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State of the Art in Drivers’ Attention Monitoring – A Systematic Literature Review

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Abstract

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Keywords

Distraction detection; Fatigue detection; Drivers Drowsiness; Fuzzy Expert System; Face Monitoring system; Intelligent Transport System

REVIEW ARTICLE

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Abstract

Recently, driver inattention has become the leading cause of automobile accidents. As a result, the driver's perception and decision-making abilities are diminished, and the driver can lose control of the car. To prevent accidents caused by driver inattention, it's vital to continuously monitor the driver and his driving behaviour and inform him if he becomes distracted or sleepy. This topic has been the subject of study for decades. Whenever feasible to recognise unsafe driving in advance, accidents could be avoided. This document presents an overview of the existing driver alertness system and the various techniques for detecting driver attentiveness.

Keywords: Distraction detection, Fatigue detection, Drivers drowsiness, Fuzzy expert system, Face monitoring system, Intelligent transport system

1. Introduction

A driver monitoring system, also known as a driver state sensing (DSS) system, is an advanced safety feature that uses a dashboard-mounted camera to detect driver fatigue or distraction and send a warning or alert to refocus the driver's attention on driving. As a result of regulatory and rating agency demands, driver monitoring systems (DMS) are expected to become a standard feature of new automobiles. The European Union, for example, has mandated the inclusion of DMS in all new vehicle models by 2024, and the European New Car Assessment Program (Euro NCAP) already grants a vehicle a point toward a 5-star rating for the presence of DMS. Drowsiness and distraction are the leading causes of automobile collisions. The identification of driver drowsiness is based on visual and non-visual feature analysis.

The features of the face, eyes, and lips are extracted using a visual analysis method. Eye and mouth examinations are crucial indicators for the detection procedure. Eye state analysis, eye blinking analysis, mouth yawning analysis, and facial analysis are the most utilised techniques in visual analysis. Image processing and machine learning are the two steps used in visual analysis. It is a non-invasive technique. The non-visual analysis comprises two categories: driver physiological signal analysis and vehicle parameter analysis. In physiological signal analysis, electrodes must be placed directly on the body of the driver while he or she is driving, which is an intrusive method. Using driving data such as steering wheel movement and brake pedal pressure also delivers reliable information. Similarly, eye and head movements are suitable for determining distraction levels [1].

This study's primary objectives are to describe tiredness measurements and their definitions, Driver Attention Monitoring methodologies, and cognitive distraction detection algorithms, aiming to identify their main drawbacks and the main directions for future development.

This paper is structured as follows: Section 2 discusses how we selected relevant driver attention monitoring system-related studies using the systematic literature review process. In section 3, we

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analyse the contributions made by the authors of the selected publications in the field under consideration and present the proposed answers to the research paper's concerns. Section 4 describes the driver face monitoring system briefly. Section 5 closes the paper and identifies future actions.

2. Methodology

2.1. Method and material used

We designed our questions based on the reasons responsible for road traffic accidents. We have mainly focused on three questions:

RQ1. What are the parameters for fatigue measurement and their definitions?

RQ2. What are the techniques proposed for Driver Attention Monitoring and alerting methods involved?

RQ3. What are cognitive distraction detection algorithms?

We have gone through different databases. Based on the research questions, we included the related studies that mainly focused on the three questions. Those give significant indications of fatigue, distraction, and attention monitoring technologies.

2.2. Selection of studies and search criteria

A standard protocol for the systematic review was followed, and an electronic search was done on related studies considering different databases like IEEE, Medline, Science Direct, Elsevier, etc. Reports from the World health organisation on road accident has been searched, and websites of transport and road from 2015 to 2022 have been taken. We examined the related studies' reference lists, took relevant studies, and excluded the irrelevant data. We have gone to the institution's websites involved in road accident research, fatigue distraction techniques, and driver's attention monitoring. The paper selection procedure is depicted in Fig. 1.

We searched for the papers, articles, and reviews in the mentioned electronic databases using more keywords: distraction, fatigue, sleepiness, drowsy driving, Intelligent Transportation technologies, accidents, etc.

We also used vital string search in AND/OR combination, summarised below in Table 1. We went through many studies related to our search topic, in which various Intelligent Transportation Technologies have been mentioned. We got 2665 papers and studies meeting the selected keywords in the search process.

After examining the selected studies by their titles and abstracts, we found that 2556 are weakly related to our study's aim and excluded them. After an intensive search between the remaining 62 papers, we found 41 studies fulfilling our review's inclusion criteria (see Fig. 1).

3. Analysis of the results

Different studies proposed different driver fatigue detection criteria and suggested various solutions for monitoring the drivers' attention. The methodologies and technologies proposed by the authors of the selected papers in the frame of the systematic review will be presented in the following sections.

3.1. Fatigue management and their definitions (RQ1)

We found that no clear definition for fatigue is available, so we made sleepiness, drowsiness, and other related things our base. We proposed measuring the eye blink rate, and re-measuring on the Karolinska Sleepiness scale and, eventually, analysing their scores. Table 2 provides further information about the chosen measurement scales.

3.2. Techniques used for driver attention monitoring and the alerting methods involved (RQ2)

Different studies proposed various driver fatigue detection criteria and suggested other solutions for monitoring the drivers' attention. The methodologies and technologies proposed by the different authors of the studies eligible in the frame of the systematic review related to this question are illustrated in Table 3.

