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Scaling effectivity in manifold methodologies to detect driver's fatigueness and drowsiness state

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ABSTRACT

The state of fatigueness and drowsiness relates to the stressed physical and mental condition of a driver that reduces the ability of a driver to drive safely leading to fatal consequences of road accidents. With a rising concerns about the road safety, the premium and modern vehicles are coming up with a sophisticated technology to detect and rise alarm during the positive case of fatigueness and drowsiness. Irrespective of availability of archives of literatures towards solving this problem, it is quite unclear about the strength and weakness of varied methodologies. Therefore, this paper presents a crisp and insightful discussion about the recent methodologies associated with detecting driver's attention, fatigueness, drowsiness along with highlights of commercial devices to realize various limiting factors and constraints associated with them. The paper contributes to introduce a well-structured flow of research trend to realize various patterns of current trend adopted towards solving varied problems and significant research gaps have been identified in this process. The outcome of this paper presents that still there is an open scope of an improvement towards accomplishing the agenda towards safer driving.

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1. INTRODUCTION

The term driver's drowsiness and driver's fatigueness is often discussed in the perspective of road safety; however, there are potential differences between these two terminologies [1]. *Driver's drowsiness* is basically related to a physical state of driver discretely characterized by driver either in verge of falling asleep. This is featured by troubled focusing on road, challenging to keep eyes open while driving, frequent yawning, and heavy eye lids. It could be due to side effect of medication or sleep disorder or inadequate sleep [2]. Drowsiness can lead to lapse in judgement, minimizing attention during driving, and impair reaction from the driver leading to chances of road accidents. On the other hand, *driver's fatigueness* is basically related to physical as well as mental state of tiredness; however, it is not necessary that a fatigued driver will fall asleep always. A fatigued driver may experience impaired decision making with minimized concentration on road, slower times of reaction, and reduced alertness [3]. It could be due to physical stress or exertion, extended driving hours, or prolonged period of wakefulness. The current study has been carried out emphasizing on both drowsiness and fatigueness are they are directly connected to the road safety as the drivers consistently drains the ability to operate a vehicle safely in either of the states. The significance of background of this research domain are manifold which are again linked with road safety. The first problem is related to *extended time required to offer reaction* of a driver e.g., swerving or sudden braking by neighboring vehicles. The second problem is related *impaired judgement* causing driver to undertake unwanted risk, failing to respond precisely to dynamically changing road condition. The third problem is associated with *microsleeps* episodes where the driver falls deep asleep for few seconds without any self-realization of it. A fraction of microsleep is heavily dangerous enough to cause vehicle colliding with an object or neighboring vehicles. Hence, irrespective of a driver experiencing drowsiness or fatigued, both of them actually contributes towards a fatal road accident [4]. Hence, a question arises that why one should see both of these terms from different angle although both these terms eventually lead to an accident. The answer for this question is that modernized vehicles are currently evolving with sophisticated road safety features where the behavior of the driver is subjected to analysis while the outcome of analysis will foretell the probability of drowsiness or fatigueness state of driver followed by alarming them to prevent accidents [5]-[12]. Although, these forms of road safety features are yet not available in all the vehicles and only few proportions of vehicles have started using it that falls under the category of premium vehicles. At present, sensors installed within such vehicle traces an appropriate signal information of driver followed by processing it to tell the actual state of driver. In reality, not many drivers are accustomed to such form of safety system as they are not available in low or medium end vehicles owing to cost factors.

Before realizing the statement of the problem, it is important to understand various form of research challenges associated with such form of safety system responsible for evaluating the state of drowsiness or fatigueness associated with driver. Following are some of the research challenges: i) none of the existing mechanism has critically differentiated drowsiness and fatigueness of a driver and mainly all the studies are linked to identifying drowsiness state only. Because of this issue, the models are not much able to offer reliability in its outcome as factors included in fatigueness may not significantly confirm drowsiness, ii) various experimental and prototyping has been carried out in existing times considering an artificially created research environment that may not match with real world driving on different roads. Hence contribution and applicability of such studies are often questionable from safety perspective although they generate an initiative framework to begin analysis, iii) it is also noted that various scientific studies carried out in this research considers physiological attributes which often demands some kind of device attached to body of a driver. Such form of models is practically less viable from practical daily usage by any driver. Hence, they may sound interesting in scientific journals but less chances of adoption in practical world. iv) There are also wide variants of studies where facial expression of driver has been used to detect the state of drowsiness or fatigueness of driver. However, there are multiple loopholes in such techniques too viz. poor illumination condition, driver wearing cap or hoodie or glasses poses serious detection constraints, etc. Such model is also subjective of specific driver whereas sometime, one vehicle is driven by multiple drivers. The rate of recognition performance significantly decreases in such way. v) it is also noted that existing devices towards detecting drowsiness/fatigueness also consider some of the parameters which are not directly linked with the health status of driver viz. steering wheel movement, and lane keeping. This is because of the fact that every driver has their own unique way of driving that cannot be linked with such parameters, vi) another significant issue found is that there are various evolving approaches to deal with this problem; however, such approaches have not considered the practical viability of operational and cost-effective features of such methods when they will take the shape of device one day installed in vehicle.

