A Survey on Drowsiness Detection Techniques*

V.E. Machaca Arceda[1][0000-0001-8990-5495], J. P. Cahuana Nina[1][0000-0002-8174-118X], and K.M. Fernandez Fabian[2][0000-0001-6006-5197]

[1] Universidad la Salle de Arequipa, Arequipa-Perú (vmachacaa, jcahuana@ulasalle.edu.pe)@ulasalle.edu.pe
[2] Universidad Nacional de San Agustín de Arequipa, Arequipa-Perú karla.m.f.f@gmail.com

Abstract. There are 1.24 million traffic accidents every year with 2.4% caused by drowsy drivers. In that context, several methods for drowsiness detection have been developed. Nevertheless, despite the huge amount of researches, the several devices on markets, and car systems; it is not clear which method is the most appropriate, what sensors are the most useful and least intrusive. This study, shows a systematic literature review of the most recently and relevant methods.

Keywords: Drowsiness Detection · Survey · Fatigue Detection

1 Introduction

According to the World Health Organization (WHO), 1.24 million traffic accidents occur every day [1]. The National Highway Traffic Safety Administration (NHTSA) mentions, that in the United States (US), there were 153,297 fatal crashes between 2011 to 2015 with 2.4% caused by drowsy drivers. Moreover, 1.25 million people die in road crashes each year, 20-50 million are injured or disabled; it cost $518 billion. More alarming, road traffics is predicted to become the fifth cause of death by 2030 [2].

Despite the huge amount of works on the field, and the several numbers of devices for drowsiness detection, it isn't clear yet which one is the best, which one is the most appropriate according to the conditions of cars and drivers, and what are future about this topic.

This work is a preliminary systematic review of drowsiness detection techniques. We just take the most recent and relevant works since 2015, we consider that this work could be the initial step, for persons that want to start their research on the filed. We take the classification proposed by Ramzan et al. [3]. They grouped drowsiness detection methods into three approaches, in Fig. 1 we present the three groups/approaches and the features computed for each group. The first one is the behavioral approach, it is based on the analysis of images and video of drivers capture from cameras. The second one is the vehicular approach, based on devices inside the vehicle, the majority are sensors embedded

* Supported by INNOVATE-PERÚ, Universidad la Salle and X-traplus.

on the steering wheel; The final group is the physiological approach, these intrusive methods are devices that a driver has to use on the head, hands, fingers, etc.

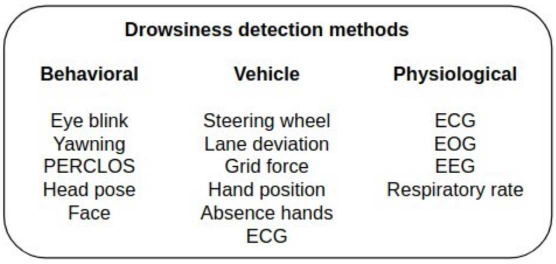

Fig. 1. Main drowsiness detection methods. EEG: Electroencephalogram, EOG: Electrooculogram, ECG: Electrocardiogram and PERCLOS: Percentage of eyelid closure.

2 Research methodology

The purpose of this work is the recognition of the best methods for drivers' drowsiness detection. All data gathered from primary studies are categorized into three approaches: vehicle, physiological, and behavioral approach. In Table 1, we present the search string used for each approach.

We performed our study on search engines such IEEE, ACM, Springer, and Google Scholar. We got 596 research papers; from those, we have selected 265 papers based on the title, those from journals, and the most recently; then 78 papers, were selected after abstract revision; finally, 48 research papers were filtered out as our primary study.

Table 1. Search string used for each approach.