The reviewed studies suggested different technologies to monitor the driver's attention responsible for drowsy driving. These technologies were based on symptoms extraction by detecting different parts of the face. It measures fatigue by detecting eye closure, eye speed, eye blink rate, and mouth detection, such as yawning. By seeing these manifestations, they respond quickly to alert about the driver's state and prevent road accidents. A study uses face monitoring techniques to discover more about fatigue and distraction symptoms by acquiring images and using intelligent software [11].

It is an essential thing in any driver behaviour monitoring system to alert the driver when the fatigue or distraction detection phase is done by using a sound system alarm, SMS, email, massage chair, or mobile application; we have gone deep through

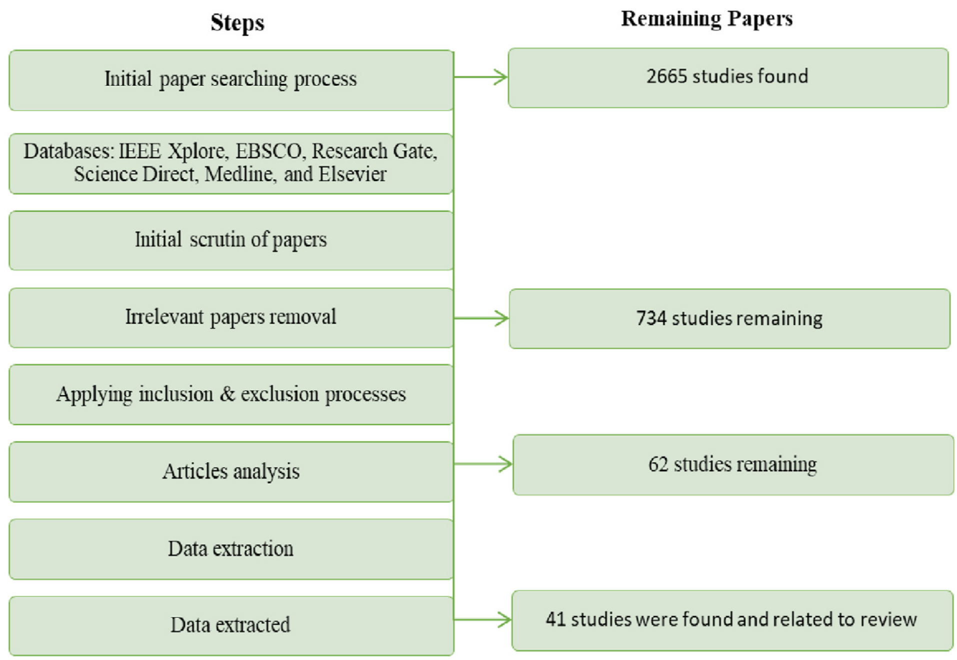

Fig. 1. Paper inclusion and exclusion process.

this matter to find the most common alert types, and we have concentrated them in Table 4.

In Table 5, we give a comparison of the technologies that are used for driver monitoring [17].

3.3. The cognitive distraction detection algorithms RQ3

In another study, the authors suggested using I.R. lightning and a camera to get realistic environmental views that are not harmful to the driver's eyes [31]. On the other side, several research papers proposed a fuzzy expert solution to detect driver's fatigue and mitigate drowsy driving [32].

Additionally, a study was conducted to detect distractions using visual sensors and an algorithmic approach [15]. This section will briefly explain the most commonly used cognitive distraction detection algorithms.

A decision tree (DT) is a tree-based technique where each path from the root to the leaf node is defined by a data-separating sequence until it reaches a Boolean result [33]. Using a decision tree to classify data means developing a tree for making decisions based on data categories. It classifies eye-closing and eye-opening performance to analyse fatigue [34].

A decision tree comprises different nodes (non-leaf nodes) that represent a specific condition or data feature. Each node branch corresponds to a possible value determined by the attribute test. Additionally, the tree contains a left node where data categories are recorded [35,36]. Fig. 2 depicts a decision tree that can classify open and closed eyes. It is the hierarchical representation of knowledge relationships using nodes and connections [37].

Sarkar Abhijit has used the Random Forest (RF) classification algorithm, consisting of many decision trees that improved the comprehension of drivers' gaze behaviour and roadway attentiveness behaviour [38]. Deep Convolutional Neural Networks (CNNs) have demonstrated better performance than classic machine learning techniques in various computer vision tasks, such as driver attention detection, as demonstrated in [39,40]. In [41], the authors compare the performance of classical

Table 1. Searched keywords.

Keywords	Closely Matched Keywords	Combination using AND OR Key strings
Drowsy Driving	Sleepiness, Fatigue	Traffic accidents OR Road accidents
Drowsiness	Distraction	Sleep OR Fatigue AND Traffic Accidents
Face Monitoring	Detection	Eye Closure AND Eye Speed OR Mouth Detection
EEG	WBAN, Sensors, Algorithms	ITS Technologies AND Fuzzy Expert Solutions

Table 2. Scales of fatigue measurement and their definitions.

