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RESEARCH ARTICLE

A Systematic Review on Driver Drowsiness Detection Using Eye Activity Measures

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ABSTRACT Driver drowsiness is a major contributor to road traffic accidents. A system capable of detecting drowsiness and consequently warning drivers at an early stage could significantly reduce the number of drowsiness-related road accidents. Although different measures can indicate driver drowsiness, eye activity measures are known to indicate drowsiness in the early stages. This study systematically reviewed empirical studies (with reported performance measures) on driver drowsiness detection (DDD) systems that use eye activities to indicate drowsiness. The objective of this review was to provide researchers and practitioners with in-depth information on DDD systems based on eye activities. Forty-one studies were identified using the preferred reporting items for systematic reviews and meta-analyses methodology. This review investigated various eye activity measures of drowsiness and provides a classification scheme for these measures. In addition, the current technologies used to measure eye activity were examined and a classification scheme for these technologies was formulated. Further, the decision-making algorithms used to classify and predict drowsiness states were investigated using their associated performance measures. Finally, future insights and ideas for utilizing eye activity measures to detect drowsiness at an early stage were discussed. This study forms the basis for future research and development of DDD using eye activities.

INDEX TERMS Drowsiness, detection, driving, eye activity, road safety.

I. INTRODUCTION

According to the World Health Organization (WHO), road accidents kill 1.35 million people worldwide annually and result in 20–50 million people suffering from serious injuries [1]. Road accidents are among the 10 leading causes of fatalities worldwide, especially in children and young adults aged 5–29 years [2]. The economic loss due to fatalities and injuries related to road accidents is estimated at USD 1.8 trillion for the period 2015–2030 [2]. Statistics indicate that road accidents represent a serious global burden, and projections suggest that this case will continue in the future [1].

Road accidents often occur because of a combination of factors related to roadways (e.g., traffic flow), environmental factors (e.g., thermal comfort), vehicles, and drivers (e.g., vigilance state) [3]. Among these factors, driver drowsiness is a major contributor to road accidents that can result in fatalities, severe injuries, and significant economic losses [4], [5]. Driver drowsiness is referred to as a reduction in the level of driver vigilance, which can be caused by long hours behind the wheel, medicines, sleeping disorders, medical illnesses, fatigue, and drowsiness [6]. Studies show that the majority of road accidents involving driver drowsiness, occurring between midnight and 6 a.m., involve a single vehicle and a sober driver traveling alone, and do not involve any attempts to avoid a crash [7].

Drowsiness is identified as a primary cause of approximately 20% of all road accidents in developed countries (e.g., 21% in Canada, 17% in Australia, 25% in the UK) [8]. According to the American Automobile Association (AAA) Foundation for Traffic Safety, 16–21% of fatal car accidents may involve driver drowsiness [4]. In the trucking industry, approximately 60% of fatal truck accidents are related to driver drowsiness [7]. The results of many surveys revealed that 66–80% of drivers had previously driven while sleeping [9]. The aforementioned data demonstrate that driver

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drowsiness has become a major concern for society; therefore, proactive efforts are required to mitigate its contribution to road accident statistics.

Over the past two decades, extensive research has been conducted on drowsiness and its impact on drivers, including reduced mental alertness and awareness, decreased individuals' ability to operate a vehicle safely, increased risk of human errors that can lead to fatalities and injuries, slowing of the driver's reaction time, and impaired judgment [10], [11], [12]. Studies have shown that the best way to prevent drowsiness at the wheel is to have an adequate amount of sleep before driving as well as regular breaks (naps) during the driving period, preferably with certain caffeine consumption, such as having a cup of coffee [13], [14]. According to Horne and Reyner [15], drivers falling asleep are unlikely to recall having done so until too late. They only recall the precursory state of increasing drowsiness (i.e., fighting off sleep before an accident). Therefore, there is a growing interest among transportation researchers in developing smart systems for detecting driver drowsiness in the early stages.

With current technological advances, it has become possible to detect driver drowsiness in the early stages before accidents, thereby significantly reducing fatalities and injuries related to road accidents [16]. The literature identifies various measures of driver drowsiness detection (DDD).

(i) Physiological measures: The alertness level of the driver is evaluated using physiological body indicators, such as heart rate, brain activity, muscle activity, and body temperature. The four main techniques that use physiological measures to detect driver drowsiness are: electroencephalography (EEG), electrooculography (EOG), electrocardiography (ECG), and electromyography (EMG) [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29].

(ii) Behavioral measures: These include facial measures, such as eye movement, head position, yawning, and facial expression that indicate the alertness level of the driver [30], [31], [32], [33], [34], [35], [36], [37], [38].

(iii) Vehicle-based measures: These include vehicle-related metrics, such as lane deviation, speed, steering movement, pressure on the accelerator, and hand position that indicate an increased likelihood of drowsiness when exceeding regular thresholds [6], [21], [39], [40], [41].

(iv) Subjective measures: The driver's individual assessments are used to evaluate the level of alertness. The two main assessment techniques are: the 9-point Karolinska Sleepiness Scale (KSS) and the 7- point Stanford Drowsiness Scale (SSS), where numerical ratings indicate different levels of alertness [6], [21], [39], [42].

The techniques based on physiological measures, despite their accuracy, are intrusive and not practically feasible in vehicles because they require sensors and electronic gadgets attached to the driver's body [39], [42]. Vehicle-based measures are non-intrusive but are considered unreliable when used solely because they provide warning signals at late stages or just before an accident [6], [43]. Subjective measures cannot instantaneously detect driver drowsiness because they depend on the driver's self-assessment [6], [39], [42]. However, behavioral measures are non-intrusive, reliable, and efficient [6], [39], [42]. In particular, measures related to eyelid/eyeball movement (i.e., ocular parameters) can indicate drowsiness in the early stages [44], [45], [46], [47], [48], [49]. This advantage is of great importance because drivers have more time to respond appropriately; hence, fatalities and severe injuries from road accidents can be significantly reduced.

This study aimed to systematically review empirical studies related to eye activity-based DDD systems, focusing on studies that have measured the performance of their detection systems. Evaluating the performance of a DDD system is critical for its integration into advanced driver assistance systems. Exploring the different performance measures of DDD systems indicates their effectiveness. A perusal of the literature reveals that there is a lack of research focusing on DDD based on eye activities. The contributions of this study to road safety literature are as follows. This review provides the research and academic communities with in-depth information on DDD systems based on eye activities. It investigates various eye activity measures that can be used to indicate driver drowsiness and proposes a classification scheme for these measures. In addition, the current technologies used to measure eye activity are investigated and classified based on their intrusiveness. Further, the decision-making algorithms used to predict drowsiness are examined based on their associated accuracy. Finally, future insights and ideas for utilizing eye activity measures to detect drowsiness at an early stage are provided.

The remainder of this paper is organized as follows. Section II presents the methods used to collect and select relevant papers. Section III presents the results of the systematic review, including a summary of the final set of included studies and the proposed conceptual framework for eye activity-based DDD systems. It also describes and classifies the identified eye activity measures indicating drowsiness, measurement technologies used to monitor eye activities, and decision-making algorithms for classifying and predicting the drowsiness state. Section IV presents a discussion and future directions, followed by the conclusion in Section V.

II. METHOD

A systematic literature search was conducted with the help of a professional librarian based on the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology [50]. The search aimed to identify empirical peer-reviewed scientific studies (journal articles and conference proceedings) that have developed eye-activity-based DDD systems and measured their detection performance.

The literature search involved the following steps: identifying relevant studies by searching databases, screening the identified studies (by removing duplicates and checking relevance), assessing eligibility by reading full-text studies,

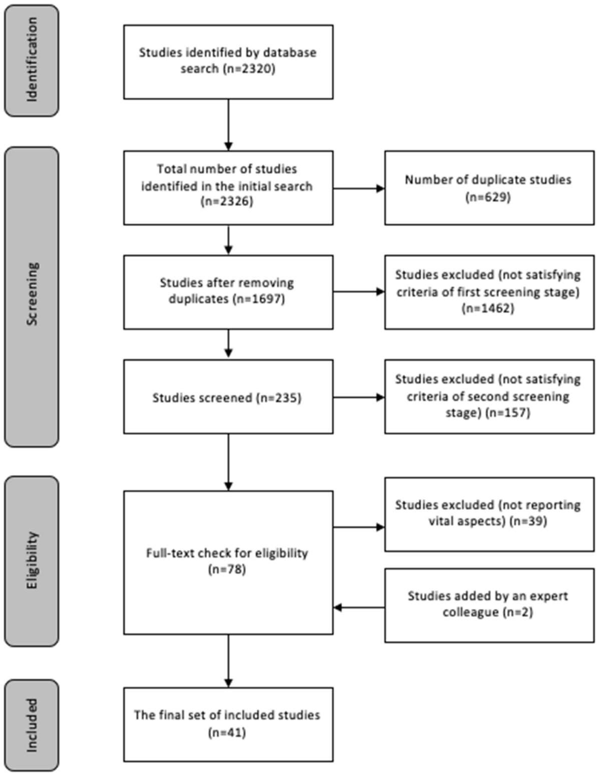

FIGURE 1. Flow diagram of PRISMA approach to identify studies on driver drowsiness detection based on eye activities.

and finally, including eligible studies in the final list of studies to be evaluated. Fig. 1 illustrates the search strategy based on the PRISMA approach.