Since the last decade, there has been evolution of various contributory study models towards addressing the above-mentioned issues as well as various other uncharted issues too. Various relevant literatures have been introduced for this purpose. Kashani *et al.* [13] have presented a framework based on data mining where tree is constructed towards performing classification and regression for investigating the prime indicators of fatigued-based accidents. Liu *et al.* [14] have developed a solution model by combining two different physiological attributes related to signals of heart and eye blinks in order to recognize the fatigued state of driver. Model constructed by Zhao *et al.* [15] have contributed towards detecting the level of distraction among the driver on the basis of estimated head poses of driver. The work presented by Nasri *et al.* [16] and Veras *et al.* [17] have discussed various methods and its associated issues towards detection of drowsiness state of driver. Yarici *et al.* [18] have used brain-signals in order to understand the fatigued state of driver. A highly comprehensive discussion about sensors and its participation towards detecting the state of mental fatigueness is presented by Sharma *et al.* [19]. Hence, there are various evolving literatures towards presenting the discussion of an effective solution for detecting the state of drowsiness/fatigueness of driver.

The proposed solution presented in this paper discusses discretely the effectiveness of methodologies associated with detecting and classification of drowsiness/fatigueness. The proposed system contributes towards highlighting the effectiveness of discrete research techniques used towards detecting the state of drowsiness and fatigueness along with inclusive highlights to current scenario of research trend. The idea is to draw the conclusive outcome in the form of research gaps that demands attention to bridge the possible trade-off in methodologies used. However, different from existing system, this manuscript offers a new value of current research as follows: i) the study presents crisp highlights of positive correlation (PC) and negative correlation (NC) associated with various attributes while using physiological based signals for monitoring driver's attention, ii) the study presents an exclusive highlights of recent methodologies introduced for detecting fatigueness and drowsiness state of driver along with accomplishment and limitation, iii) updated information is presented about usage scenario of commercial devices for various available brands of vehicles to understand the difference between research work and commercially available devices status with highlights of an issues, iv) an elaborated research trend is presented to realize the current direction and pattern of studies, v) a crisp highlights of identified research gap is presented to showcase the open-ended issues that have not yet been attended by any current research publications. The next section presents briefing of the methodology adopted to carry out the current study.

2. METHOD

The core notion of this study is to present the facts associated with recently implemented methodologies towards detection of drowsiness and fatigueness of driver. It is noted that there are various mechanisms presented at this point of time and hence a unique methodology is required to make it more structured discussion. The methodology adopted in proposed study is shown in Figure 1 exhibiting various stages involved in carving proposed methodology.

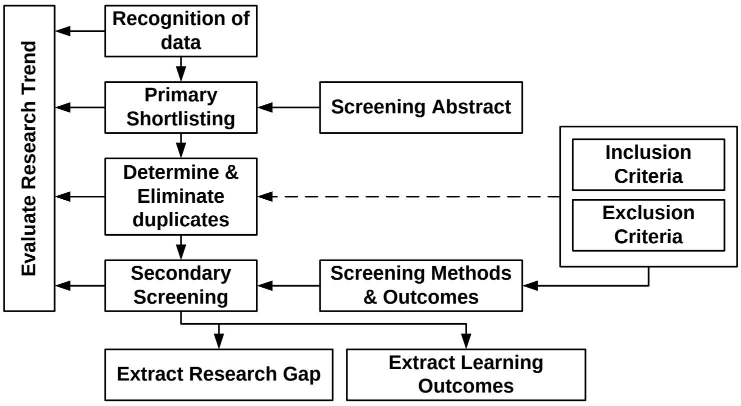

Figure 1. Adopted method in present investigation

According to Figure 1, the first stage is associated with recognition of data where various research articles have been collected classifying to methods used in drowsiness detection and fatigue detection. The second stage involves primary shortlisting of an aggregated documents on the basis of screening abstract. The idea is of this stage is to confirm that the paper has an inclusion of problem domain as well as solution using specific methodology to be reviewed. The third stage of the proposed methodology is to determine and eliminate all form of duplicates while this stage is further guided by inclusion and exclusion criteria that is also further used for screening methods and outcomes in order to arrive at secondary screening methods. The inclusion criteria involve viz; i) considering only journal articles, ii) the article should posses discrete discussion of methods and clear discussion of result achieved, iii) emphasis towards various implementation methods are prominent given and less emphasis is given towards filtering the type of signals being used in order to get a global perspective of research trend. The exclusion criteria involve; i) no discussion or conceptualized paper should be involved while attempting to identify the recent methods of drowsiness and fatigueness detection, ii) papers published prior to 2015 is not considered while reviewing essential recent methods. The adherence of above method leads to filtering of only the useful recent scientific article where the agends of the proposed review work can be met. Apart from this, the discussion doesn't involve much highlights of all the survey study and has been restricted to discuss only few reviews work to showcase the difference between existing review and presented review. Hence, consideration of recent and unique journals adds more updated value-added information contributing towards highlighting essential facts associated with strength and weakness of existing studies. The next section discusses results accomplished.

3. RESULTS AND DISCUSSION

This part of the paper discusses about varied approaches that have been introduced towards monitoring the state of driver that considers driving process, distraction, fatigue, and driving style. Existing studies have been carried out considering emphasis towards driver, vehicle, driving environment and. The prime contribution is towards understanding the essential information associated with adopted methodologies.