SN	Scales	Definition
1.	ESS (Epworth Sleepiness Scale).	It generally measures daytime sleepiness and was proposed by Australian Dr Murray Johns in 2019 [2].
2.	PERCLOS for eye closure and tracking.	PERCLOS (Percentage of Eyelid Closure over the Pupil) is described as the percentage of time (70 or 80 percent) that the eyes are closed during a unit of time (often 1 min or 30 s) [3].
3.	SOFI.	It is a questionnaire developed to measure work-related perceived fatigue [4].
4.	Image processing software ALISA.	It detects the driver's sleep onset by processing video images from the driver's eyes and face [5].
5.	Copilot system.	It is a video-based method for measuring the eyelid's slow closure using a structured illumination approach [6].
6.	EDA (Electro Dermal Activity).	EDA provides information about the human skin by generating electric response signals. It helps detect the electrical characteristics of the driver' skin (varying with the moisture level) to identify drowsiness and prevent automobile accidents [7].
7.	KSS (Karolinska Sleepiness Scale).	KSS mainly measures sleepiness levels during the daytime. This scale defines the psycho-physical state experienced in the recent 10 min. It is sensitive to fluctuations [8].
8.	CAS fatigue score.	This scale is generally used to measure the risk of diminished alertness while working. It typically assesses operational fatigue and performs schedule optimisation [9].
9.	Stanford Sleepiness Scale (SSS).	It is an old scale for measuring subjective parameters in use today. Hodges and its associates in 1972 first presented it. It measures the driver's condition on a scale from 1 to 7; Higher scores indicate more severe drowsiness levels. There are many other descriptors, ranging from feeling vital, aware, or fully awake (score = 1) to giving up trying to fall asleep, falling asleep soon, and having dream-like thoughts (score = 7) [10].

procedures for features classification combined with typical machine learning methods to the implementation of deep learning approaches. Their findings indicate that deep learning methods significantly outperform other approaches. In [42], the authors proposed using CNN to classify photos of drivers texting or speaking on their phones. They achieved a 99 percent rate of accuracy. However, the diversity of picture datasets used for training is limited, as these images are derived from video clips obtained from simulated experiments. The authors of [43] proposed detecting important points in driving pictures and combining image patches surrounding these critical points as the input to a CNN. They mixed random patches from photos of the same class to enhance the training dataset. However, the resulting visuals are unnatural [44]. Convolutional Neural Networks (CNNs) are artificial neural networks modeled after human brain working mechanisms. As depicted in Fig. 3, a typical CNN consists of four layers: an input layer, convolutional layers, pooling layers, and fully connected layers. The input image to a CNN is a three-dimensional tensor (width, height, and depth) [44].

AdaBoost is a method for learning that employs the pattern recognition process known as boosting. Its benefits include a high classification performance, a quick identification procedure, and the possibility of extending recognition features [45]. AdaBoost's learning process comprises the generation of several classifiers and the iterative modification of the learning data's weighting. The final classifier function is then derived from these various classifiers using a weighted majority decision. Individual classifiers are known as "weak classifiers," whereas a combination of classifiers is known as a "strong classifier" [46].

Based on the statistical learning technique, the support vector machine (SVM) can be used for

Table 3. Detail of studies meeting our review aim.

First Author	Country	Published	The technique proposed for Driver Attention Monitoring
J Gonçalves [12].	Germany	2015	Highly Automated Driving
M Abulkhair [13].	Saudi Arabia	2015	Mobile platform/FDS Software
A Shaout [14].	USA	2015	FUZZY LOGIC/MATLAB
A Fernández [15].	Spain	2016	Visual Sensors And Algorithms
R Negra [16].	Tunisia	2016	WBAN
X Zhang [17].	China	2017	Wearable EEG
L Geng [18].	China	2019	Embedded Platform, ARM
K Bylykbashi [19].	Japan	2020	Fuzzy Expert System
A Celecia [20].	Brazil	2020	Fuzzy Interface

Table 4. The standard alerting methods.

First Author	Published	Features	The method of alert
Venkata Rami Reddy Chirra [21]	2019	The eye state	Alert the driver with an alarm when the state of the eye is drowsy.
The Duy Tran [22]	2018	Distraction detection	Generates voice alerts to the driver if the distraction is detected.
S. Uma [23]	2022	Face detection, Alcohol detection, Smoke/air pollution detection, and gas leakage detection	Sound System, SMS/mail alert
Eddie E. Galarza [24]	2018	Face detection, Eye state, Head movement	Audible and visual alarm
Brandy Warwick [25]	2015	drowsiness detection	a mobile app to warn a driver if drowsiness is detected.
Xiaoliang Zhang [26]	2017	drowsiness detection	The massage chair begins to work.
M.S. Satyanarayana [27]	2021	The eye state	Ring an alarm and alert the service provider if the driver appears to be drowsy
Panwar Prachi [28]	2022	Distraction detection	Alert system in case the driver is detected to be distracted or drowsy with the minimum response time.
Jie Yi Wong [29]	2019	The eye state	providing a medium loud beeping sound.
Anh-Cang Phan [30]	2021	The eye-aspect ratio (EAR) The mouth-opening value (LIPdistance)	Sound System

pattern categorisation and infer nonlinear relationships between variables. This technology has been applied successfully to detecting, verifying, and recognising faces, objects, handwritten letters and digits, text, voice, and speakers, as well as retrieving data and images. The SVM approach is suited for assessing the cognitive states of humans due to its learning technique. SVMs can generate linear and nonlinear models and compute nonlinear models with the same efficiency as linear models. Given input data collection, this method transforms the input domain using a kernel. It then searches the modified environment for a hyperplane that separates the data with minimal error and the highest gain [47]. Finally, the hyperplane is converted back to the input domain to yield the potentially nonlinear decision bounds. Fig. 4 depicts the activities done by the algorithm. Starting the system, which includes the camera in front of the user, is the logical initial step. After capturing an image, the face is identified. There are numerous ways for calibration. However, an SVM-based software solution was studied for greater accuracy [48].