Approach	Search strings	Total	Selected
Physiological	(drowsiness OR drowsy fatigue OR alert) AND physiological (drowsiness OR drowsy fatigue OR alert) AND (ECG OR EOG OR EEG OR Respiratory)	59	9
Vehicle	(drowsiness OR drowsy fatigue OR alert) AND (Vehicle OR Automobile) (drowsiness OR drowsy fatigue OR alert) AND (Steering OR land OR hand)	67	8
Behavioral	(drowsiness OR drowsy fatigue OR alert) AND Image (drowsiness OR drowsy fatigue OR alert) AND (DEEP LEARNING OR MACHINE LEARNING)	139	28

3 Drowsiness detection techniques

3.1 Vehicle approach

In this section, we included all the non-intrusive methods, they basically relies on sensors embedded on the steering wheel that measures the Steering Wheel Angle (SWA), Steering Wheel Reversal (SWR), Steering Wheel Movements (SWM), Steering Wheel Velocity (SWV), angular velocity, grid force, hand position, absence hands, and Approximate entropy (ApEn). Actually, we could divide the researches in two groups: the cutoff-analysis methods: that measure certain features and use a cutoff in order to detect drowsiness (See Table 3) and machine-learning-based methods that uses machine learning models (See Table 2).

One of the pioneers methods that associated steering wheel data with drowsiness were Platt in 1963 [4]. Since then, several researches studied different methods and features in order to detect drowsiness. In Fig. 2 (right), we present a generalized framework for drowsiness detection based on sensors on the steering wheel.

An important aspect in these methods are the frequency they used to log data. For instance, the SWA is logged with 100Hz [5], 60Hz [6], 25Hz [7] and 1Hz [8]. Moreover, Haupt claimed that driver's reaction cannot change faster than 50Hz [9]. Also, for EEG and ECG, usually 256Hz is used and 512HZ for EOG [10].

Moreover, the methods based on steering wheel data are dependant of road geometry and curvature [6]. In that context, the road curvature on steering have to be remove. The majority of works use Equation 1:

$$M_\theta = \frac{1}{W} \sum_{k=n_l}^{n_l+w-1} \theta(k) \tag{1}$$

$$\theta^*(k) = \theta(k) - M_\theta \tag{2}$$

where, W is the length of sliding window, n_j, the first point of window and M_θ, the average of steering angle. $\theta(k)$ stands for the raw signal and $\theta^*(k)$ is the preprocessed signal.

In Fig. 2 (left), is presented the effect of road curvature, the read lines stands for the raw data and the blue lines represent the preprocessed data (after curvature effect removal). As we can see, the read curve have spikes that represent the rad curvature.

3.2 Physiological approach

In this section, we include intrusive methods, they basically measures the Heart Rate (HR), Heart Rate Variability (HRV), Pulse Rate (PR), Breathing Rate (BR), Respiratory Rate (RR), body temperature, electrical brain activity and electrical eye activity. The device used are electroencephalogram (EEG), Electrooculogram (EOG), Electromyogram (EMG) and electrocardiogram (ECG).

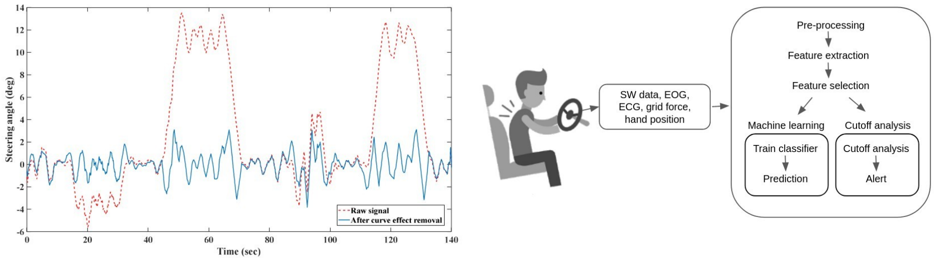

Fig. 2. Left: Road curve effect removal. Source: [6]. Right: Generalized framework for drowsiness detection based on sensors embedded on the steering wheel.