A. SEARCH KEYWORDS AND DATABASE

Four databases were searched in this review (Web of Science, Scopus, IEEE Xplore Digital Library, and PubMed) to identify studies that used eye activity in DDD system development. Additional relevant literature identified by a colleague involved in similar work was manually screened. A database search was performed using three sets of keywords using the AND logic. The first set of keywords included drowsiness, sleepiness, and fatigue. The second set included ocular, eye activity, eye movement, blink, eyelid closure, PERCLOS, saccadic, gaze, and pupil. The third set included keywords related to performance measurement, such as accuracy, correlation, precision, and error. The search process considered all possible combinations of keywords from all three sets (e.g., drowsiness AND blink AND accuracy or sleepiness AND blink AND error). After running the search on the four databases, all articles were downloaded to a database manager (RefWorks) and all duplicates were removed. The starting year of publication was not restricted, and the year of publication was 2023. A study was required to have at least one combined term from the final keywords list in its title and abstract to be considered in the sample of identified studies.

B. SCREENING OF STUDIES

The identified studies were screened in two stages. The first screening stage included literature that was in English and peer-reviewed journal articles or conference proceedings that explicitly involved using eye activities in developing DDD systems in their abstracts and related to driving. The second stage included empirical studies that measured and reported the performance of the developed DDD systems. Theoretical studies and literature reviews were excluded from the analysis. Finally, the screened studies were reviewed for eligibility.

C. DATA EXTRACTION AND ANALYSIS

In this step, core results were extracted from the final list of selected studies, and relevant information was presented in tabular and graphical formats. A summary of each study included in the review is provided, including details of the experiment, ocular parameters used, additional parameters used, eye measurement technology, drowsiness detection classification methods, and performance measures. The primary components of ocular-based DDD systems have been identified, and various classification schemes have been presented. All eye activity measures were identified and classified based on the moving part of the eye. Secondary measures of drowsiness (additional to eye activity measures) were identified. Different measurement technologies were discussed and categorized based on their intrusiveness and the manner in which they operate. Different algorithms for classifying alertness state were identified. Finally, future directions were discussed based on the findings.

III. RESULTS

The total number of studies identified in the initial search was 2326, among 1697 remaining after removing duplicates. Only 235 studies were deemed relevant after initial screening. The final number of studies conducted after the second screening was 39. The list was reviewed by a colleague who participated in a similar study. Two studies were added to the list, resulting in a total of 41 studies (27 journal articles and 14 conference proceedings).

Approximately 48% of the articles appeared in computer science and engineering journals, 37% in health and human sciences journals, 7.5% in transportation journals, and 7.5% were multidisciplinary. Conference proceedings constituted 34% of the identified studies, of which 86% were related to computer science and engineering, and 14% to transportation. All identified studies involved driving experiments (83% simulated driving and 17% real driving). The number of participants in the driving experiments ranged from 4–60 (for real driving) and 6–76 (for simulated driving). A summary of the final set of studies included in this systematic review is presented in Table 1.

Table 1 provides information about experiment type and duration, sample size, drowsiness measures, measurement technologies, classification algorithms and performance metrics. The following subsections (A-E) provide more details about the findings of the included studies. First, we describe the general framework and main components of the driver drowsiness detection systems. We then report the identified ocular parameters and classify them based on the nature of eye activity. We also report secondary measures of drowsiness (additional to eye activity measures). Additionally, we discuss the measurement technologies used to detect drowsiness and classify them based on their functional properties. Finally, we report classification algorithms used to detect drowsiness along with their performance measures.

A. FRAMEWORK OF DROWSINESS DETECTION SYSTEMS

This section presents the conceptual framework and main components of eye activity-based DDD systems. Analysis of the identified studies revealed three main components of DDD systems: technologies used to measure eye activities, eye activity measures indicating drowsiness, and decision-making schemes to classify/predict drowsiness. Fig. 2 illustrates the main components and the proposed framework of the DDD systems. The proposed framework provides a basis for the analysis of studies identified through a systematic search.

This review reveals three classification perspectives of eye-activity-based DDD systems: measurement technology, measures indicating eye activity, and decision-making algorithms. Many DDD systems have been classified based on the nature of the eye activity measures used to indicate drowsiness in eyelid movement-based systems, eyeball movement-based systems, and a combination of eyelid/eyeball movement-based systems. Eyelid movement measures include blinking behavior (e.g., blink frequency, blink duration, and blink amplitude) and eyelid closure (e.g., PERCLOS). Eyeball movement measures included pupillary parameters (pupil diameter, latency of pupillary oscillations), saccadic eye movement (saccadic duration, fixation duration, and saccadic speed]), and gaze. This classification perspective has also been reported in previous studies [14], [45], [52], [56], [86], [87].

Other DDD systems have been classified into active (electro-based) and passive (contact-free) systems based on the technology used to monitor eye activities. In active systems, the measurement technology uses electrodes attached to the skin of the driver to measure designated eye activities such as EEG, EOG, and EMG. In passive systems, the measurement technology depends on contact-free methods to measure designated eye activities, such as video image analysis and infrared reflectance. This classification perspective has also been reported in previous studies [14], [52], [86], [87], [88], [89].

The last classification perspective classified DDD systems based on the type of embedded decision-making algorithm into machine-learning-based and non-machine-learning-based systems. The former uses supervised, deep, and unsupervised learning algorithms to classify and predict drowsiness states. The latter uses classical statistical methods and rule-based techniques to classify and predict drowsy states. Many previous studies have indicated these criteria for classifying DDD systems [14], [55], [90], [91].

Other uncommon classification perspectives have also been reported in the literature. For example, Dinges et al. [88] classified DDD systems into four groups based on their similarities: readiness-to-perform and fitness-for-duty screeners, mathematical models/algorithms, vehicle-based driver performance measurements, and vehicle-based operator alertness/drowsiness monitoring devices. In 2005, Williamson and Chamberlain investigated fatigue and drowsiness monitoring systems. They classified the DDD systems into three groups based on the methodology used to indicate drowsiness-related changes: systems related to the driver's current state (i.e., eye and physiologically related changes), technologies related to the driver's performance (e.g., lateral position and headway), and technologies including a combination of the driver's current state and performance. Wright et al. [14] proposed another classification of DDD systems. Five categories were proposed based on the variables used to reflect drowsiness: systems related to physiological measures correlated with sleepiness; systems based on physical variables (i.e., movement and activity); systems using behavioral indices, including performance or activity related to driving tasks (e.g., steering wheel pattern); model-based systems; and systems combining all the previous categories. Jo et al. [92] indicated that DDD systems can be classified into three groups: systems that depend on driving behavioral, biological, and visual attributes.

The majority of studies reported the following three main steps for developing DDD systems: selecting eye activity measures to indicate drowsiness, selecting the measurement technology to monitor the selected eye activity measures, and selecting the decision-making algorithm to classify/predict the drowsiness state. The selection made at each step significantly affected the performance of the developed DDD system.

B. REPORTED EYE ACTIVITY MEASURES INDICATING DROWSINESS

A total of 78 eye activity measures of drowsiness were reported from the included studies. In this review, a classification scheme was proposed, based on the moving part of the eye, to classify eye activity measures into: measures related to eyelid movement and measures related to eyeball movement. The former class included blinking behavior (i.e., blink frequency, blink duration, and blink amplitude) and eyelid closure (i.e., closure level and PERCLOS). The latter class included pupillary parameters (i.e., pupil diameter, pupillary latency, pupillary oscillations, and pupillary constriction amplitude), saccadic eye movements (i.e., saccadic duration, saccadic speed, and fixation duration), and eye gaze. Fig. 3 shows the eye activity measures associated with each class.

The majority of the studies (approximately 68%) reported measurements related to eyelid movement (58% related

TABLE 1. Summary of the final set of studies included in the systematic review.