Fatima et al. [49] used SVM and Adaboost to find whether the eye is closed or open, and they got 99.9% and 98.7% accuracy for face and eye detection, respectively. The flowchart of the classification algorithm used by them is shown in Fig. 5.

Extreme Learning Machine (ELM) is a novel machine learning tool that has garnered significant attention because of its simple structure, excellent generalisation capabilities, and rapid processing performance. ELM is a 1-hidden-layer feedforward network equipped with a high-speed, direct training algorithm, making it a perfect fit for our technique. In addition, ELM has become an increasingly important area of research in machine learning due

Table 5. Comparison of technologies used for driver attention monitoring.

Country	Categories	Technologies	PROS
USA, South Korea, China, Japan	Vehicle Behaviour-based technology	Lane Departure, Pressure on Driving pedals, Wheel Steering Movement	It enables noninvasive drivers surveillance by, e.g., detecting drowsiness based on the respiration rate acquired by monitoring the chest movement
USA, UK, France	Driver Behaviour Based system	Eye tracking, Eye closure, and facial expressions	It can measure the vigilance of the driver by using computer hardware and machine vision.
China, Japan, USA, U.K.	Algorithms based on Driver-Physiological-signal	Using EEG (EOG) Electrooculograph and heart-rate variability (HRV)	This system is quite reliable, as physiological sleepiness mechanisms are well understood.

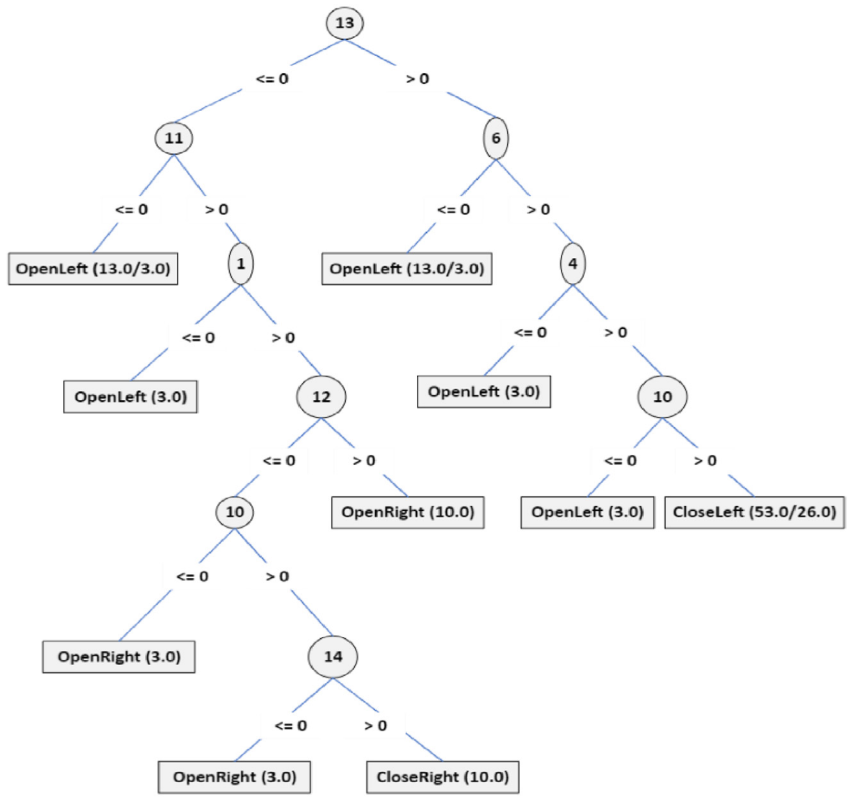

Fig. 2. Example of a decision tree for classifying open and closed eyes.

to its rapid training, strong generalisation, and universal approximation capabilities. ELM has also been used with good performance in driver distraction recognition systems [50].

Using eye movement and driving performance data, ELM and SVM were applied to detect driver workload using eye movement and eye movement in combination with other features. In most instances, ELM outperformed SVM even though the findings indicated that both techniques could accurately determine drivers' workloads.

Detailed analysis of sleepiness detection systems is based on driver behaviour, vehicle data, and biological parameters. A comparison of the influence of specific circumstances on the effectiveness of the drowsiness detection technique is shown in

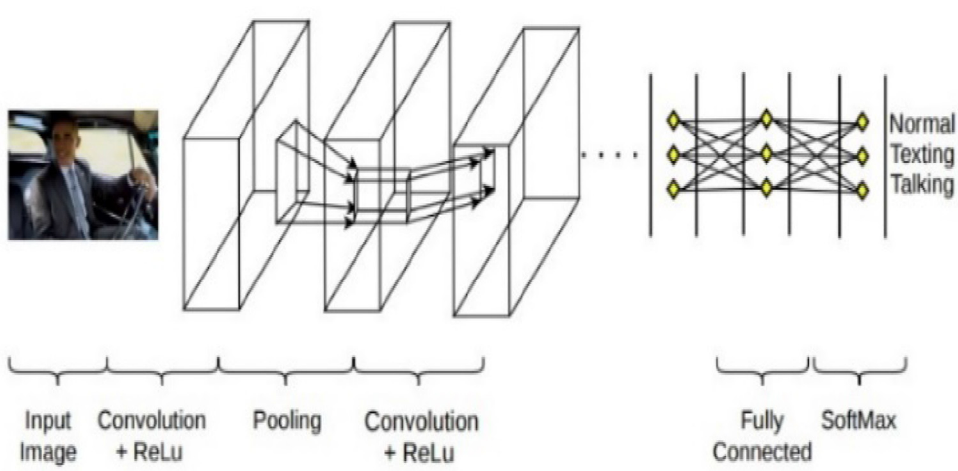

Fig. 3. Structure typical of a Convolutional Neural Network.