Table 2. Machine learning methods which use sensors embedded on the steering wheel for drowsiness detection. SWA: steering wheel angle, ECG: electrocardiogram, SVM: support vector machine, ANN: artificial neural network, ApEn: Approximate entropy, LD: lateral displacement, EB: eye blinking, PD: pupil diameter, MOL: multilevel ordered logit, DT: decision tree, LR: logistic regression.

Ref	Features	Method	Acc
2019 [10]	SWA and ECG	SVM	0.94
2019 [7]	SWA	Multilevel SVM and ANN	0.73
2019 [6]	SW data	ANFIS PSO and SVM	0.98
2017 [5]	ApEn of SWA	Binary classifier	0.78
2017 [11]	ApEn of SWA	Decision-tree	0.82

These methods are more reliable and accurate [3] but are intrusive for drivers. In Table 4, we present the publications related to physiological methods.

The EEG is the most common device, a EEG have 7 bands representing the state of brain, the bands most used are α, β and θ. Moreover, these methods could be divide in FFT-based spectral analysis, wavelet-based spectral analysis and Higher Order Statistics-based analysis [15]. As other methods, these are difficult to compare because of the lack public database, each research built its own database in a simulated environment.

Other methods use the Hearth Rate data [16–18], with wavelet transform. Also, respiratory rate data [16, 17] and even body temperature [18] are used.

3.3 Behavioral approach

Behavioral methods are based on image processing of drivers capture with a camera. Features as eyes, mouth, head pose, percentage of eye closure (PERCLOS), face, eye blink, eye closure are used, the majority uses machine learning classifiers. These methods are non-intrusive and depend a lot from illumination and the image quality but with the introduction of deep learning and best

Table 3. Cutoff-analysis methods which use sensors embedded on the steering wheel for drowsiness detection. SW, steering wheel, AD: angular displacement, SWA: steering wheel angle, SWM; steering wheel movements, ECG: electrocardiogram, LD: lane deviation.

Ref	Features	Method
2017 [8]	SW angular velocity.	Time series analysis
2017 [12]	Absence hands	Detect absence hands
2016 [13]	Grip force	Detect low grid force
2015 [14]	Entropy of SWM	Analysis of entropy of SWM

Table 4. Physiological methods for drowsiness detection. ECG: electrocardiogram, EEG: electroencephalogram, HR: hearth rate, FFT: fast fourier transform, ANN: artificial neural network, PR: pulse rate, HRV, hearth rate variability, EOG: Electrooculogram, MEMS: micro-electro-mechanical systems, OSS: objective Sleepiness Score.

Ref	Features	Method	Acc
2017 [19]	ECG and EEG	SVM	0.80
2016 [18]	PR and temperature	Viola-Jones and Haar cascade	0.81
2015 [16]	HR, respiratory rate	FFT and ANN	-
2015 [17]	HR, PR, RR, stress level	Wristband sensors and SVM	0.98
2015 [20]	HRV	Hearth pulse sensor on fingers	-
2015 [15]	EEG	Smarthwatch system with SVM	0.92

camera devices, these methods become promising. Moreover, databases are used for both, image and video processing. Some public databases are DROZY [21], ZJU [22], NTHU [23], and RLDD [24], all of them are recorded in offices, and rooms with ideal conditions. In this work we divided this method into two: the image processing methods that use a single image in order to detect drowsiness, meanwhile, the video processing methods use various frames of video.

Image processing methods These methods just take one image to detect drowsiness. In Table 5, we listed the most relevant works. Some of them use eyes to detect eye blinking [25, 26], others used eyes and mouth to detect yawns [18, 27, 28] and head positions [29]. Also, the majority use machine learning models such as SVM, ANN, and CNN [28, 30–33]. Also, microcontrollers [34], Raspberry [35, 36], and Android [26, 31] are used.

In this approach, almost every research have been built its own dataset [25, 27, 35, 37–39] without the release of it. This is a big problem since it is difficult to replicate the results.