No.	Study	Experiment			Drowsiness measure		Measurement technology	Classification method	Performance metric
		Type	No. of participants	Time	Primary (Eye activity measures)	Secondary			
1	Summala et al. (1999) [51]	Real driving	4 participants	12 hours/participant	Blink frequency, blink duration	Steering-wheel inputs	Video oculography (4 video cameras)	Comparing drivers' performance with passengers' performance	Two-tail t-tests (p< 0.05)
2	Caffier et al. (2003) [52]	Real driving	60 participants	Several sessions (morning and evening)	Blink frequency, blink duration, closing time, reopening time, closed time, and proportion of long closure duration blinks		Infrared oculography (An infrared sensor clipped to an eyeglass frame)	Comparing measured parameters with subjective measures (personal state scale and visual analogue scale)	Two-tail t-tests (p< 0.001)
3	Galley et al. (2004) [53]	Simulated driving	76 participants	2.5 hours/participant	Blink interval, blink duration, delay of reopening, blink amplitude, opening duration, opening speed, standardized opening speed, closure speed, and standardized closure speed		Video oculography (IR camera)	Comparing measured parameters with subjective alertness scores and EOG	Correlation coefficient = 0.97
4	Damousis et al. (2007) [54]	Simulated driving	35 participants	45-90 min/participant	Blink duration, eyelid closing time, amplitude/peak closing velocity, eyelid opening speed, eyelid closing speed, delay of eyelid reopening, eyelid opening time, and blink interval		Video oculography (video-based system called SmartEye)	Comparing measured parameters with Karolinska Sleepiness Scale and EOG	Accuracy = 90%
5	Boyraz et al. (2008) [55]	Simulated driving	30 participants	1.5 hours/participant	Eye closure, pupil area, gaze vector	Head motion	Video oculography (a monocular complementary metal–oxide–semiconductor (CMOS) camera)	Fuzzy inference system and artificial neural networks	Accuracy = 98.00%
6	Schleicher et al. (2008) [56]	Simulated driving	13 participants	134 min/participant	Blink duration, delay of lid reopening, blink interval, and standardized lid closure speed		Video oculography (a video camera)	Comparing measured parameters with subjective self-ratings and video ratings	Correlation coefficient = 0.64
7	Morad et al. (2009) [57]	Real driving	29 participants	2 months	Saccadic velocity, pupillary diameter, pupillary constriction latency, and pupillary constriction amplitude		Infrared oculography (an infrared pupillometry device)	Comparing measured parameters before/after work	Two-tail t-tests (p<=0.02)
8	Flores et al. (2010) [58]	Real driving	5 participants	100-frame sequence	Blinking frequency, and PERCLOS	Head tilt	Video oculography (a video camera)	Condensation algorithm and neural networks	Accuracy = 98.00%
9	Zhang et al. (2012) [59]	Simulated driving	6 participants	20 min/participant	Eyelid closure, blink frequency, opening and closing velocity of the eyes		Video oculography (RGB camera)	Computer Vision Technology	Accuracy = 86.00%
10	Hachisuka, (2013) [60]	Simulated driving	13 participants	1 hour/participant	Eyebrows rise	Facial muscle activities	Video oculography (a video camera)	Active Appearance Model and K-Nearest-Neighbor algorithm	RMSE = 0.91
11	Dwivedi et al. (2014) [61]	Simulated driving	30 participants		Eye size	Skin tone, facial structure, hair, fringes, facial hair	Video oculography (a remote camera)	Convolutional neural networks	Accuracy = 88.00%
12	Han et al. (2015) [62]	Simulated driving	8 participants	30 min/participant	PERCLOS and blink rate		Video oculography (a video camera)	Vision based and feature extraction	Accuracy = 90.45% Correlation Coefficient = 0.91
13	Guo et al. (2016) [40]	Simulated driving	21 participants	110 min/participant	Eyelid movement and gaze	Heart rate, pulse rate, head movement	Video oculography (a video camera)	Bayesian Network	Accuracy = 79.50%
14	Wang and Xu (2016) [63]	Simulated driving	16 participants	8 hours	Eyelid opening, pupil diameter, and eye blink (PERCLOS),		Video oculography (4 cameras)	Multilevel ordered logit model, ordered logit model, and artificial neural networks	Accuracy = 88.80%

TABLE 1. *(Continued.)* **Summary of the final set of studies included in the systematic review.**

15	Eskandarian and Mortazavi (2017) [64]	Simulated driving	13 participants	52 miles (morning) and 52 miles (night)	Eye closure	–	Video oculography (4 infrared digital cameras)	Artificial neural networks	Accuracy = 97.00%
16	Huynh et al. (2017) [65]	Simulated driving	36 participants	1.5 million frames recorded	Eye closing	Nodding and yawning	Video oculography (high performing tracker with a Haar-feature face detector)	3D convolutional neural network to extract features and gradient boosting for drowsiness classification	Accuracy = 87.46%
17	Park et al. (2017) [66]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Eye blinking	Nodding and yawning	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Deep neural networks	Accuracy = 73.06%
18	Reddy et al. (2017) [67]	Simulated driving: publicly available dataset (NTHU-DDD)	11 participants	70,000 images	Facial landmark		Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Deep neural networks	Accuracy = 89.5%
19	Shih and Hsu (2017) [68]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Blink rate	Nodding and yawning	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Multistage Spatial Temporal Network	Accuracy = 82.61% F1-score = 87.97%
20	Weng et al. (2017) [69]	Simulated driving	36 participants	360 videos	Blink rate	Yawning and falling asleep	Video oculography (RGB and IR cameras)	Hierarchical temporal deep belief network	Accuracy = 84.82% F1-Score = 85.39%
21	de Naurois et al. (2018) [21]	Simulated driving	21 participants	110 min/participant	Behavioral (blink duration, blink frequency, PERCLOS, and saccade frequency)	Physiological (heart rate and respiration rate); vehicle-based (e.g., lateral distance from closest lane and center of car, time to lane crossing, and steering angle); behavioral (head position and head rotation)	Video oculography (A webcam video-recorded participants)	Artificial neural networks	Performance is improved by 40% for prediction and 80% for detection
22	Bamidele et al. (2019) [70]	Simulated driving	22 participants	1 hour, 46 minutes and 53 seconds	Percentage of eyelid closure (PERCLOS), blink frequency, and maximum Closure Duration		Video oculography (high resolution camera)	K-Nearest-Neighbor algorithm, support vector machine, logistic regression, and artificial neural network	Accuracy = 72.25% Sensitivity = 83.06%
23	Guo and Markoni, (2019) [34]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Facial landmark (position of eyes)	Position of mouth	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Hybrid convolutional neural networks and long short-term memory	Accuracy = 84.85%
24	Liu et al. (2019) [71]	Simulated driving: publicly available dataset (NTHU-DDD)	22 participants	380 video clips	Eye image	Mouth image	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	multi-task cascaded convolutional neural networks	Accuracy = 97.06% Sensitivity = 96.74%
25	Vijayan and Sherly, (2019) [72]	Real driving			Eye blinking	Yawning and head swaying	Video oculography (RGB camera)	Convolutional neural networks	Accuracy = 78.61%
26	Vu et al. (2019) [73]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Driver's face		Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	convolutional neural networks	Accuracy = 84.81% F1-score = 86.28%

TABLE 1. ***(Continued.)*** **Summary of the final set of studies included in the systematic review.**

27	Yu et al. (2019) [74]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Eye condition	Head and mouth condition	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	3D-deep convolutional neural network	Accuracy = 76.20% F1-score = 76.50%
28	Ed-Doughmi et al. (2020) [75]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Eye blinking	Nodding and yawning	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Recurrent neural networks	Accuracy = 92.00% F1-Scrore = 85.00%
29	Ghourabi et al. (2020) [76]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Eye closure	Yawning	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Multi-layer perceptron and K-Nearest-Neighbor algorithm	Accuracy = 94.31% F1-Score = 79.00%
30	Gwak et al. (2020) [77]	Simulated driving	16 participants	30 min/participant	Eye blink and closure		Video oculography (a video camera in front of the driver)	Majority Voting Classifier and Random Forest	Accuracy = 95.4%
31	Jabbar et al. (2020) [78]	Simulated driving: publicly available dataset (NTHU-DDD)	22 participants	9.5 hours	Blinking rate	Yawning and head movements	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Convolutional neural networks	Accuracy = 88.00%
32	Saif and Mahayuddin, (2020) [79]	Real driving: (iBUG 300 W dataset)	40 participants	4 hours	Pupil occlusion	Head pose	Video oculography (monocular video camera)	Distributed convolutional neural networks	Accuracy = 98.97%
33	Wijnands et al. (2020) [80]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Closing eye	Yawning, nodding, looking aside, talking and laughing	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	3D convolutional neural networks	Accuracy = 77.6%
34	Zhang et al. (2020) [81]	Simulated driving	27 participants	1 hour	Eyelid closure (PERCLOS), pupil diameter, blink frequency, and blink duration		Video oculography (4 cameras)	Mixed-effect ordered logit model	Accuracy = 62.84%
35	Zhao et al. (2020) [82]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Driver face and facial landmarks		Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	3D Convolutional neural networks	Accuracy = 88.6%
36	Bakheet ang Al Hamadi (2021) [16]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Eye-pair	Yawning and head and mouth status	Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Histogram of Oriented Gradient features	Accuracy = 85.62% F1-Score = 87.84%
37	Chen et al. (2021) [2]	Simulated driving: publicly available dataset (NTHU-DDD)	36 participants	9.5 hours	Eye and face area		Video oculography (surveillance digital camera with infrared LEDs and IR Illuminators)	Hybrid convolutional neural networks and long short-term memory	Accuracy = 93.30%
38	Dua et al. (2021) [38]	Simulated driving	31 participants	250 video clips	Eye blinking	Hand gestures, yawning and head movements	Video oculography (RGB camera)	Deep convolutional neural networks	Accuracy = 85.00% Sensitivity = 82% F1-Score = 84.09%