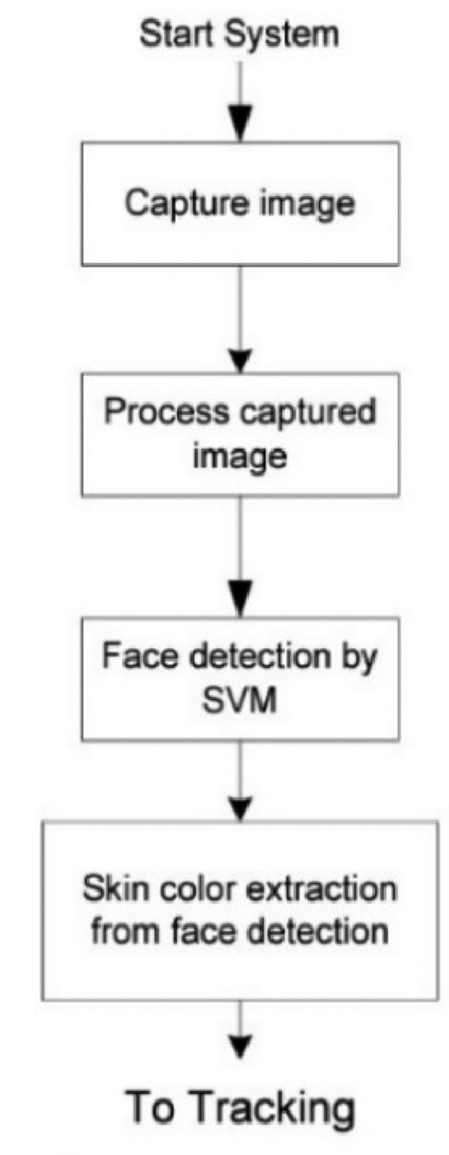

Fig. 4. The SVM algorithm used in image processing.

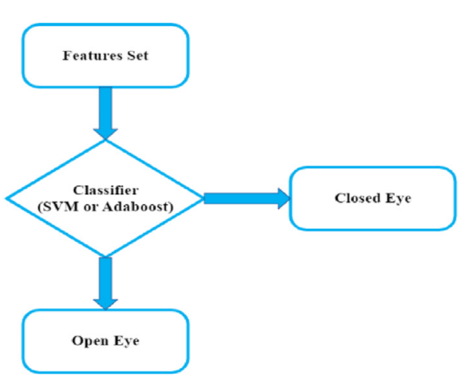

Fig. 5. Flowchart for eye-state classification.

Fig. 6, where poor illumination, enough illumination, the geometric state of roadways, and drivers wearing sunglasses and moustaches are discussed. This investigation demonstrated that biological parameters provide steady and accurate findings if appropriate values of these settings exist. In contrast, the performance of behavioural parameter-based strategies is diminished under dim lighting, while driving with spectacles, and while sporting a beard. In addition, the poor geometric condition of roadways reduces the efficacy of biological parameter-based approaches [51].

In Table 6, we have concentrated on the contributions related to using supervised algorithms for cognitive distraction detection.

4. Drivers face monitoring system

A driver Face Monitoring system provides information about the driver's physical and mental condition by analysing face images. We can detect the driver's state by detecting his eyelid closure, his gaze direction, his eyes' blinking rate, yawning, and head movement. Such a system should generate an alarm about the driver's state, like drowsiness, fatigue, and distraction. Fig. 7 shows a schematic diagram of an example of a driver's attention monitoring system [56]. The eyes are the central part of the face that detects fatigue. Also, some other features are considered to be fatigue in drivers. Here, we are explaining. Researchers use imaging techniques, specialised hardware platforms, and intelligent software applications [57]. We discovered that no clear definition of weariness exists, so we used sleep, drowsiness, and other related concepts as a starting point. We can next measure and grade the eye blink rate and eye closure using the Karolinska Sleepiness scale.

The symptoms related to fatigue and distraction were divided into four categories: Eye region Related Symptoms, Mouth Region Related Symptoms, Head Region Related Symptoms, and Face Region Related Symptoms. These are some common symptoms found in almost every person. However, they can be different in quality and pattern for each person. These symptoms can change over time. Therefore, these issues must be considered during any analysis [57].

4.1. Eye region related symptom

Drowsiness and distraction are immediately seen in the eyes; thus, the eyes are a critical region of the body where these symptoms can manifest swiftly.