In addition, there is not a comparison between all methods but the most prominent works, could be Haruna et al. [40], they got a high accuracy using 84,898 images with SVM models. Other research is proposed by Reddy et al. [30], he used a CNN with the DROZY dataset. Moreover, despite CNN's performance, currently, SVM and image's feature vectors are still used.

Table 5. Articles about drowsiness detection based on images processing. DE: dropping eyelids, EB: eye blink, CE: Closed eyes, HE: histogram equalized, CMOG: Co-occurrence matrix of oriented gradients

Ref	Features	Method	Acc
2020 [40]	Facial features, extract histogram	SVM, LBP, binary pattern	0.99
2020 [41]	Facial features HAAR, image binarization	CNN, Viola Jones	-
2019 [28]	Facial features	ResNet, VGG16 and Inception	0.78
2018 [31]	Face image	Android, CNN, Haar cascades	0.81
2017 [30]	Eyes and mouth.	Multi-Task Cascaded CNN	0.89
2016 [29]	EB detection and head pose	Point Distribution Model	0.92
2016 [36]	CE	Haar Cascade and Raspberry Pi	-
2015 [34]	Percentage of DE	Viola Jones and microcontroller	-
2015 [37]	EB detection.	CMOG	0.95
2015 [25]	EB detection	HOG, SVM and PERCLOS	0.91

Video processing methods Video processing methods are based on the analysis of frames in a video sequence, they consider temporal information.

Table 6. Articles about drowsiness detection based on video processing. ECG: electrocardiogram, EAR: eye aspect ratio, FST: finite state machine

Ref	Features	Method	Acc
2020 [42]	ECG, AER, MAR and BPM	CNN and DBN	0.94
2020 [43]	VIGNet, SEED-VIG dataset	CNN, EEG	0.96
2020 [44]	DRSA, UTKFace Dataset	RNN with LSTM	0.96
2020 [45]	Vander Lugt Correlator	VLC	0.95
2020 [46]	EAR, KSS, Drozy Dataset	ML, SVM	0.94
2020 [47]	Frames	CNN and Bi- LSTM	0.96
2019 [48]	MOR and EAR	Haar Cascade	0.98
2019 [49]	Behavioral monitoring	CNN, GSM/GPRS	-
2019 [50]	EAR, jetson TX2	HOG and SVM	-
2017 [51]	Frames	Deep residual CNN	-

After analysis, it is appreciated that SVM is the most widely used classifier, as it provides mostly greater precision and speed, but it does not work well for large data sets, in Table 6 we present the most relevant methods. On the other hand, both CNN and HMM are slow in training and expensive. The methods that have the highest percentage of certainty are those that work with deep learning, and most of them use CNN,since it uses special convolution and pooling operations and performs parameter sharing. This enables CNN models to run on any device, making them universally attractive. The majority of works carried out tests for the detection of drowsiness with databases in simulated environments, and the lesser number of works that carried out tests in an uncontrolled environment, which required gathering more than one method or combining characteristics to achieve the detection with less margin of error, the work that proved to be most relevant with deep learning is Babitha et al. [44].

4 Conclusions

The state of art methods for drowsiness detection was reviewed in this study. Three main approaches were analyzed: behavioral approach, based on the analysis of image and video of drivers; vehicular approach, based on devices inside the vehicle, the majority are sensors embedded on the steering wheel; and the physiological approach, these intrusive methods are devices that a driver has to use on the head, hands, and fingers.

Some authors claim that the physiological methods have the highest accuracy but there is no clear evidence of a comparison between them Moreover, deep learning is used intensively, but SVMs and features vectors are still used.

The main disadvantage in this field is related to the dataset. The researches are not releasing them. Moreover, and more alarming, the few public datasets, are not in real conditions, they are recorded in offices or are simulated, as opposed to having your own training data from a larger sample of participants, while including new distinct signals of drowsiness (sudden head movement, hand movement, or even tracking eye movements, and others).