TABLE 1. ***(Continued.)*** **Summary of the final set of studies included in the systematic review.**

39	Quddus et al. (2021) [83]	Simulated driving	38 participants	30 min/participant	Blinking, eye closure, saccades and fixation		Video oculography (two 60 Hz video cameras with infra-red illumination)	Recurrent Neural Network to detect the drowsiness and long short-term memory for classification	Accuracy = 95% □
40	Rajamohana et al. (2021) [84]	Simulated driving: (MRL Eye Dataset)	37 participants	2208 images	Facial image, eye blink, and eye closure		Video oculography (a video camera)	Hybrid convolutional Neural Networks and bidirectional long short-term memory	Accuracy = 96.00%
41	Siddiqui et al. (2021) [85]	Real driving	40 participants	10 hours	Eye blink and eyeballs movement	Respiration and heartbeat	Video oculography (a video camera)	Support vector machine, decision tree, logistic regression, and multi-layer perceptron	Accuracy = 87.00% F1-score = 73.00%

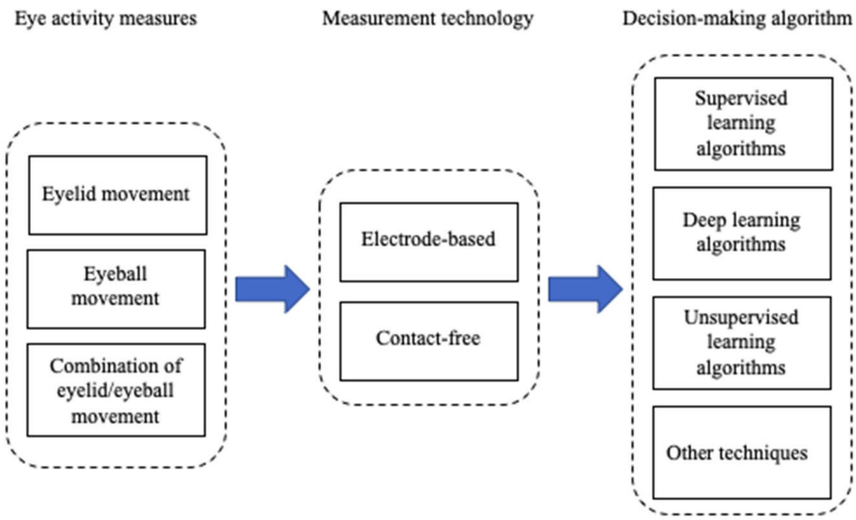

FIGURE 2. **Proposed framework of driver drowsiness detection systems.**

to blinking behavior and 34% related to eyelid closure). Whereas measures related to eyeball movement were reported in 19% of the studies (12% related to pupillary parameters, 7% related to saccadic eye movement, and 5% related to eye gaze). Fig. 4 illustrates the percentage of appearance of each type of eye activity measured in this review.

Among the blinking behavior measures, blink frequency was the most frequent (36.5% of studies), followed by blink duration (29% of studies), and blink amplitude (5% of the studies). Among the blink duration measures, lid closure duration was the most frequent parameter (12% of the studies), followed by lid closure speed (9.5% of the studies), lid reopening speed and duration (each with 7.5% of the studies), and delay in lid reopening (5% of the studies). Among eyelid closures, closure level was the most frequent (19.5% of the studies), followed by PERCLOS (14.5% of the studies).

Among the measures related to pupillary parameters, pupil diameter was the most frequent measure (9.5% of the studies), followed by the latency of pupillary, pupil oscillation, and pupillary constriction amplitude (each appeared in 2.5% of the studies). Among the saccadic eye movements, saccadic speed was the most frequent (5% of the studies), followed by saccadic duration and fixation duration (each appeared in 2.5% of the studies). Further details regarding each step are presented in the following sections.

1) DROWSINESS MEASURES RELATED TO EYELID MOVEMENT

Two types of eyelid movement measures were identified in this review: blinking behavior and eyelid closure (PERCLOS). Blinking behavior includes blink frequency, blink duration, and blink amplitude. The following subsections provide additional information about the history, meaning, and implications of each type.

a: BLINKING BEHAVIOR

An eyeblink is defined as the state of the eye when it is temporarily hidden, and the upper and lower lids touch each other [93]. There are two main types of eyeblinks: voluntary (controlled by individuals) and involuntary (spontaneous). The latter can be further divided into spontaneous blinks, which occur at approximately constant intervals, and involuntary fright-blink reflexes, which occur in response

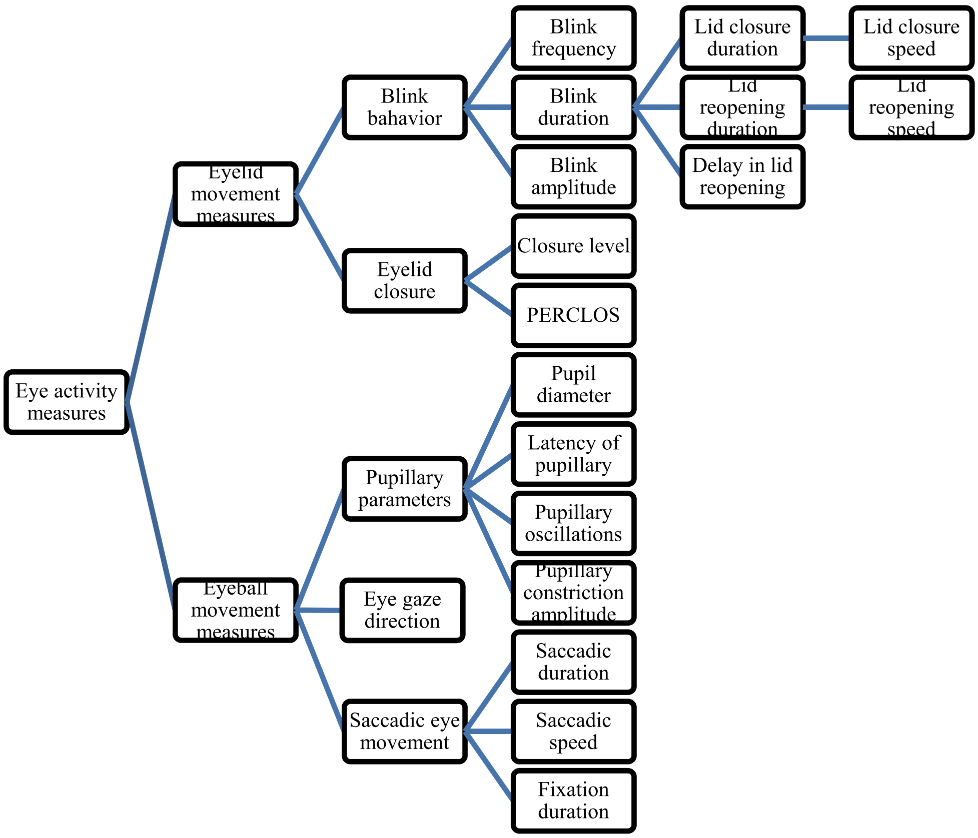

FIGURE 3. **Classification scheme of reported eye activity measures of drowsiness.**

to external corneal stimuli. In this review, three blinking behaviors were identified: blink frequency [blinks/minute], blink duration [ms] and its subcomponents (lid closure duration/speed, lid reopening duration/speed, and delay of lid reopening), and blink amplitude [mV]. The first two are the most frequently used measures in this review, as shown in Fig. 3. Results showed that blink frequency and blink duration are the most frequently appeared drowsiness measures in this review, with percentage of appearance of 36.5% and 29%, respectively.

Many researchers have extensively investigated the relationship between blinking behavior and drowsiness. Studies have shown that spontaneous blinking behavior is a sensitive indicator of drowsiness [14], [92], [94], [95]. Moreover, blinking behavior is a suitable measure of drowsiness for the following reasons: it is natural, easily observable, easily measurable with contact-free devices, and most importantly, it reflects the activation state of the central nervous system [52].

