system's excellent 89% accuracy rate in recognizing the blinks was obtained. Fig. 9 and Fig.10 provide a visual summary of these findings that demonstrate how well the model detects tiredness in controlled setting.

However, in practical usage several limits were revealed. When the driver is not looking straight ahead the model has trouble and frequently interprets the gaze direction incorrectly mistaking it for tiredness even though it may not be. Furthermore, the model's ability to identify eye characteristics is significantly reduced when drivers wear glasses because of reflections or occlusions from the lenses.

Various modifications and alternative strategies have been presented by subsequent studies to solve these issues. For instance a 2023 study by Zhang et al. presented a convolutional neural network (CNN) based on deep learning that combines facial landmark identification with head rotation and gaze tracking for improved accuracy when the driver's focus is diverted from the road. The model was able to increase overall resilience in real-time monitoring systems by reducing false positives caused by off-road looks by combining gaze and head posture estimation alongside eye characteristics.

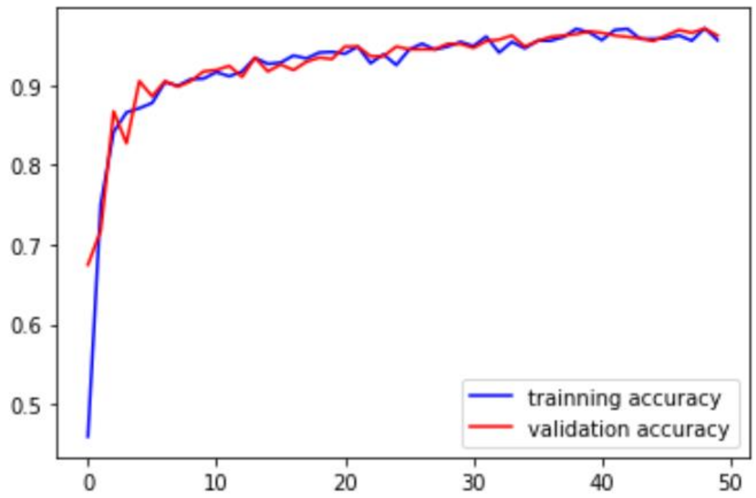

Fig. 9. Accuracy

Liu et al.'s 2024 study used infrared (IR) cameras which are less impacted by the reflections from glasses to address the problem of drivers wearing spectacles. This technique offered a more dependable way to monitor the eye movements even in difficult or dimly lit environments. Additionally by fusing accelerometer and optical data, their multi-sensor fusion technique greatly improved the identification of head tilts and micro sleeps two important signs of tiredness. This enhanced the system's performance over traditional visual-only techniques by improving blink and gaze detection accuracy overall.

Furthermore, the physiological variables including heart rate variability (HRV) and electroencephalogram (EEG) data were incorporated into the sleepiness detection framework by Wang et al. in 2024 using a multimodal approach. The hybrid model demonstrated exceptional efficacy in surmounting vision impairments caused by spectacles or inadequate illumination. When physiological data was added, the model was able to follow internal fatigue levels even in situations when outward eye characteristics were challenging to observe, resulting in a more thorough diagnosis of driver weariness.

Even with the advances in technology real time processing and computing efficiency are still difficult especially when multimodal data is involved. Although it adds complexity, the use of wearable technology and other sensors like heart rate monitors or EEG bands has the potential to improve accuracy in subsequent models.

In conclusion, even though the existing model produces impressive results (89% accuracy in blink detection) a number of enhancements are still required to guarantee its application in a variety of real world circumstances. Future versions of sleepiness detection systems might offer much improved accuracy and dependability by utilizing the most recent advancements in multimodal integration, gaze tracking, and physiological monitoring. This would eventually result in safer roads and more effective driver monitoring solutions.

VI. Conclusion

This research has reviewed a number of cutting-edge methods for detecting driver drowsiness. The detection of anomalies in the driving pattern is the basic tenet upon which all these strategies operate.