References

1. WHO. World health organization - infographics on global road safety 2013. `https://www.who.int/violence_injury_prevention/road_safety_status/2013/facts/en/`, 2013.
2. ASIRT. Annual global road crash statistics. `https://www.asirt.org/safe-travel/road-safety-facts/`, 2020.
3. Muhammad Ramzan, Hikmat Ullah Khan, Shahid Mahmood Awan, Amina Ismail, Mahwish Ilyas, and Ahsan Mahmood. A survey on state-of-the-art drowsiness detection techniques. *IEEE Access*, 7:61904–61919, 2019.
4. Fletcher N Platt. A new method of measuring the effects of continued driving performance. *Highway Research Record*, (25), 1963.
5. Zuojin Li, Shengbo Eben Li, Renjie Li, Bo Cheng, and Jinliang Shi. Online detection of driver fatigue using steering wheel angles for real driving conditions. *Sensors*, 17(3):495, 2017.
6. Sadegh Arefnezhad, Sajjad Samiee, Arno Eichberger, and Ali Nahvi. Driver drowsiness detection based on steering wheel data applying adaptive neuro-fuzzy feature selection. *Sensors*, 19(4):943, 2019.

7. Meng Chai et al. Drowsiness monitoring based on steering wheel status. *Transportation research part D: transport and environment*, 66:95–103, 2019.
8. Gao Zhenhai, Le DinhDat, Hu Hongyu, Yu Ziwen, and Wu Xinyu. Driver drowsiness detection based on time series analysis of steering wheel angular velocity. In *2017 9th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)*, pages 99–101. IEEE, 2017.
9. Daniel Haupt, Petr Honzik, Peter Raso, and Ondrej Hyncica. Steering wheel motion analysis for detection of the driver's drowsiness. In *2nd International Conference on Mathematical Models for Engineering Science*, pages 253–261, 2011.
10. Margarida João Castro Neves Fernandes. Driver drowsiness detection using non-intrusive eletrocardiogram and steering wheel angle signals. 2019.
11. Zuojin Li, Shengbo E Li, Renjie Li, Bo Cheng, and Jinliang Shi. Driver fatigue detection using approximate entropic of steering wheel angle from real driving data. *International Journal of Robotics and Automation*, 32(3), 2017.
12. F Maita, SA Bruno, A Castiello, M Ruggeri, A Pecora, and L Maiolo. Integrated steering wheel system based on nanostructured elastomeric sensors for real time detection of driver drowsiness status. In *2017 IEEE SENSORS*, pages 1–3. IEEE, 2017.
13. KYEHOON LEE, SUNG-AE HYUN, and SHEZEEN OAH. Detecting driver fatigue by steering wheel grip force. *International Journal of Contents*, 12(1):44–48, 2016.
14. Zhen Long Li, Xue Jin, Bao Ju Wang, and Xiao Hua Zhao. Study of steering wheel movement under fatigue driving and drunk driving based on sample entropy. In *Applied Mechanics and Materials*, volume 744, pages 2001–2005. Trans Tech Publ, 2015.
15. Gang Li, Boon-Leng Lee, and Wan-Young Chung. Smartwatch-based wearable eeg system for driver drowsiness detection. *IEEE Sensors Journal*, 15(12):7169–7180, 2015.
16. Brandy Warwick, Nicholas Symons, Xiao Chen, and Kaiqi Xiong. Detecting driver drowsiness using wireless wearables. In *2015 IEEE 12th International Conference on Mobile Ad Hoc and Sensor Systems*, pages 585–588. IEEE, 2015.
17. Lee Boon Leng, Lee Boon Giin, and Wan-Young Chung. Wearable driver drowsiness detection system based on biomedical and motion sensors. In *2015 IEEE SENSORS*, pages 1–4. IEEE, 2015.
18. Yogesh Chellappa, Narendra Nath Joshi, and Vaishnavi Bharadwaj. Driver fatigue detection system. In *2016 IEEE International Conference on Signal and Image Processing (ICSIP)*, pages 655–660. IEEE, 2016.
19. Muhammad Awais, Nasreen Badruddin, and Micheal Drieberg. A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability. *Sensors*, 17(9):1991, 2017.
20. Herlina Abdul Rahim, Ahmad Dalimi, and Haliza Jaafar. Detecting drowsy driver using pulse sensor. *Jurnal Teknologi*, 73(3), 2015.
21. Quentin Massoz, Thomas Langohr, Clémentine François, and Jacques G Verly. The ulg multimodality drowsiness database (called drozy) and examples of use. In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1–7. IEEE, 2016.
22. Andrej Fogelton. Zju eyeblink database. `www.blinkingmatters.com/research`, 2007. Accessed: 2020-03-31.
23. National Tsing Hua University . `www.nhtsa.gov/risky-driving/drowsy-driving`, 2017.