According to many researchers, blink duration and frequency are the best eye activity measures to indicate driver alertness [44], [56], [96]. It is well established that drowsiness is associated with increased blink frequency [21], [53], [54], [87], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106], increased blink duration [14], [21], [45], [56], [104], [107], [108], and decreased blink amplitude [14], [109], [110], [111], [112].

Many researchers have concluded that different blink parameters are controlled by different processes; hence, they indicate different levels of drowsiness (e.g., [44], [45], [53], [56]). For example, a study conducted by Hargutt [44] concluded that before a driver falls asleep, he goes through two successive processes: 1) reduced vigilance (light fatigue), indicated by an increase in blink frequency, and 2) drowsiness (severe fatigue), wherein an increase in blink frequency is accompanied by an increase in blink duration. Galley et al. [53] proposed that sleepiness is not a unidimensional process; rather, it comprises two components that can be reflected through blinking behavior. The first component is increasing sleep propensity, and the second component is the maintenance of wakefulness. In 2004, Galley and Schleicher stated that sleepiness while performing undergoes three partially independent processes: decreasing attention (indicated by blink interval), decreasing alertness (indicated by blink duration and amplitude), and finally, the effort to maintain the required level of alertness (indicated by velocities of the lid and saccadic movements).

Other researchers have investigated the sub-components of blink duration separately, namely lid closure duration/speed or closing time, lid reopening duration/speed, and delay in

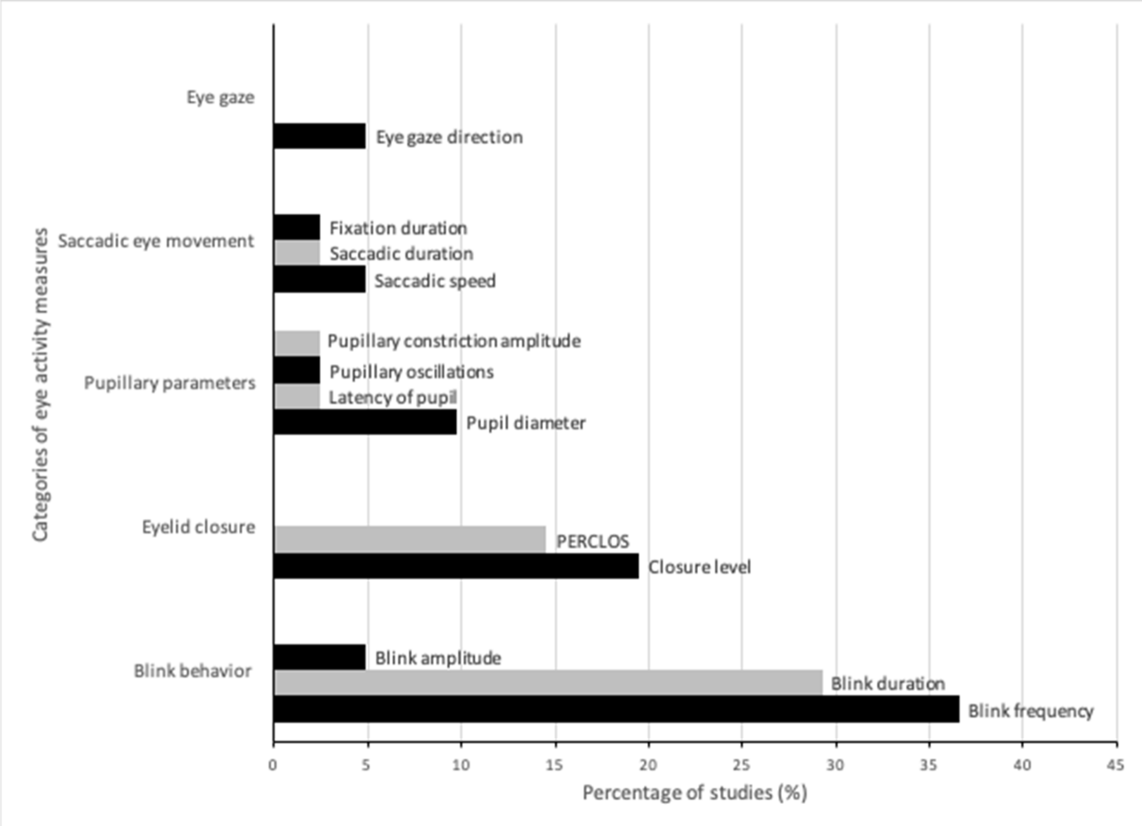

FIGURE 4. **Percentage of appearance associated with each type of eye activity measure.**

lid reopening [45], [52], [53], [56], [113]. For example, Caffier et al. [52] found that blink duration was positively correlated with its subcomponents. The results demonstrated that the correlation with the lid closure duration (closing time) was the weakest, whereas that with the lid reopening duration was the strongest. In 2004, Galley and Schleicher concluded that the increase in lid closure and reopening duration is controlled by one process, and the delay in the reopening of the eyelid is controlled by another process, wherein both processes contribute independently to the increase in blink duration. Schleicher et al. [56] investigated different parameters related to eye activity and sleepiness. These parameters include blink duration (including its subcomponents), blink frequency, and saccadic parameters. All parameters, including the respective (mean, median, and standard deviation) were computed in standardized (with regard to blink amplitude) and unstandardized manners. The results showed that all three subcomponents of blink duration increased with sleepiness; however, the delay in lid reopening contributed the most to the increase in blink duration. They suggested that the delay in lid reopening might represent a marker of the beginning and end of sleepiness. Moreover, it has been established that blink duration including (mean, median, and standard deviation) in both standardized and unstandardized forms is by far the most important indicator of both subjective and objective sleepiness. Another subcomponent of the blink duration is the average eye-closure speed (AECS), which is defined as the speed at which a person fully opens or closes the eye. It can be used as a feature for drowsiness detection because drowsy people blink significantly slower than awake people who are awake [114].

Few studies have investigated blink amplitude, although certain researchers have considered this parameter a meaningful indicator of drowsiness. A six-step procedure was proposed by [53] for warning devices based on different blink parameters (including the blink amplitude). Factor analysis was used to control blinking behavior during wakefulness and drowsiness because the blink parameters showed considerable individual differences. Galley and Schleicher [45] proposed that blink amplitude, in conjunction with blink duration, indicated a reduced level of alertness. A study conducted by [115] found a linear relationship between blink amplitude and blink velocity under alert conditions. This relationship changes during the development of drowsiness, resulting in a longer blink duration. A model for defining the different stages of drowsiness was developed based on this characteristic. In 2003, Thorslund used the method developed by [115] to develop a drowsiness detection system. The blink parameters were detected using an EOG during the truck driving simulation. The developed drowsiness detection system exhibited some correspondence with KSS ratings higher than 75%.

b: EYELID CLOSURE

Two types of eyelid closure measures, closure level and PERCLOS, are reported in this review. Results showed that both measures were the next most frequent drowsiness measures that appeared in this review (after blink frequency and blink duration), with percentages of appearance of 19.5% and 14.5%, respectively. Eyelid closure is among the earliest measures considered as reliable indicators of drowsiness. Many researchers have found a strong relationship among eyelid closure, sleep onset, and performance impairment [45], [56], [88], [91], [92].

The literature has shown certain inconsistencies in defining eye closure levels and their relationship to eye blinks, which has led to several investigations in this regard [116], [117], [118]. In fact, eyelid closure is different but at the same time related to eye blinks. An eye blink can be described as a combination of two consecutive operations: quick eyelid closure, followed by quick eyelid reopening, which normally lasts for 150–200 ms. A change can be observed in the eyeblink when the subject starts feeling sleepiness or drowsiness, from the normal eyeblink to prolonged eyeblink states. This change is considered among the most important indicators of drowsiness. However, as drowsiness continues to increase, the eye blink can gradually progress from a prolonged eye blink to the eye closure state. The threshold time (in milliseconds) required for the transition to the eye-closure state depends on the definition of the blink duration. For example, certain researchers have defined the blink duration as the time difference between the beginning and end of the blink, where the beginning and end points are measured at the point where half of the amplitude is reached. Based on this definition, eye closure can be described as a blink that exceeds 1000 ms [116], [117]. Others have defined blink duration differently to avoid possible measurement problems owing to the simultaneous occurrence of blinks and vertical eye movements, such as the sum of half the rise time and half the fall time in the blink complex [93], [117], [119]. Consequently, eye closure is defined as a blink that exceeds 500 ms [45], [56], [117].