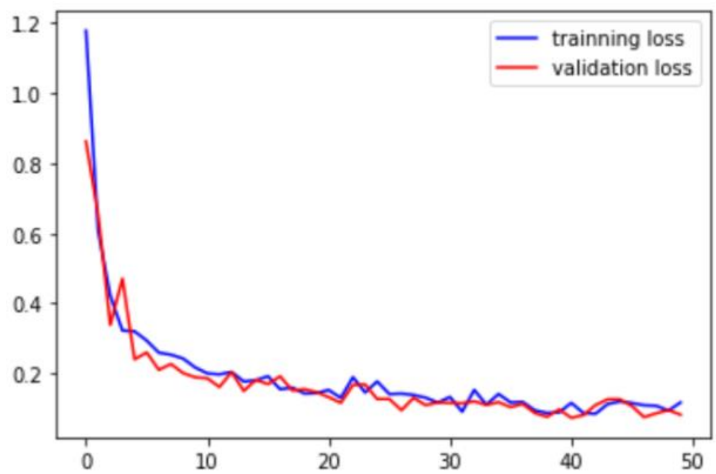

Fig. 10. Loss

These methods employ a variety of measurements including:

1. Subjective,
2. Behavioral
3. Physiological
4. Vehicular.

- Subjective measures alert the driver but do not provide an exact estimate of drowsiness.
- Physiological measures use invasive techniques that can disturb the driver.
- Vehicular measures require complex and costly infrastructure.
- Behavioral measures have been found to be the easiest and most cost-effective for detecting driver drowsiness.

Driver drowsiness has been detected more accurately using head movement-based methodologies than other behavioral indicators as eye state, eye blink rate, yawning and head movement. Computing systems have a difficult time detecting tiredness. This article's method offers a dependable and expandable approach. When compared to other methods, it is more affordable, and anyone with camera rights can utilize it.

REFERENCES

[1] National Highways Development Project: An Overview (GoI), pp. 1-2, Accessed [20 Feb 2016].

[2] Road Accidents in 2013, Available: http://www.morth.nic.in/showfile.asp?lid=1465, Accessed [20 Feb 2016].

[3] Bengler, K., Dietmayer, K., Farber, B., Maurer, M., Stiller, C., Winner, H., "Three Decades of Driver Assistance Systems: Review and Future Perspectives", Intelligent Transportation Systems Magazine, Vol. 6, No. 4, pp. 6-22, 2014.

[4] Vandana Saini, Rekha Saini, "Driver Drowsiness Detection Systems and Techniques: A Review", 2014.

[5] Namratha Raj; Kusumika Krori Dutta; Archit Kamath, Lane Prediction by Autonomous Vehicle in Highway Traffic using Artificial Neural Networks,2021 Fourth International Conference on Electrical, Computer and Communication Technologies(ICECCT), DOI: 10.1109/ICECCT52121.2021.9616881.

[6] Vahid Kazemi, Josephine Sullivan, "One Millisecond Face Alignment with an Ensemble of Regression Trees", 2014.

[7] Nafis Irtija, Mahsius Sami, Md. Atiqur Rahman Ahad, "Fatigue detection Using Facial Landmarks", 2018.

[8] Maryam Hashemi, Alireza Mirrashid, Alisaghar Beheshti Shirazi, "Driver Safety Development: Real-Time Driver Drowsiness Detection System Based on Convolutional Neural Network", 2020.

[9] Chen Z., Wu C., Zhong M., Lyu N., Huang Z., "Identification of common features of vehicle motion under drowsy/distracted driving: A case study in Wuhan, China", Accident Analysis and Prevention, Vol. 81, pp. 251259, 2015.

[10] Otmani, S., Pebayle, T., Roge, J., Muzet, A., "Effect of driving duration and partial sleep deprivation on subsequent alertness and performance of car drivers", Physiology and Behavior, Vol. 84, pp. 715-724, 2005.

[11] G. M. Bhandari, A. Durge, A. Bidwai, U. Aware, "Yawning analysis for driver drowsiness detection", Int. J. Res. Eng. Technol., vol. 03, no. 2, pp. 502-505, Feb. 2014.