3.1. Existing studies towards monitoring driver's attention

Majority of the studies dealing with monitoring driver's attention has used physiological/biological sensors and sensors withing-outside of vehicle. The data are acquired from these sensors followed by feature extraction and classification that is further subjected to decision making that finally leads to an outcome in the form of alarm or display. Table 1 highlights the usage of various signals e.g., skin temperature (ST), electro-derman activity (or galvanic skin response (GSR)), electromyography (EMG), electrooculography (EoG), electroencephalogram (EEG), and electrocardiogram (ECG). Further, ECG signals that are used for monitoring driver's attention are heart rate (HR), varied forms of frequency i.e., low/high frequency (LF/HF), very low frequency (VLF), heart rate variability (HRV), and respiration rate (RR). The attributes in EoG that are used for analyzing attention degree of driver are movement of eyeball, delay in lid opening, duration of closed eye (PERCLOS), duration, amplitude, and frequency of blinks.

Table 1. Summary of existing approaches

Signal Type	Problem	Accuracy	Connection with Fatigue	Alternative Sensors
ST [20]	Detecting fatigue	-N/A-	PC: -N/A- NC: ST	MAXIM3025, Temperature Probe, Series ofYSI 400
EDA [21]	Detecting fatigue	80%	PC: Skin Resistance NC: EDA	Grove-GSR, Empatica Wristband, Shimmer 3
EMG [22]	Detecting fatigue	94%	PC: gain lower frequency from center frequency NC: EMG Amplitude	Quasar Sensor, Trigno Mini Sensor, NeuroSky Dry Sensor, Neuronode, SX230
EoG [23]	Alertness Detection	82%	PC: Duration of blink, Blink Frequency, PERCLOS NC: amplitude of Blink, movement of eye	Eye Tracking Glasses, Comnoscreen, Google glass, NeuroSky's Dry Sensor
EEG [24]	Detection of Distraction & Fatigue	97%	PC: α, θ band power, latency NC: β band power, amplitude, entropy	Flex sensor, Quasar sensors, NeuroSky Dry sensor, MinWave Headset, Imotive headset, Drypad sensor
ECG [25]	Detecting fatigue	96%	PC: HRV, HF NC: RR, LF/HF, VLF, Heart rate	Quasar sensor, NeuroSky Dry sensor, Drypad sensor, Ambulatory ECG, Alivecor system, Flex sensor, Omron

Further, it is seen that there are varied studies which considers hybrid techniques in order to increase the possibilities of accomplishing better accuracies. Hybrid techniques are noted to combine band power of EEG and PERCLOS [26]. Further, spectral power of EEG is combined with ECG [27] while work done in [28] integrates sample entropy, spectral component of EEG, and entropy of ECG. Integration of information of breathing rate, blinking, HRV, and heart rate was witnessed in work of [29].

3.2. Existing studies towards driver's fatigueness

The term fatigueness of driver is basically subjective combination of compromised performance as well as drowsiness feeling and is contextually vary from the term distraction. Chronic fatigueness leads to compromization of safety and eventually leads to an accident. Abbas and Alsheddy [30] have presented a study towards detecting driver's fatigueness with an aid of multi-sensors. The prime notion of this study is to derive the significance of multi-modal feature processing based on cloud, smartphone, and sensors. The work carried out by Anber *et al*. [31] have used transfer learnig for predicting drowsiness behaviour of driver while AlexNet has been used for feature extraction. Further, the model has also used non-negative matrix factorization (NMF) for feature reduction and support vector machine (SVM) for classification. Adoption of multi-modal modelling is also reported in work of Karuppusamy and Kang [32] where image as well as information from gyroscope and EEG is considered for identifying the fatigue state of driver.

Arefnezhad *et al*. [33] have presented a study of risk of fatigueness during automated driving and used difference of PERCLOS for analyzing the proportion of eye closure in order to determine driver's fatigueness. Adoption of eye closure is also reported in work of Dzuida *et al*. [34] and Shang *et al*. [35] while similar trend of work is also reported by Chen *et al*. [36] where facial detection is initially carried out using Adaboost while tracing of facial movement is done by Kalman filter. Further facial landmarks were detected using regression tree of cascaded form followed by using backpropagation neural network for training. Equivalent trend of study using facial landmark is also presented by Xiao *et al*. [37] where the region of the face is acquired from multi-scale feature and pooling method using spatial pyramid. Using convolution layer, the mechanism of facial landmark is rendered lightweight. Further, the outliers are controlled using statistical and adaptive thresholding. Work carried out by Chen *et al*. [38] have used machine learning approach with a differential evolution with a notion towards evaluating heartbeat signals and respiration rate to confirm the fatigueness of driver. Dong *et al*. [39] have used deep learning-based approach where the facial detection is carried out by single shot scale-invariant (SSSI) identification of face that is further followed up by constructing network of face alignment for feature extraction. The classification is features are carried out using convolution neural network (CNN) while random forest (RF) is used for analysis of condition of driving. Adoption of CNN has been also witnessed in work of Xiang *et al*. [40] where an attention method along with three-dimensional CNN model has presented for assessing the fatigue state of driver. The study uses CNN for extracting feature map from spatial and temporal information while attention method is used for controlling the feature weights. Adoption of attention method is also reported in work of Ye *et al*. [41] that is capable of key feature extraction in adaptive manner while the identification of fatigueness is carried out using degree of mouth opening and PERCLOS. Further, the study model uses ear aspect ratio (EAR) and Mouth Aspect Ratio (MAR) for analysis. Similar perspective of modelling is also carried out by Zhu *et al.* [42].