In 1994, Wierwille et al. proposed a measure of drowsiness that is associated with eye closure, known as PERCLOS (Percent Eye Closure). This is defined as the proportion of time that the driver's eyelids are closed 80% or more for a specified time interval, and it reflects slow eyelid closures (eye droop) rather than eye blinks. High PERCLOS values are strongly correlated with drowsiness [101], [105], [120], [121], [122], [123], [124]. Dinges and Grace [125], Wierwille [126] developed the PERCLOS system that detects drowsiness based on eye closure and drooping. This system has been validated in on-road driving tests [127] as well as with the PVT [88], [125]. Moreover, PERCLOS is superior to EEG, eyeblink, and head-nodding technologies [88]. In addition, PERCLOS was found to be significantly correlated with lane departures and lapses of attention; thus, several researchers consider it the "gold standard" measure of drowsiness [90]. The PERCLOS parameter has a limitation in detecting drowsiness accurately when the driver wears glasses or is sleeping with eyes open [129].

In 2004, Kruger et al. investigated the relationship between eyelid activity and drowsiness. This study indicated that different eyelid-related parameters may indicate different stages of drowsiness, wherein the "eyelid closure" measures may indicate late stages of drowsiness. Moreover, [56] indicated that any drowsiness detection system should not solely depend on eye closure measures since certain drivers manage to keep their eyes open and "stare" when they are drowsy, which makes it difficult to measure eyelid closure.

2) DROWSINESS MEASURES RELATED TO EYEBALL MOVEMENT

Eyeball movement measures appeared in approximately 19% of the studies identified in this review. Three types of measurements were identified: pupillary parameters, saccadic eye movements, and eye gaze direction. The following subsections provide additional information about the history, meaning, and implications of each type.

a: PUPILLARY PARAMETERS

Four pupillary parameters were identified in this review, pupil diameter, latency of pupil, pupillary oscillations, and pupillary constriction amplitude, with the former being the most frequent (9.5% of the studies).

The pupil is involuntarily controlled by the autonomic nervous system, is non-invasively and visually observable from outside the body and enables us to separately evaluate sympathetic and parasympathetic nervous activities. Thus, pupillary parameters can function as a potential objective indicator of drowsiness [129]. In addition, pupillary parameters can be good indicators of drowsiness in situations wherein drivers stare and have few blinks or saccades. Several studies have investigated the relationship between pupillary parameters and drowsiness. In general, results have shown that drowsiness is associated with changes in pupillary parameters such as a decrease in pupil size or diameter [57], [130], [131], [132], [133], an increase in pupil constriction latency or latency of pupillary reaction to light [57], [134] and changes in speed at which pupil size changes (pupillary oscillations) [106], [135].

A simulation study was conducted to investigate changes in pupil diameter associated with drowsiness [129]. Two reference measures were used in this study: subjective reports (to indicate drowsiness) and an anti-saccade task to measure cognitive and motor performance. The results demonstrated that the transition to drowsiness was characterized by specific changes in pupil diameter. It was confirmed that the pupil diameter fluctuated with large amplitudes at low frequencies when the subjects were aware of their drowsiness.

Moreover, prior to this fluctuation, there was a gradual decrease in pupil diameter, during which the subjects were not aware of sleepiness. The authors concluded that this gradual decrease in pupil diameter could be used to predict drowsiness. Du et al. [136] developed a driver fatigue detection method based on eye-state analysis. Three parameters were used to analyze the eye state: pupil height, eye area, and width-to-height ratio. The results demonstrated the validity of the proposed method under realistic conditions.

Another study investigated the use of pupillary parameters related to pupil size and reaction to light as objective screening tools for a driver's fitness for duty [57]. Based on the normality assumption for these parameters, an index was calculated to indicate driver alertness level. The results showed that pupillary parameters, namely pupillary diameter, pupillary constriction latency, and pupillary constriction amplitude, may serve as screening tools for fatigued drivers. The literature has mentioned certain disadvantages of pupillary parameters; for example, they are affected by changes in illumination and the levels of cognitive demands. Moreover, the measurement of pupillary parameters is mostly based on eye image processing, implying that eye blinks and saccadic eye movements can affect the measurements. Hence, several methods have been proposed to accurately measure pupillary parameters without blinking artifacts [137], [138].

b: SACCADIC EYE MOVEMENT

In this review, three types of saccadic eye movement were identified: saccadic speed, saccadic duration, and fixation duration, with the former being the most frequent (5% of the studies). Saccadic eye movement (or saccades) is the rapid movement of both eyes from one fixation point to another. The time between two saccades is called the fixation duration. Saccadic eye movements occupy only 10% of the total time spent in eye movements, while the rest are occupied by the fixation duration [139]. Studies have focused less on saccadic parameters than on eye blink parameters because of the difficulties in measuring saccadic parameters. For example, unlike registering eye blinks, registering saccadic parameters requires devices with a high sampling rate (500–1000 Hz), which can only be achieved by advanced video systems [56]. Further, using EOG is not an option for in-car drowsiness detection devices because of its intrusiveness and obtrusiveness.

Despite these challenges, several studies have reported a relationship between drowsiness and saccadic parameters. For example, saccadic speed has been considered by many authors as a reliable indicator of drowsiness [53], [57], [133]. An experiment was conducted under sleep-deprived conditions to investigate the possibility of evaluating alertness using saccadic eye movements [140]. The results showed that saccadic eye movement parameters, namely peak velocity/duration ratio, normalized peak velocity, and normalized duration, were strongly correlated with sleepiness and subjective alertness. In 2004, Galley and Schleicher indicated that the compensatory effort applied by drivers to maintain alertness could be indicated by the velocities of the lid and saccadic eye movements. Schleicher et al. investigated several saccadic parameters such as saccadic duration, speed, and amplitude. The study included the mean, standard deviation, and median of the standardized and nonstandardized forms of these parameters. Among these saccadic measurements, the standard deviation of saccadic duration showed the highest correlation with objective fatigue. In addition, the fixation duration (categorized according to length) shows specific changes with increasing drowsiness [141]. Saccadic parameters are useful in revealing drivers who stare and rarely show blinks [107].

c: EYE GAZE DIRECTION

Eye gaze direction has appeared in only 5% of the studies included in this review. Many researchers have considered gaze direction as an indicator of inattentive driving rather than drowsiness or sleepiness [142], [143], [144], [145]. However, other studies have associated gaze direction with inattention and/or fatigue while driving [58], [67], [100], [101], [131], [143], [146], [147]. Although looking straight ahead while driving may indicate that the driver is paying attention to the road, this does not necessarily mean that he or she is aware of it [149]. Fixed gaze is considered a remarkable behavioral change that indicates drowsiness [143].

Gaze tracking systems are used to track eyeball movements to determine gaze directions through a calibration process. This process compensates for the error, the difference between the actual gaze direction and that measured by the tracking system, caused by individual and environmental differences, such as eyeball shape, facial features, and light conditions [145]. Although eye-gaze tracking systems have become extremely sophisticated, they still suffer from certain technical problems; for example, they are sensitive to fast-changing in-vehicle conditions (lighting conditions), do not give accurate results when drivers wear glasses or under strong illumination changes, are sensitive to large head movements, and require certain training for each individual subject.

C. REPORTED SECONDARY MEASURES INDICATING DROWSINESS

All the studies identified in this review used ocular measures as the primary measure of drowsiness. In addition to ocular measures, different secondary measures were used in approximately 56% of the studies. Three types of secondary drowsiness measures were reported: behavior measures (54% of the studies), physiological measures (7% of the studies), and vehicle-based measures (5% of the studies). Behavioral measures included head position, yawning, mouth position, and facial expressions. The physiological measures included heart and respiratory rates. The vehicle-based measures included the steering angle, time to lane crossing, lateral distance to the closest lane, number of direction changes, accelerator pedal angle, vehicle speed, and number of run-off roads per minute. Fig. 5 shows the percentage of appearance of each type of secondary measure. Among the secondary drowsiness measures, head position (nodding) and yawning were reported the most with percentages of appearance of 41% and 27%, respectively.

D. MEASUREMENT TECHNOLOGIES USED TO MONITOR EYE ACTIVITIES

The current technologies used to measure eye activities are investigated and classified based on their intrusiveness (both physically and psychologically) to drivers. According to [177], there are three levels of intrusiveness: low, moderate and high. The first level indicates measurement technologies that have no intrusion and are unnoticeable by the driver, such as sensors fully immersed within a car seat. The moderate level of intrusiveness includes two types: psychological intrusiveness (when a driver is monitored by video and can be easily identified) and physical intrusiveness (where minimal contact is required). The high level of intrusiveness includes physically intruding sensors.

The decision about the technology used to measure eye activities for drowsiness detection is important because it can affect the accuracy of the recorded ocular measure, and hence, the performance of the detection system. The selection of the type of measurement technology depends on several factors, such as the purpose of measuring eye activity, the type of transportation system, the nature of light, and environmental conditions.