[12] Kusumika Krori Dutta, Dr. Premila Manohar, Falak Naaz, Meenakshi Lakhminarayan, Shwethaa Rajagopalan, "Eye State Detection from Electro-Encephalography Signals using Machine learning Techniques", IEEE Mysurucon 2022, 16-17, Oct'2022. DOI: 10.1109/MysuruCon55714.2022.9972567.

[13] C. Sun, J. Li, Y. Song, L. Jin, "Real-time driver fatigue detection based on eye state recognition", Appl. Mech. Mater., vol. 457-458, pp. 944952, 2014.

[14] J. Jo, S. J. Lee, K. R. Park, I.-J. Kim, J. Kim, "Detecting driver drowsiness using feature-level fusion and user-specific classification", Expert Syst. Appl., vol. 41, no. 4, pp. 1139-1152, Mar. 2014.

[15] Tawari, Ashish, Sujitha Martin, Mohan Manubhai Trivedi, "Continuous head movement estimator for driver assistance: Issues, algorithms, and on-road evaluations", IEEE Transactions on Intelligent Transportation Systems, Vol. 15, No. 2, pp. 818-830, 2014.

[16] Lew, M., Sebe, N., Huang, T., Bakker, E., Vural, E., Cetin, M., Ercil, A., Littlewort, G., Bartlett, M., Movellan, J., "Drowsy driver detection through facial movement analysis", In Human-Computer Interaction, Springer: Berlin, Germany, Volume 4796, pp. 618, 2007.

[17] Khushaba, R.N., Kodagoda, S., Lal, S., Dissanayake, G., "Driver drowsiness classification using fuzzy wavelet-packet-based feature-extraction algorithm", IEEE Trans. Biomed. Eng., Vol. 58, pp. 121-131, 2011.

[18] Vicente, J., et al., "Drowsiness detection using heart rate variability", Medical and biological engineering and computing, 2016, pp. 1-11.

[19] Sampei, K., et al., "Mental Fatigue Monitoring Using a Wearable Transparent Eye Detection System", Micromachines, Vol. 7, No. 2, 2016, pp. 20.

[20] Li, M.-a., Zhang, C., Yang, J.-F., "An EEG-based method for detecting drowsy driving state", 2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), Volume 5, 2010.

[21] Yeo, M.V.M., et al., "Can SVM be used for automatic EEG detection of drowsiness during car driving?", Safety Science, Vol. 47, No. 1, 2009, pp. 115-124.

[22] Fu, C.L., Li, W.K., Chun, H.C., Tung, P.S., Chin, T.L., ”Generalized EEG-based drowsiness prediction system by using a self-organizing neural fuzzy system”, IEEE Trans. Circ. Syst., Vol. 59, 2012, pp. 20442055.

[23] M. Benz, “Mercedes Benz safety - s class.” [Online]. Available: https://www.mercedes-benz.co.uk/passengercars/mercedes-benzcars/models/s-class/saloon-w222/safety/intelligent-drive.module.html, 2004.

[24] Kusumika Krori Dutta, Sarita Kumari, Kehkashan Jalal, Harsha K,”Lane Change Control of Autonomous Vehicle on Highway Traffic”, 7th International Conference on Computer Applications in Electrical Engineering-Recent Advances (CERA), October 27 - 29, in IIT Roorkee , DOI: 10.1109/CERA59325.2023.10455399

[25] Rachid Ahdid, Khaddouj Taifi, Said Safi, Bouzid Manaut, ”A Survey on Facial Feature Points Detection Techniques and Approaches”, 2016.

[26] T. Soukupova, J. Cech, ”Real-time eye blink detection using Facial landmarks”, Computer vision workshop, 2016.

[27] Nora Kamarudin, Nur Anida Jumadi, et al., ”Implementation of Haar Cascade Classifier and Eye Aspect Ratio for Driver Drowsiness Detection Using Raspberry Pi”, 2019.

[28] Isha Gupta, Novesh Garg, Apoorva Aggarwal, Nitin Nepalia, Bindu Verma, ”Real-Time driver’s Drowsiness Monitoring Based on Dynamically varying Threshold”, 2018.