Further adoption of deep learning is also witnessed in work of Ed-Doughmi *et al*. [43] where recurrent neural network (RNN) has been used. He *et al.* [44] have carried out an investigation towards driving dynamics as well as indicators for eye tracking using CAN bus system, smart eye pro, and stanford sleepiness scale. Kassem *et al*. [45] have presented a predictive model where real dataset has been subjected towards analyzing the fatigueness of driver using infrared radiation-based camera considering head and facial attributes. The model presented by Salvati *et al*. [46] have used variability of pulse rate in order to identify the fatigue state of driver, where the outcome have been compared and validated with PERCLOS indicators. Sheykhivand *et al*. [47] have used deep neural network where EEG is used for involuntary identification of fatigue state of driver. The study has integrated CNN with long short-term memory (LSTM) for learning hierarchical feature learning. The discussion carried out by Wang *et al.* [48] have presented significance of auditory stimulation towards detection of fatigue state of driver. The study subjects the input of EEG signal towards decomposition using variational mode to generate different functions of intrinsic mode. Least square (LS) technique is used for select the best intrinsic funation followed by error extraction. Zheng *et al*. [49] have presented a study using deep learning methodologies where ShuffleNet is used for identification of driver face followed y acquisition of coordinate points of driver face. Finally, recognition of fatigue state is carried out using EAR and MAR. Table 2 [32]-[49] (see appendix) highlights the summary of above-mentioned study methodologies.

3.3. Existing studies towards driver's drowsiness detection

The term drowsiness is directly linked with the state of being sleepy and can be stated as a subset of the term fatigueness of the driver. Albadawi *et al*. [50] have used machine learning in order to detect the state of driver's drowsiness by extracting features associated with head pose, EAR, and MAR. Adoption of hybrid machine learning is witnessed in work of Altameem *et al*. [51] where skin segmentation and face detection have been carried out followed by eye monitoring. SVM is applied in order to determine the drowsiness state using yawning as the prime indicator. Amidei *et al*. [52] have implemented a machine learning model where the data is derived from wrist device for acquiring skin conductance signal followed by using ensembled learning algorithm. The work carried out by Bajaj *et al*. [53] have presented a model integrating facial features with skin response data where further CNN has been used for identifying facial features associated with driver's drowsiness. Similar trend of considering two different signals were also witnessed in study of Esteves *et al*. [54] where facial features and ECG is used for facilitating continuous learning towards predictive analysis of driver's drowsiness. Ebrahimian et al. [55] have integrated CNN with LSTM in order to classify the driver's drowsiness considering the rate of respiration, variability of heart rate as well as its power spectrum. Adoption of CNN is also witnessed in work of Florez *et al*. [56] and Jahan et al. [57] where the detection of drowsiness state of the driver is carried out using eye extraction method adopting multiple neural network model. The discussion presented by Khan *et al*. [58] have developed an experimental setup for assessing the drowsiness for multiple drivers using Android mobile application. Adoption of edge computing is presented in work of Lamaazi *et al*. [59] where the driver's condition-based information is captured and subjected to data fusion model where CNN is used for detecting local information while YoLov5 model is used for detecting global information of facial expression linking with state of drowsiness. Finally, LSTM is implemented to decide. Further, adoption of CNN is reported in work of Li *et al*. [60] where wearable glass is constructed for extracting rate of blinks and PERCLOS while a network is constructed for assessing eye opening and closing event. Adoption of PERCLOS and inclusion of facial aspect ratio (FAR) has been reported in work of Maheswari *et al*. [61], where further the region of interest is subjected to CNN algorithm to perform detection. The work carried out by Savas and Becerikli [62] have used PERCLOS-based modelling where the fatigue state of driver is assessed via yawning and closure of eye attributes mainly using CNN. The study towards sensitivity attributes associated with PERCLOS70 has been carried out by Murata *et al*. [63] where rates associated with karolinska sleepiness scale (KSS) has been evaluated over real experiments. The study shows that PERCLOS70 is effective for detection of drowsiness. Adoption of generative adversarial network (GAN) in work of Ngxande *et al*. [64] shows that it can performan effective data augmentation and predictive performance on CNN. Another unique study is formulated by Paulo *et al*. [65] where image encoding is used for representing EEG signals in spatiotemporal form followed by using CNN for classification. Sunagawa *et al*. [66] have used multimodal information e.g., indices of drowsiness, blinkness, posture, and physiological index for performing predictive analysis of drowsiness using radial basis function-based regression approach for support vector. Further, Vijaypriya and Uma [67] have presented CNN model using flamingo search algorthm (FSA) while Zhang *et al*. [68] have used federated transfer learning for detection of drowsiness. Table 3 highlights the summary of existing studies on drowsiness detection.