This review identified three types of measurement technologies: passive (or contact-free), active (or electrode-based) and embedded technologies. Passive technology includes video oculography (VOG) and infrared oculography (IR-OG). Passive technology is considered the second most accurate in identifying drowsiness. It has low physical intrusiveness, but high psychological intrusiveness since the driver is personally monitored by video and can be easily identified. The majority of studies (approximately 95%) reported contact-free measurement technologies because of their practicality and cost-effectiveness in the real-time monitoring of driver eye activities. Active technology is concerned with measuring brain waves (EEG), muscle fatigue (EMG), cardiovascular measurements (ECG), and eye movement and closure (EOG). Although this technology is considered the most accurate, it is also the most intrusive for identifying drowsiness. The embedded technology includes sensors that are completely immersed within the vehicle. These sensors have low intrusiveness to the driver, but considered the least accurate methods for identifying drowsiness. The embedded technology was excluded in this review because it does not depend on eye activity measures. The following subsections present further details regarding the two types of measurement technologies.

1) CONTACT-FREE (PASSIVE) EYE MONITORING TECHNOLOGIES

This review identified two contact-free measurement technologies for monitoring driver eye activities: VOG (based on video image analysis) and IR-OG (uses infrared reflection technology). These two types are described in detail in the following subsections.

a: VIDEO OCULOGRAPHY

VOG, or video image analysis technology, has been widely used to measure eye activity to monitor drowsiness [86], [149], [150], [151], [152], [153]. VOG is the most commonly used technology for real-time drowsiness detection based on eye activity [35], [84], [154]. This is because VOG technology is contact-free, non-intrusive, and non-obtrusive, and hence suitable for real-time vehicle-based driver alertness monitoring systems [148]. Moreover, the eyelids are known to be among the most movable parts of the body; thus, image analysis technologies may provide a better evaluation of eyeblink patterns [155]. In addition, these technologies offer the flexibility to be integrated and positioned in the vehicle depending on the cabin design such that they can monitor the driver's head and eyes without being intrusive or obtrusive to the driver. A study conducted by [14] mentioned that image analysis technologies enable the eye point to be measured through the combined use of head and eye positions, and therefore, may provide information that helps in detecting sleepiness as well as inattention.

Systems that use video image analysis to detect driver drowsiness mainly comprise a video camera (to capture images of the driver while driving), image processing software (to analyze the images and then identify different eye activity parameters such as eyelid opening, head position, and gaze direction), and light sources (to provide adequate illumination under all ambient conditions). These systems operate as follows: A camera is mounted in the cabin in a position such that it can monitor the driver's head and face continuously. Certain specifications and requirements must be met, such as adequate resolution, frame rate, sensitivity, and field of vision (must include the driver's face in different head and body postures, as well as different seating positions). The camera continuously captures images of the driver's head and eyes and uses an infrared spot to lighten the retina such that the pupil and retina can be easily identified. These images are then sent periodically to the image processor for analysis to determine the different eye activity parameters; more details are provided in [148].

Previously, video image analysis technologies were used with caution, particularly when dealing with situations such as drivers wearing glasses because reflections from lenses or frames may cause errors during image processing and evaluation, unfavorable lighting conditions, and large head movements [14], [148]. Moreover, VOG technology requires heavy image recognition software and hardware [156]. The limited specifications of video imaging technologies made

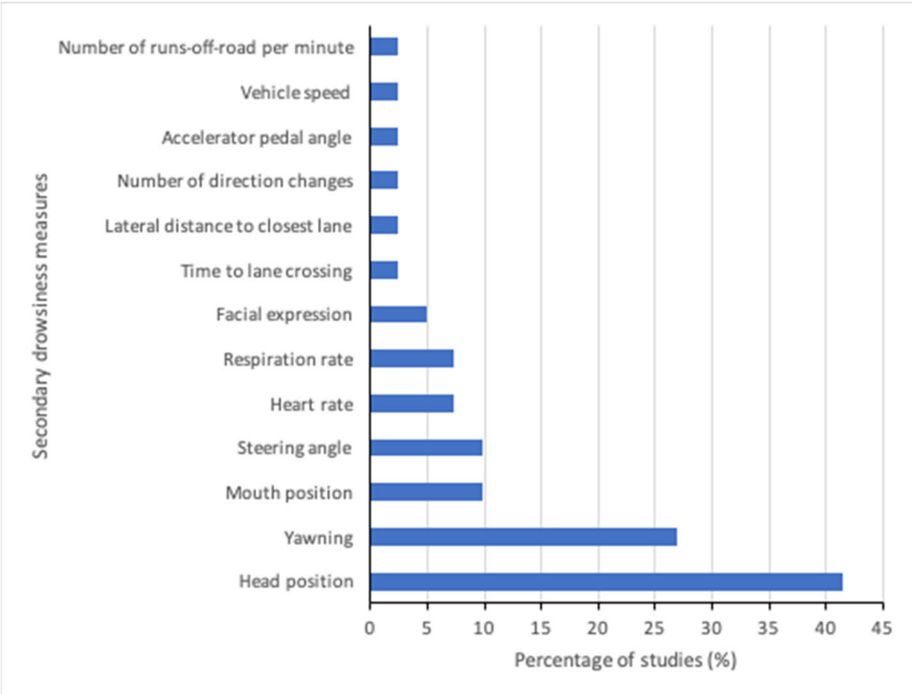

FIGURE 5. Percentage of appearance of secondary drowsiness measures.

it difficult to overcome the previously mentioned situations and caused certain difficulties in measuring fast eye movements. For example, in 1995, Nissan developed a drowsiness detection technology based on monitoring a driver's eye activity (i.e., blink duration and blink frequency) using a video camera and an image processor. One of the disadvantages of this technology is its inability to detect fine eye movements owing to the frame rate of the installed video camera (50–75 fps), which limits the best time resolution limit (13–20 ms) [96]. However, recent advances in video imaging technologies have facilitated the monitoring of different eye activities in real-time and under all driving conditions [10].

Ejidokun et al. [149] used a low-cost webcam with a capture rate of 30 fps to monitor the blinking behavior of drivers. The proposed approach achieved a blink accuracy of 94.8% and a missed blink error of 2.4%. Varma et al. [99] developed a real-time fatigue tracking system based on a front camera equipped with an infrared illuminator. The system uses eye blinking and head movements to determine the driver's degree of fatigue. Lenskiy and Lee [98] used monocular color cameras with infrared illumination to monitor eye blinking and ocular closure time. Jin et al. [100] used video cameras with infrared lighting on a dashboard to track eye movements and detect tires. Dasgupta et al. [157] developed a smartphone-based drowsiness detection system that uses the percentage of eyelid closure obtained from images captured using a front camera. The system uses near-infrared lighting for the driver's face during nighttime.

b: INFRARED OCULOGRAPHY

Although video image analysis technologies have shown efficiency, particularly in laboratory experiments, they suffer from serious problems in real-life implementation, which may affect the accuracy of the entire monitoring system. Alternatively, IR-OG, or infrared reflection technology, is more suitable for real-life implementation because of its ability to measure a driver's eye activity under different light conditions, with or without prescription glasses, contact lenses, or sunglasses [86], [158], [159], [160], [161]. In addition, it is portable, wearable, contact-free, non-intrusive, and inexpensive compared to electrode-based technologies [156].

Infrared reflection technology involves a transmitter and receiver mounted on a pair of spectacles worn by the driver, and a beam of infrared light directed at the eyelids of the driver [14], [110], [162]. This is based on the idea that, if a fixed light source is directed against the eye, the amount of light reflected back to a fixed detector changes with the eye-opening level and pupil position [156]. IR-OG technology can be described as follows. Brief pulses of infrared light are directed repeatedly from a small light-emitting diode (LED) attached to the frame of the glasses against the eye. The total infrared light reflected from the eye and eyelid is received by a detector beside the LED. This detector is sensitive only to infrared light and is not affected by other light sources [156]. The characteristics of each reflected infrared pulse depend mainly on two factors: 1) the color, shape, and texture of the reflectance; and 2) the proximity of each part of the reflecting surface (cornea, iris, sclera, conjunctiva, and skin of the eyelids) to the infrared light source [86]. This claim coincides with the conclusion of Hoffman et al. that the amount of light reflected from the eye is proportional to the degree of lid closure [163]. This indicates that different eye activities are associated with different reflected infrared pulse characteristics.

A study conducted by Castro demonstrated that when IR-OG technology is used to measure several eye activities in addition to eyelid movement, blinks could cause certain problems. For example, after blinking, the eye retracts slightly, affecting the amount of reflected infrared pulse for a short time, which in turn affects the measurement accuracy. In addition, the eyes are covered by lids during blinking, which causes errors in the measurements. However, this technology would be considered convenient if mainly used to measure parameters related to eyelid movement. Another drawback of this technology is the pair of spectacles worn by the driver, which can be considered partially obtrusive.