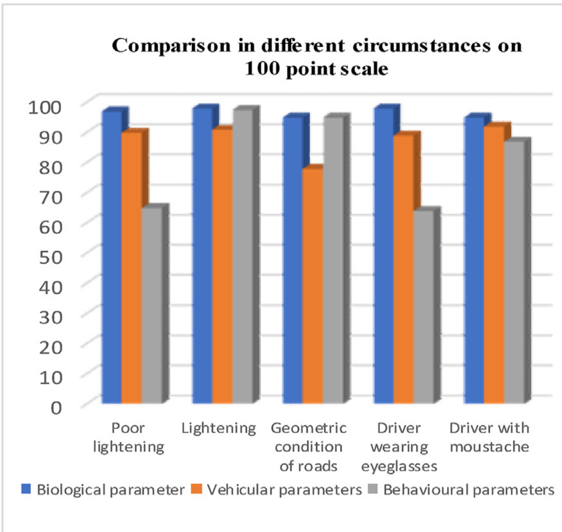

Fig. 6. Comparative graph of drivers' state detection technique [51].

Generally, we rely on the eyes to detect fatigue and preoccupation in drivers' facial monitoring. This section illustrates some of the symptoms related to the eye region.

- Eye closure: The drowsiness can be easily discernible by eye closure. It gives valuable information about the drivers' drowsiness or even anaesthesia. We use eye closure in two different ways for the detection of the state of drowsiness. One is the continuous eye closure method, and the second is the percentage of eye closure in a particular period. If the eyes remain closed for a certain period, the first method detects drowsiness [58].
- Distance between the eyelids: Eyelid distance can also indicate the state of drowsiness. Usually, eyelids' distance decreases when there is fatigue. This category of algorithms computes the eyelid distances based on the eye region's horizontal projection [49].
- Speed of eye blink: The opening and closing time difference of eyelids is known as eye speed. Drowsiness is detected if the blink is longer than a threshold (about 0.5–0.8 s) [58].
- Gaze direction: Using this symptom, we can determine the driver's lack of attention to the road. This symptom can also predict whether the driver will change the direction/lane [46].

4.2. Mouth region-related symptom

Another indicator of exhaustion is the detection of yawning, which can occur while the mouth is opening—speaking while driving is considered a symptom of distraction. Both are mouth region symptoms that can be used to identify the driver's drowsiness. An open mouth is detected as a symptom based on the ratio of the width to the height of the mouth; if the mouth is closed, the ratio will be low and high when the mouth is open [59]. Fig. 8 shows a case of face and mouth detection [60].

4.3. Head Region-Related Symptoms

- Head Nodding: Head nodding is a sign of identifying drowsiness in drivers. The symptom is related to drowsiness or anaesthesia. The following study presents a method that uses this symptom to detect drowsiness [61].
- Head Orientation: Head orientation is another significant indication of a driver's drowsiness and

Table 6. Cognitive distraction detection: Algorithms' features and accuracy.

Author	Classifier	Algorithm Features	Accuracy (%)
Yimyam et al. [34]	Decision Trees	Detect face and classify opening and closing eyes	99.93
Sarkar et al. [38]	Decision Trees	drivers' gaze behaviour	96
Kose et al. [52]	CNN	drivers' distraction level and movement decisions	99.10
Abouelnaga et al. [53]	CNN	distracted driver	95.98
Oroni et al. [54]	SVM	gaze direction	93
Fatima et al. [49]	SVM	face and eye detection	96.5
Fatima et al. [49]	AdaBoost	face and eye detection	95.4
Fatima et al. [49]	SVM and AdaBoost	Face detection	99.9
Fatima et al. [49]	SVM and AdaBoost	Eye detection	98.7
Chen et al. [55]	ELM with 100 Hidden Layer Nodes Number	driver's fatigue state detections	89.09
Chen et al. [55]	ELM with 150 Hidden Layer Nodes Number	driver's fatigue state detections	94.25
Chen et al. [55]	ELM with 200 Hidden Layer Nodes Number	driver's fatigue state detections	95.04

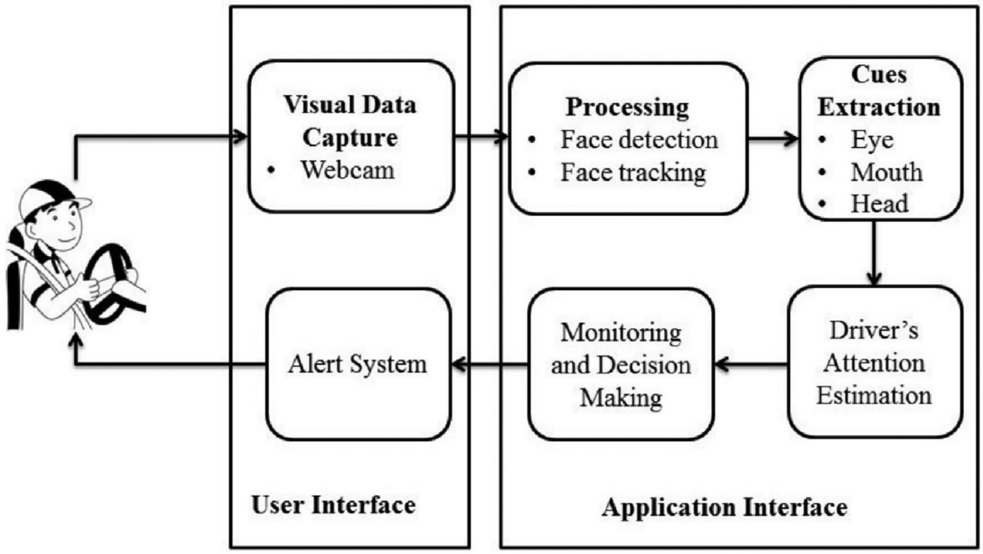

Fig. 7. Schematic diagram of driver's attention monitoring system [56].

can also predict whether the driver will change the lane. The drivers' drowsiness can be detected using a three-dimensional head model [62].