Table 3. Summary of studies towards driver's drowsiness

Authors	Problem	Methodology	Accomplishment	Limitation
Albadawi *et al*. [50]	Detection of Drowsiness	Facial features analysis, SVM, Neural Network, RF	99% accuracy	
Altameem *et al*. [51]	Detection of Drowsiness	Skin segmentation, face detection, eye tracking, SVM	96% accuracy	Lower accuracy for emotion identification
Amidei *et al*. [52]	Detection of Drowsiness	Skin-conductance, ensembled machine learning	89% accuracy	Lower accuracy
Bajaj *et al*. [53]	Detection of Drowsiness	CNN (cascaded)	91% accuracy	Includes intrusive way too
Esteves *et al*. [54]	Multimodal detection of drowsiness	ECG, facial features	Improved identification	Lower Accuracy
Ebrahimian *et al*. [55]	Classification of Drowsiness	CNN, LSTM	Supports multi-level classification, 91% accuracy	Higher processing demand
Florez *et al*. [56], Jahan *et al*. [57]	Detection of drowsiness	CNN (ResNet50V2, VGC16, InceptionV3, VGG19, 4D)	99% accuracy	Requires higher number of computational resources
Khan *et al*. [58]	Detection of drowsiness	Experimental prototype (Raspberry), android mobile, cloud	96% accuracy	Low analysis scope towards extensive applications
Lamaazi *et al*. [59]	Detection of Drowsiness	Edge Computing, CNN, YoLov5, LSTM	97% accuracy	Training time is higher
Li *et al*. [60], Maheswari *et al*. [61]	Detection of Drowsiness	Wearble glass, rate of blink, PERCLOS, network of lightweight glass, CNN	95% accuracy	All models assessed on same dataset
Savas and Becerikli [62]	Detection of Drowsiness	PERCLOS, CNN	98% accuracy	Mobility/ position of head missing from modelling
Murata *et al*. [63]	Detection of Drowsiness	Analytical modelling using KSS, PERCLOS70	Statistically effective model	Model sensitive to alteration in level of drowsiness
Ngxande *et al*. [64]	Detection of Drowsiness	GAN, CNN, ResNet	Assessed over multiple dataset	Test accuracy is much lower than validation accuracy
Paulo *et al*. [65]	Detection/Classification of Drowsiness	Image encoding of EEG, CNN	Applicable for spatiotemporal analysis	Lower accuracy of 75%, presence of physical constraint on real-time usage
Sunagawa *et al*. [66]	Detection of Drowsiness	Multimodel drowsiness detection scheme	Efficient computation of drowsiness state	Practical not cost effective
Vijaypriya and Uma [67]	Detection of Drowsiness	Complex wavelet transfor, CNN, FSA	98% accuracy	No benchmarked
Zhang *et al*. [68]	Privacy preservation of detected information	Federated Transfer Learning	Higher model flexibility	Higher resource consumption

3.4. Commercial devices in current era

At present, there are various commercial devices of drowsiness and fatigueness detection system installed in modern vehicles in order to ensure safer driving. Table 4 showcases that such forms of devices are either car-based or driver-based while closer look into the elements of the Table 4 will show that car-based approaches are more than driver-based approaches. The car-based approaches can be seen in manufacturing brands like Ford [69], Benz [70], BMW [71], Audi [72], and Volkswagen [73] while driver-based devices has been seen in Toyota [74]. All these are premium brands of vehicles where manifold features have been used for detection of drowsiness viz. warning System, time of driving, duration of journey, monitoring departure of lanes, analysis of steering behaviour, monitoring-based on camera as shown in Figure 2.

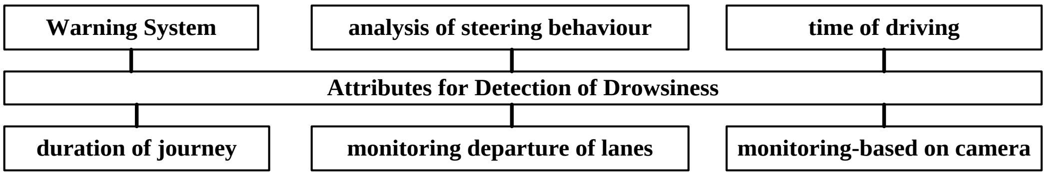

Figure 2. Attributes for detection of drowsiness in current era

Table 4. Summary of existing approaches

Vehicle Brand	Charecteristic	Detection System	Parameters used	Warning mechanism
Ford [69]	Cruise control (adaptive), Detection of blindspot, auto-lane management,	Steering sensor, Camera, radar	Proximity Detection, Lane position stability	Display, vibration
Benz [70]	Assisting driver attention, detection of blind spot, night view, behaviour and profile of driver, auto-lane management	Steering sensor, Camera, radar	Speed and movement of steering wheel	Display, Audio
Toyota [71]	Detection of pedestrian, cruise control (dynamic), alerting lane departure, obstacle detection	Steering sensor, Camera, radar	Head motion, eye tracking	Display/Audio
BMW [72]	Assistive parking, alerting crossroad, semi-automated driving, night vision, alerting lane change	Thermal Camera, camera, radar	Detection of proximity, lane keeping	Display, vibration
Audi [73]	Night vision, assisting traffic jam, assisting truning, collision avoidance	Thermal Camera, camera, radar, Far Infrared Camera	Detection of proximity, lane keeping	Display, vibration, Audio
Volkswagen [74]	Fatigue detection	Steering sensor, Camera	Lane keeping	Visual, audio