24. Reza Ghoddoosian, Marnim Galib, and Vassilis Athitsos. A realistic dataset and baseline temporal model for early drowsiness detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 0–0, 2019.
25. Leo Pauly and Deepa Sankar. Detection of drowsiness based on hog features and svm classifiers. In *2015 IEEE International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, pages 181–186. IEEE, 2015.
26. Eddie E Galarza, Fabricio D Egas, Franklin M Silva, Paola M Velasco, and Eddie D Galarza. Real time driver drowsiness detection based on driver's face image behavior using a system of human computer interaction implemented in a smartphone. In *International Conference on Information Theoretic Security*, pages 563–572. Springer, 2018.
27. BN Manu. Facial features monitoring for real time drowsiness detection. In *2016 12th International Conference on Innovations in Information Technology (IIT)*, pages 1–4. IEEE, 2016.
28. Vineetha Vijayan and Elizabeth Sherly. Real time detection system of driver drowsiness based on representation learning using deep neural networks. *Journal of Intelligent & Fuzzy Systems*, 36(3):1977–1985, 2019.
29. In-Ho Choi, Chan-Hee Jeong, and Yong-Guk Kim. Tracking a driver's face against extreme head poses and inference of drowsiness using a hidden markov model. *Applied Sciences*, 6(5):137, 2016.
30. Bhargava Reddy, Ye-Hoon Kim, Sojung Yun, Chanwon Seo, and Junik Jang. Real-time driver drowsiness detection for embedded system using model compression of deep neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 121–128, 2017.
31. Rateb Jabbar, Khalifa Al-Khalifa, Mohamed Kharbeche, Wael Alhajyaseen, Mohsen Jafari, and Shan Jiang. Real-time driver drowsiness detection for android application using deep neural networks techniques. *Procedia computer science*, 130:400–407, 2018.
32. Anjith George and Aurobinda Routray. Real-time eye gaze direction classification using convolutional neural network. In *2016 International Conference on Signal Processing and Communications (SPCOM)*, pages 1–5. IEEE, 2016.
33. Fang Zhang, Jingjing Su, Lei Geng, and Zhitao Xiao. Driver fatigue detection based on eye state recognition. In *2017 International Conference on Machine Vision and Information Technology (CMVIT)*, pages 105–110. IEEE, 2017.
34. TP Nguyen, Moi-Tin Chew, and S Demidenko. Eye tracking system to detect driver drowsiness. In *2015 6th International Conference on Automation, Robotics and Applications (ICARA)*, pages 472–477. IEEE, 2015.
35. Jang Woon Baek, Byung-Gil Han, Kwang-Ju Kim, Yun-Su Chung, and Soo-In Lee. Real-time drowsiness detection algorithm for driver state monitoring systems. In *2018 Tenth International Conference on Ubiquitous and Future Networks (ICUFN)*, pages 73–75. IEEE, 2018.
36. Oraan Khunpisuth, Taweechai Chotchinasri, Varakorn Koschakosai, and Narit Hnoohom. Driver drowsiness detection using eye-closeness detection. In *2016 12th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*, pages 661–668. IEEE, 2016.
37. Bo Zhang, Wenjun Wang, and Bo Cheng. Driver eye state classification based on cooccurrence matrix of oriented gradients. *Advances in Mechanical Engineering*, 7(2):707106, 2015.