- Fixed Head: A fixed head position for a more extended period suggests a sign of the driver's distraction. When a driver settles his head on something, he focuses on something else except driving. This is one of the most acute symptoms of driver distraction [63].

4.4. Face Region-Related Symptoms

Emotions, verbal and non-verbal communication, and physiological activities result from facial expressions. If the facial muscles change, then the face images also change. The features of the face are extracted and processed via spatial–temporal algorithms and data structures. Some basic emotions are expected: happiness, sadness, astonishment, and anger. By facial expression, researchers verified the unexpected change in human physical condition. Gabor features and SVM are techniques for monitoring human facial expression, detecting unforeseen human physical conditions such as heart attacks, and calculating the driver's consciousness level based on his napping patterns, yawning, and neglect. Using critical facial feature points at varying pre-accident intervals, minor or significant accidents can be predicted [64]. Fig. 9 shows two states; in the first one, we note the driver is below the drowsiness threshold, and the alarm has been triggered to alert the driver; in the second one, we note the alarm has been triggered about the driver's inattention, The three Euler angles are roll, pitch, and yaw. After the Euler angles are computed, the value axes of the head position are generated. By tracking the value of these axes, the system can determine if the driver is turning their head to the left or the right [29].

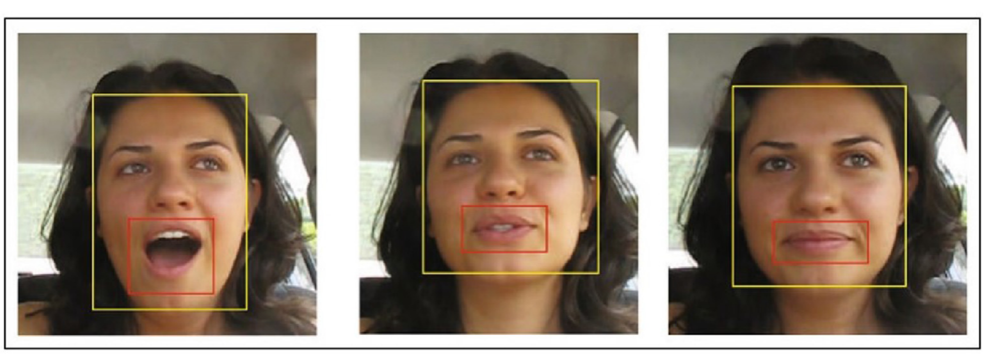

Fig. 8. Examples of both face and mouth detection [60].

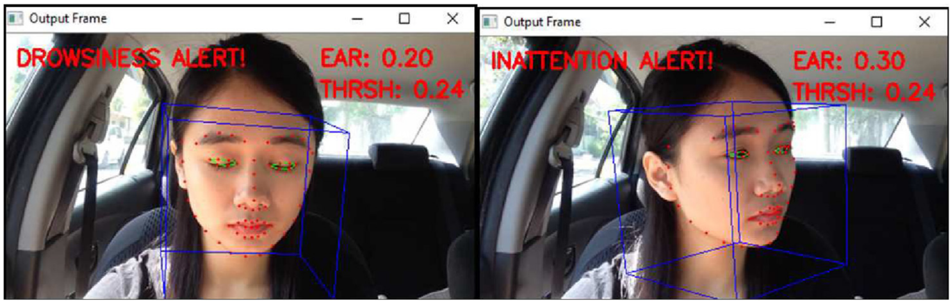

Fig. 9. Detection results (left) drowsiness alert and (right) inattention alert [29].

In Fig. 10, we have presented a schematic diagram of the Driver Fatigue Detection system [65], which classifies facial feature points as PERCLOS1 when the eyes with or without glasses are open and PERCLOS2 when the driver's eyes, with or without glasses, are closed. At the same time, the mouth's height-width ratio can be calculated in real-time. Finally, the authors took the above types of data as samples and trained with them the AdaBoost classifier to determine whether the eyes are open or closed and whether the mouth is open or closed and, based on these, to make a decision related to the drowsiness state of the driver [65].