From the above table, it is noted that there a are various commercial devices already in practiced in real-world and hence a reason question arises that *what is the need of further investigating drowsiness/fatigue detection of driver*? There are some valid reasons behind this which can be stated by reviewing some of the existing discussion in prior sections. The current commercial devices suffer from outliers leading to *false positives* or *false negative*. False positive will furnish wrong outcome that driver is sleepy whereas driver may be quite awake while false negative may result in not alerting the driver when they are sleepy. Majority of existing devices works using camera and sensors mainly which gather heterogeneous information and often struggle towards reaching accuracy for such diversity as every driver has different driving habbit. Hence, existing devices cannot handle or get them synced with *variability of driver*. It is highly possible that driver can get themselves adapt to their monitoring and alerting system which makes the performs sub-optimal. Such devices cannot work differently when driver's *adaptation over time* is witnessed. There is quite a fair possibility that various environment factors e.g., reflection, glare of vehicle coming from opposite direction, or poor lightning condition. *Lack of balance of effectivity between car-based and driver-based system* is another serious issue in current commercial applications. Existing car-based devices focuses on parameters associated with external environment (lane, direction of car, speed) while driver-based devices focus on internal environmental parameters (head movement, and driving posture). Also, a closure looks into Table 4 shows that these features are available only for premium brands of cars in limited quantity as implementing this detection system will increase the *complexity as well as cost* of vehicle manufacturing which will increase the on-road price of vehicle exponentially. Usage of camera and sensor will also encounter gradual *wear and tear* which will affect the accuracy of detection. Adoption of physiological parameters (EEG, EOG, and ECG) is less likely to precise and accurate in driving scenario of real-life and this possibility arrises for presence of interference and noise leading to *inaccurate measurements*. Current commercial products don't focus on detecting driver's drowsiness on the base of their distracting behaviour that can compromise the driving safety. There could be some event when the device confirms that the driver is not drowsy but they can be eventually distractive while driving leading to potential reason for accidents.

Hencem current commercial products doesn't emphasize on *interaction with driver distraction* while monitoring drowsiness/fatigues. Figure 3 highlights the issues of current commercial devices of drowsiness detection and monitoring.

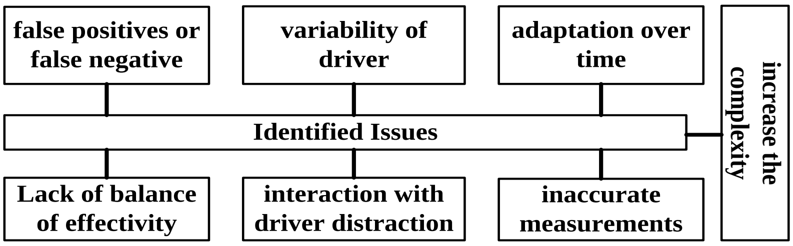

Figure 3. Issues in current commercial drowsiness detection devices

3.5. Research trend

In the process of understanding the research trend, it can be seen that drowsiness is one the frequently adopted terminology associated with fatigueness and reduced score of driving vigilance among the drivers. Referring to this standard publication, it is known now that there are three types of techniques used for drowsiness detection which are; i) biological-based approaches, ii) vehicle-based approaches, and iii) image-based approaches.

- Biological-based approaches are those schemes where various forms of devices are attached to driver's body to acquire specific set of biological information e.g., blood pressure, electro-oculography (EOG), electromyography (EMG), electrocardiography (ECG), and electroencephalography (EEG) [75]-[78]. The prime limitation of such approach is that driver should be always connected to some devices or electrodes without which the biological signals cannot be acquired although it can give clinically accurate indication of LoV state of driver.
- Vehicle-based approaches uses data associated with movement patterns of vehicle using varied forms of sensors attached to vehicle with respect to parameters connecting with street and vehicle mainly. The idea is to obtain the degree of variation or abnormal readings in car movement pattern associated with lane deviation, speed, and angle of steering wheel, [79]-[80]. The prime limitation of this approach is that this scheme emphasizes more on car parameters and less on driver. The parameters used in this approach could be possibly affected by skill of driving by driver, climatic and road condition, habits of driving, etc, which has no connection with vigilance of driver.
- Image-based approaches performs calculation of drowsiness or non-healthy state of a driver on the basis of image acquired from driver's head, eyes, mouth, and face. This scheme considers various facial parameters as well as movement of head or movement of mouth in order to confirm the LoV state of driver [81]-[83]. The limitation of this approach is associated mainly with variable state of illumination as well as quality of feed capturing devices (it could be a sensor or camera). Various anomaly condition of occlusion, face covered with mask or cap or spectacle will also affect the accuracy of this technique. However, compared to all the approaches, image-based approach is preferred technique to investigate LoV owing to its non-invasive nature of data acquisition. Further, a pilot study is carried out to find that Artificial Intelligence-based approaches has a significant number of contributory research journals towards solving the problem of drowsiness detection [84]-[87].