38. Jun-Juh Yan, Hang-Hong Kuo, Ying-Fan Lin, and Teh-Lu Liao. Real-time driver drowsiness detection system based on perclos and grayscale image processing. In *2016 International Symposium on Computer, Consumer and Control (IS3C)*, pages 243–246. IEEE, 2016.
39. Amna Rahman, Mehreen Sirshar, and Aliya Khan. Real time drowsiness detection using eye blink monitoring. In *2015 National Software Engineering Conference (NSEC)*, pages 1–7. IEEE, 2015.
40. Haruna Bassi, Hakeem A Sulaimon, and Muhammad Aminu Ahmad. Drowsy driver detection and monitoring system using support vector machine. *ATBU Journal of Science, Technology and Education*, 8(3):122–130, 2020.
41. Pavan Kumar Tadiparthi, Venkata Suma Priya Kankipati, Jessie Alekhya Kandimalla, Priyanka Gottimukkala, and Pradeep Kumar Bheemavarapu. An effective model to alert a drowsy driver using eye closure rate.
42. Q. Abbas. Hybridfatigue: A real-time driver drowsiness detection using hybrid features and transfer learning hybridfatigue: Driver fatigue detection by abbas q. *International Journal of Advanced Computer Science and Applications*, 11(1), 2020. cited By 0.
43. W. Ko, K. Oh, E. Jeon, and H.-I. Suk. Vignet: A deep convolutional neural network for eeg-based driver vigilance estimation. 2020. cited By 0.
44. D. Babitha, M. Ismail, S. Chowdhury, R. Govindaraj, and K.B. Prakash. Automated road safety surveillance system using hybrid cnn-lstm approach. *International Journal of Advanced Trends in Computer Science and Engineering*, 9(2):1767–1773, 2020. cited By 0.
45. Elhoussaine Ouabida, Abdelaziz Essadike, and Abdenbi Bouzid. Optical correlator based algorithm for driver drowsiness detection. *Optik*, 204:164102, 2020.
46. Caio Bezerra Souto Maior, Márcio José das Chagas Moura, João Mateus Marques Santana, and Isis Didier Lins. Real-time classification for autonomous drowsiness detection using eye aspect ratio. *Expert Systems with Applications*, page 113505, 2020.
47. Sumeet Saurav, Shubhad Mathur, Ishan Sang, Shyam Sunder Prasad, and Sanjay Singh. Yawn detection for driver's drowsiness prediction using bi-directional lstm with cnn features. In *International Conference on Intelligent Human Computer Interaction*, pages 189–200. Springer, 2019.
48. Suvarna Nandyal and PJ Sushma. An automated system for driver drowsiness monitoring using machine learning. In *International Conference on Intelligent Data Communication Technologies and Internet of Things*, pages 466–476. Springer, 2019.
49. Abid Ali Minhas, Sohail Jabbar, Muhammad Farhan, and Muhammad Najam ul Islam. Smart methodology for safe life on roads with active drivers based on real-time risk and behavioral monitoring. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–13, 2019.
50. Nashwan Adnan Othman, Ilhan Aydin, and Mehmet Karakose. An efficient embedded security system for reduce car accident to build safer world based on iot. In *2019 International Artificial Intelligence and Data Processing Symposium (IDAP)*, pages 1–5. IEEE, 2019.
51. Ki Wan Kim, Hyung Gil Hong, Gi Pyo Nam, and Kang Ryoung Park. A study of deep cnn-based classification of open and closed eyes using a visible light camera sensor. *Sensors*, 17(7):1534, 2017.