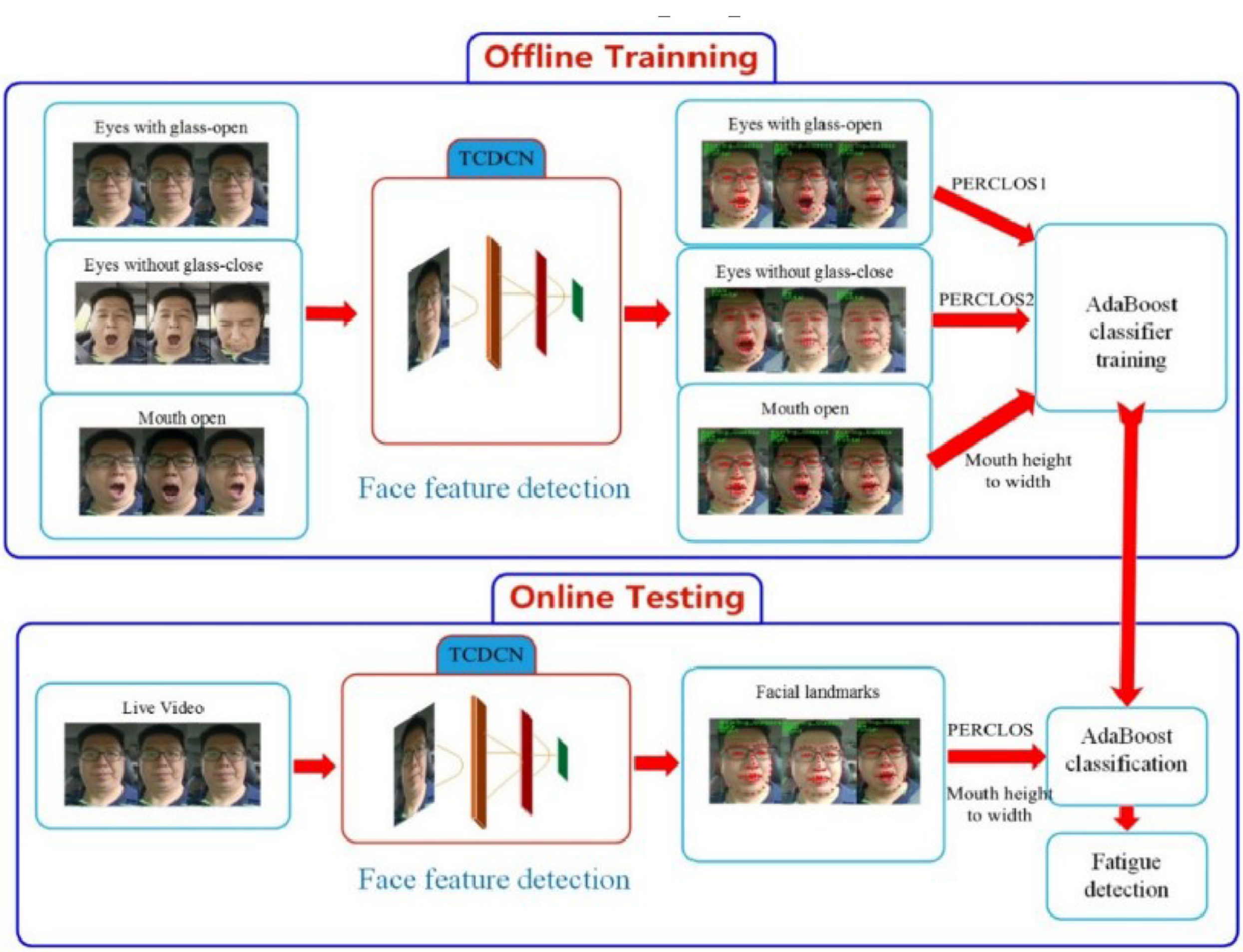

Fig. 10. Schematic diagram of driver fatigue detection system [65].

5. Conclusion and future work

After the studies analysed in this review, we found many solutions for monitoring the driver's attention. The result shows that the researchers have identified various technologies to detect driver fatigue and distraction causes. As we stated in the introduction, our primary objective was to determine the multiple approaches used for measuring fatigue in drivers. As such, we have searched for a precise definition of fatigue but found none in the literature. As a result, we used sleepiness, drowsiness, and other related concepts as a starting point and considered measuring and scoring eye blink rate and eye closure using the Karolinska Sleepiness scale. Then, we shifted our focus to fatigue assessment and its definitions and continued our research on the approaches most commonly used for Driver Attention Monitoring. We discovered that these technologies were based on symptom extraction by recognising the various facial features. It measures fatigue by detecting eye closure, eye speed, eye blink rate, and mouth detection, such as yawning. By seeing these manifestations, they generate alerts quickly (such as sound system alarms, SMS, email, massage chair, or mobile application) about the driver's state and prevent road accidents. It is essential to understand the cognitive distraction detection algorithms used in DAMS, so in our study, we conducted a brief review of them and discussed the previous studies that used these algorithms, as well as the accuracy rates that they obtained. We discovered that some algorithms have achieved an accuracy rate of more than 99%, such as DT, CNN, and SVM, and that CNN has been selected as the deep learning framework for the recognition system. Using these technologies, information can be obtained about the real intention of the driver while driving; they can give critical information about the driver's state. Our study began the search process from the year 2015. In the future, we will delve into Driver Attention Monitoring Systems (DAMS) based on computer vision and artificial intelligence. We intend to consider state-of-the-art DAMS (wearable/non-wearable) and driver's behavioural health monitoring such as comfort, breathing patterns, or heart rate and inform/signal alerts for medical attention. A statistical review curve might be used to study such systems' False and True favourable rates, which would be compared to determine the precision ratio of driver attention monitoring systems. Additionally, we will focus on the active roles of DAMS in ensuring driver safety and minimising road accidents and life hazards.

We intend to continue by generating questions for future research and conducting a more exhaustive search in additional databases using new keywords or keyword combinations. E.g., What are the advantages and disadvantages of the previous driver monitoring systems? Or what are the required techniques to improve the response rate for building typical DAMS? We also intend to go deep through implementing distraction detection algorithms and compare their performance to select the best one with reasonable accuracy for a specific system; it is also essential to study the delay time between the detection and alerting stages in the future.

Conflict of interest

There is no conflict of interest.

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