Further, it is noted that machine learning (ML) and deep learning (DL) are the frequently adopted techniques in perspective of AI-methodologies for solving this problem. Apart from the above-mentioned evidence, there are various other literatures that have been studied. The work carried out by Magan *et al*. [88] have used deep learning-based approaches towards image sequences by using recurrent neural network (RNN) and CNN. Adoption of CNN is also reported in work of Minhas *et al*. [89]; however, the work objective has a unique proposition where focus is given towards monitoring driver's disturbances and not level of fatigueness. However, this scheme is equally is linked with state of driving methodology which is also one of the essential attributes towards safe driving. Similar direction of research work towards adoption of machine learning approaches is reported in work of Siddiqui *et al*. [90]. The study has used multilayered perceptron (MLP), extra tree classifier, gradient boosting (GB), logistic regression (LR), decision tree (DT), and SVM. Another unique work is seen in literature by Tarafder et al. [91] where ocular indices were acquired from EEG sign further followed up by using training operation using multiple machine learning models e.g., bagged and boosted tree model, k-nearest neighbour (KNN), SVM. The work carried out by

Kumar *et al*. [92] have presented a comparative evaluation of various techniques where deep learning approach is used for analysing the eye condition of driver followed by implementing viola-jones encounter detection and CNN for performing learning and identification. Further, adoption of reinforcement learning is reported in work of Langroodi and Nahvi [93] where fuzzy logic has been used together to prove its effectiveness over conventional artificial neural network (ANN) based approaches. Finally, the study carried out by Tian and Cao [94] have discussed about usage of electrooculography which is quite different from other approaches in order to determine fatigueness in driver. According to findings of this study, the aggregated approaches on electrooculography is found to be effective in contrast to other methods. Further, the work carried out by Arakawa *et al*. [95] has discussed about various upcoming prospective of estimation technology involved in drowsiness detection. The existing work carried out towards AI-based scheme shows that it is an evolving solution towards identifying the state of drowsiness with claimed better form of an outcome; however, it is also associated with an open-end research problem:

- The primary issue/gap is drowsiness is just one effective way of represent state of fatigueness in driver. However, it is not the only parameter for vigilance or complete healthy state of driving. The diversion, position, dynamic movement of body also constitute towards vigilance state of driving.
- The most critical issue is related to response time. It is noted that existing approaches uses various sophisticated approaches, which are generally iterative in nature, demands extensive trained data, considers long training as well as testing time too. Hence, usage of sophisticated learning scheme will only result in increase accuracy at the cost of extensive response time, which doesn’t fulfil the demand of monitoring fatigueness in driver. Further, not all the deep learning schemes (e.g., reinforcement learning) have been assessed for mitigating the detection and classification issues.,
- The research methodology adopted in existing cases are not proven for their computational effectiveness or burden. Extensive adoption of deep learning will enormously demand computational resources which will be unpractical deployment idea. Extensive use of machine learning will lead to reduction in accuracy and dependency of higher training to gain more accuracy. Less emphasis is given from practical-viewpoint.

From the above discussion, it can be noted that there are basically two cadres of problem domain i.e., detection of drowsiness and detection of fatigueness and there is more research carried out towards detection of fatigueness as noted in Table 5. However, in-depth study of literatures shows more studies on fatigues are actually confined to drowsiness state itself.

Table 5. Trend of research publication in detection of drowsiness and fatigueness

Publication	Drowsiness Detection No.	Fatigueness Detection No
IEEE	106	423
MDPI	70	63
Springer	1610	9926
Elsevier	105	7857
Hindawi	8491	~10000
ACM	16183	21430

Table 6 showcase those studies related to adoption of facial features towards detection and classification of drowsiness/fatigueness of driver is quite lesser compared to other schemes of EEG, ECG. EoG, EMG, and skin temperature (ST). However, some of the studies are also found to involve hybrid mechanism too by combining varied forms of signals. The outcome shows face-based study demands more attentions. Table 7 showcase that studies towards machine learning (ML) based approaches are slightly more (n=63474) as compared to studies in deep-learning (DL) based approach (n=57291). A deeper insight towards each ML and DL techniques shows further two learning outcome of research trends i.e., i) majority of existing ML and DL schemes are implemented in the form of ensembled and not as a standalone much, ii) SVM and CNN are the most frequently adopted schemes of ML and DL based approaches towards detection and classification of driver’s drowsiness/fatigueness.

Table 6. Trend of usage of varied signal input

Publication	EEG	ECG	EoG	EMG	ST	Face
IEEE	23	3	2	0	0	21
MDPI	11	5	2	1	1	4
Springer	454	245	102	165	308	480
Elsevier	107	107	106	107	357	427
ACM	35160	35109	35057	35092	37777	23007

Table 7. Trend of AI Methods

Publications	ML	DL
IEEE	21	18
MDPI	22	19
Springer	410	389
Elsevier	389	400
ACM	62632	56465

3.6. Identified research gap

After reviewing the existing solutions presented towards identifying state of drowsiness and fatigueness, it is found that each of the contributions in the form of scientific journals are significant in its own form. The existing solutions are found to address its stated problem and some of the articles are also found to offer its effectiveness with the assistance of an extensive analysis both in simulation and in experimental form. However, still some open-end issues persist that are highlighted as follows in the form of research gap: i) Majority of the existing studies considering vehicle-based attributes (e.g., steering wheel behaviour, and lane departures) doesn't connect itself to any true indicative parameters that could state the reliable state of driver's fatigueness, ii) studies focusing on wearble devices proved its applicability however, they are less practical in sense and frequent change of drivers will induce overhead in the system computation just to identify the driver, iii) the experiments carried out using human subjects are often witnessed to exhibit exaggerate expressions that could significantly differ in driver's facial expression in real driving event, iv) adoption of ML and DL are quite frequently witnessed as a preferred solution; however, almost all the approaches involve a complex learning mechanism deployed for detection of fatigueness state of driver, v) there is no record of any implementation work which offers a robust balance between higher accuracy and lower computational effort, vi) existing studies also showcases lower emphasis towards ensuring optimal signal (input) quality prior to subjecting it on learning algorithms.

Prior to highlighting the issues, it is necessary to realize that existing experimental-based approaches mainly emphasizes towards acquiring and extracting the single images (or frames) from each video from dataset followed by validating the perfectness of classification. However, such approaches have not been proven to draw a contextual relationship between the streams of frames and hence their outcomes are indicated to be low reliability features. Therefore, the identified research problems are as follows: i) Existing experimental/hardware-based approaches are found to emphasis more on vehicle-based attributes that doesn't link with driver state of fatigueness, ii) adoption of bodily-attached devices or invasive procedure offers accuracy but they are not practically viable for the driver to follow, iii) existing visual-based approaches are testified using real-time test-subjects with unnatural expression which often doesn't match during practical driving condition, iv) adoption of different variants of AI schemes calls for using sophisticated, iterative, and higher dependency towards dataset which consumes enough time to respond.

4. CONCLUSION

The current work has presented a potential and crisp insight of recent methodologies adopted towards detection of drowsiness and fatigueness of driver. Although there were prior studies towards similar discussion, but the proposed study has inclusion of certain novel attributes that makes it different from existing studies. The novelty of outcomes associated with proposed study are as follows: i) One of the prominent learning outcomes is that there is no much dedicated research concentration separately for detecting fatigueness from drowsiness state of driver., ii) although ML techniques are slightly more in publications from DL techniques, but recent trend is more into maximized adoption of DL approaches, iii) CNN is one of the widely used approaches in perspective of DL techniques used in detection and classification, iv) studies using facial images have been quantitively less investigated in contrast to adoption of other psyhiological signals either in standalone form or in mixed form. The above-mentioned outcomes are first to be reported in this manuscript and hence contributes to some of the essential research findings that assists towards framing up identified research gap. Hence, the future work direction will be towards addressing the identifying research gap while more importance will be given towards modelling a software architecture that can balance the demands of accuracy, reliability, and computationally cost effectiveness. Future work will be also towards offering more preference to fatigueness detection which is quite a complex case study compared to drowsiness detection problems.

APPENDIX

Table 2. Summary of studies towards driver's fatigueness

Authors	Problem	Methodology	Accomplishment	Limitation
Abbas and Alsheddy [30]	Multi-modal feature processing	Joint modelling of cloud, smartphone, and sensor, learning	A comprehensive evaluation platform	System response time not involved in analysis
Anber *et al*. [31]	Detection of fatigueness	Transfer Learning, AlexNet, NMF, SVM	Overall accuracy of 99%	No benchmarking
Karuppusamy and Kang [32]	Detection of fatigueness	Image, gyroscope, EEG, deep neural network	Accomplishes 93% accuracy	Accuracy could be more increased, higher response time

Table 2. Summary of studies towards driver's fatigueness (*continue*)

Authors	Problem	Methodology	Accomplishment	Limitation
Arefnezhad *et al*. [33], Dzuida *et al*. [34], Shang *et al*. [35]	Fatigueness in automated driving	PERCLOS-based model	Outcome contributory towards automated transmission	No Benchmarking
Chen *et al*. [36]	Detection of fatigueness	Adaboost, Kalman Filter, Regression tree, Backpropagation Neural network	93.3% of accuracy accomplishment, simplified model	Demands higher iteration for higher accuracy
Xiao *et al*. [37]	Identification of fatiguness	Multi-scale feature, spatial pyramid pooling	99% accuracy	Increased response time
Chen *et al*. [38]	Detection of fatigueness	Machine Learning, Differential evolution on heart signals	94% of accuracy	Insufficient samples of training
Dong *et al*. [39]	Detection of fatigueness	SSSI, network for face alignment, RF, CNN	97% accuracy	Higher resource consumption, higher feasibility of maximized response time
Xiang *et al*. [40]	Detection of fatigueness	Three-Dimensional CNN, Attention	95% of accuracy	Drains excessive computational power
Ye *et al*. [41]	Detection of fatigueness	Channel Attention network, estimation of head pose	99% accuracy	Insufficient calibration of camera position
Zhu *et al*. [42]	Detection of fatigueness	EAR, MAR, PERCLOS, CNN, K-Nearest Neighbor (KNN)	95% accuracy	Computationally complex over a long run
Ed-Doughmi *et al*. [43]	Real-time detection of fatigueness	RNN	92% accuracy	Lower accuracy, gradient issue not addressed
He *et al*. [44]	Impact of passive fatigueness on behaviour	Observation-based model	Conclude importance of passive fatigueness in modelling	No extensive analysis
Kassem *et al*. [45]	Detection of fatigueness	Predictive model using deep neural network (OpenCV)	93% accuracy	No analysis over uncontrolled environment
Salvati *et al*. [46]	Detection of fatigueness for medium range drive	Detection based on variability of pulse rate	Simplified model design	Lower accuracy (60%)
Sheykhivand *et al*. [47]	Involuntary identification of Fatigueness	CNN, LSTM on EEG data	98% accuracy	Overfitting issues
Wang *et al*. [48]	autotory stimulation to mitigate fatigued driver	Multi-scale entropy, decomposition using variational mode, LS	Flexible model architecture	Outcome lacks semantic contents to confirm reliable signals
Zheng *et al*. [49]	Detection of fatigueness	ShuffleNet V2K16, ShuffleNet V2K20	98% of precision	Higher response time

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