2) ELECTRODE-BASED (ACTIVE) EYE MONITORING TECHNOLOGIES

This review identified three types of electrode-based measurement technologies: EEG, EMG, and EOG. Studies have shown that vigilance can be defined using criteria derived from EEG, EOG, and EMG. These techniques have been frequently used for drowsiness detection, particularly in laboratory experiments, because they provide direct and objective measures of drowsiness. An early study by Loomis et al. [164] indicated profound changes in the appearance and spectrum of EEG signals during drowsiness [165]. In 1968, Rechtschaffen and Kales [166] reported a correlation between EEG power-band measurements and visually defined sleep stages. Other studies on the appearance of EEG during drowsiness indicated that in different subjects, EEG can take a variety of routes from wakefulness to sleep [165], [167]. In EOG, three silver/silver chloride or gold electrodes are placed on the skin around the eye to measure the potential difference between the front and back of the eyeball, which is directly related to eye movements and blinking [117], [176]. It has been established that the EOG is a suitable measure for the objective characterization of drowsiness [45], [168], [169], [170]. Thus, EOG can be used as a validation method during the development of a new drowsiness detection system [117]. Khushaba et al. [171] proposed a fuzzy-based approach for classifying drowsiness levels based on EOG signals.

Other researchers believe that EOG is not as reliable as EEG, although it performs fairly well; thus, they recommend the use of EEG as a reference for drowsiness detection and EOG as a complementary measure [172]. Furthermore, EMG uses electrodes to capture signals from muscles close to the eyes because it is well established that the muscular tonus decreases as the alertness level decreases to reach its minimum when asleep [172], [173]. It is usually used in conjunction with EEG to distinguish between different alertness levels during the gradual transition from wakefulness to sleep [174].

The main drawback of electrode-based technologies (EEG, EOG, and EMG) is that they are obtrusive because they require electrodes to be attached to the driver. Hence, they are not suitable for use in in-vehicle real-time drowsiness detection systems [117]. Other disadvantages have been mentioned in [156], such as the movement of the driver, which could cause artifacts in the signal; electrodes could detach from the skin for any reason (e.g., if the driver is sweaty), which could cause poor recording quality; and plaster that holds up the electrodes could cause local irritation or disturb the driver.

E. DECISION-MAKING ALGORITHMS

The majority of the identified decision-making schemes used for the classification and prediction of drowsiness states are based on machine-learning algorithms. Three decision-making schemes were identified in this review: deep learning algorithms (58.5% of the studies), supervised learning algorithms (53.7% of the studies), and rule-based techniques (2.5% of the studies). Fig. 6 illustrates the identified decision-making schemes with the associated classification accuracy.

Deep learning algorithms include convolutional neural networks, long short-term memory, deep neural networks, recurrent neural networks, multistage spatial temporal networks, and hierarchical temporal belief network. Convolutional neural network was the most frequent classification algorithm observed in the identified studies (34.1% of the studies). Supervised learning algorithms include artificial neural networks, k-nearest-neighbor, support vector machine, ordered logit model, logistic regression, gradient boosting, random forest, histograms of oriented gradient features, decision trees, and Bayesian networks. Artificial neural networks were the second most frequent classification algorithm that appeared in the identified studies (19.5% of the studies). Fuzzy logic was the only rule-based technique identified in one of the studies in this review.

The classification accuracy associated with each decision-making algorithm is shown in Fig. 6. The classification accuracy of convolutional neural networks (reported based on 14 studies) ranged from 77–99% with an average of 87.5%. When convolutional neural networks were used in conjunction with long short-term memory algorithm, the average classification accuracy increased to 91.5%. The average classification accuracy of artificial neural networks as reported based on 8 studies was 97.5%. The k-nearest-neighbor algorithm was reported in three studies, with an average classification accuracy of 94%. Recurrent neural networks were used in conjunction with long short-term memory algorithm, with an average classification accuracy of 95%. Random forest algorithm was reported in one study with a classification accuracy of 95.5%. Fuzzy logic was reported in one study with an average classification accuracy of 98%. The variation in the classification accuracy of different algorithms (between 79.5–99%) is due to several factors related to: 1) the classification algorithm (e.g., whether it depends on deep learning, supervised learning or rule-based algorithms and whether it is used solely or in conjunction with another algorithm). For example, the results indicate that the highest classification accuracy obtained by convolutional neural networks was 99%, in comparison to the one obtained by fuzzy logic (98%) and by random forest algorithm (95%). Moreover, the results showed that average classification accuracy of convolutional neural networks was 87.5%. However, when convolutional neural networks were used in conjunction with long short-term memory algorithm, the average classification accuracy increased to 91.5%. 2) the dataset (e.g., richness of the dataset, preprocessed vs. not preprocessed, and robustness of features) [175], [176].

IV. DISCUSSION AND FUTURE DIRECTIONS

The quality assessment and risk of biasness associated with included studies were performed based on the following criteria: performance measure, participants' diversity and sample size. The majority of the included studies used accuracy metric to evaluate their proposed DDD systems. Accuracy is a good indicator of how well the system can identify true positives (TP) and true negatives (TN), especially when the data are balanced (i.e., the number of alert and drowsy drivers are equal in an experiment) [183]. However, in a real-life scenario, data are usually unbalanced with more awake drivers on the road than drowsy drivers. In this case, accuracy metric will be biased towards the class with more samples. Therefore, to avoid this biasness, performance metrics, such as sensitivity and precision work better with unbalanced data [183]. Precision indicates the proportion of correctly identified drowsy drivers to those labeled as drowsy (whereas they are alert in reality). Low precision means the system may give a false alarm by incorrectly identifying alert drivers as drowsy. On the other hand, sensitivity indicates the proportion of correctly identified drowsy drivers to those labeled as alert (whereas they are drowsy in reality). Low sensitivity means that the system may fail to identify drowsy drivers, which could result in serious accidents. Therefore, the sensitivity metric is important in evaluating the performance of DDD systems. This review showed that only three studies [22], [24], and [38] used sensitivity, in addition to accuracy, to evaluate their proposed DDD systems.

The included studies – [17], [18], [19], [23], [24], [26], [27], [28], [29], [31], [33], [35], [36], and [37] – used the most diverse publicly available dataset. The review showed that gender and ethnicity biasness were largely present in the remaining 27 studies. Gender and ethnicity splits are important especially in behavioural-based dowdiness detection where facial features can differ across different gender and ethnicity groups. Moreover, two studies [2] and [3] included a sample size of 60 and 76, respectively. The remaining 39 studies included a sample size lower than 40 participants. DDD systems developed with such a low sample size have been criticized with their poor generalizability, especially when using deep learning algorithms that require large amounts of training data [178].

A. CHALLENGES AND LIMITATIONS

Different studies used different performance metrics to evaluate the efficiency of their classification methods. The included performance metrics were: accuracy (in 34 studies), F1-Score (in 7 studies), sensitivity (in 3 studies), Student's t-test (in 3 studies), correlation coefficient (in 3 studies) and root mean square errors (RMSE) (in one study). The variations of performance measures made the comparison across studies very difficult. In addition, the analysis using area under the receiver operating characteristic curve (AUC) could not be performed, owing to the small number of studies reporting sensitivity and specificity of the driver drowsiness detection methods.

Although majority of the included studies (83%) used accuracy metric, it is very difficult to compare accuracy measurements across studies. This is because classification accuracy depends on a variety of factors that cannot all be accounted for when comparing between the studies. These factors include: 1) training, testing and validation splits; 2) level of drowsiness used; 3) number of drowsiness levels; 4) number and diversity of participants; 5) differences in the dataset used; 6) differences in the type of experiments (simulator vs. on-road); 7) differences in modelling (per subject vs. cross-subject); 8) differences in acquisition configuration; 9) lighting and environmental factors. All the aforementioned factors contributing to the outcome, make the comparison across studies challenging [177].

In addition to variations in performance measures, the included studies are highly diverse in: the data/measures used (real-time experiment vs. publicly available dataset), extracted features, driving setting (on-road vs. simulator), sample sizes (ranging from 4 to 76 participants) and classification algorithms including machine learning (i.e., supervised, deep, and unsupervised learning algorithms) and non-machine learning algorithms (i.e., classical statistical methods and rule-based techniques). Therefore, performing a meta-analysis is out of the scope of this review.

Although many studies ([5], [8], [15], [24], [30], [32], [39], and [40]) showed high classification accuracy (95-99%), the reliability of these studies is questionable and need be tested under real driving conditions (i.e., normal traffic with no experimenter on the car), where variety of situations and unpredictable events may occur. This type of studies is known as naturalistic driving studies and it is out of the scope of this review.

As in any review, one limitation is that the findings of the study were limited by the quantity and methodological quality of the included studies. This suggests that there may

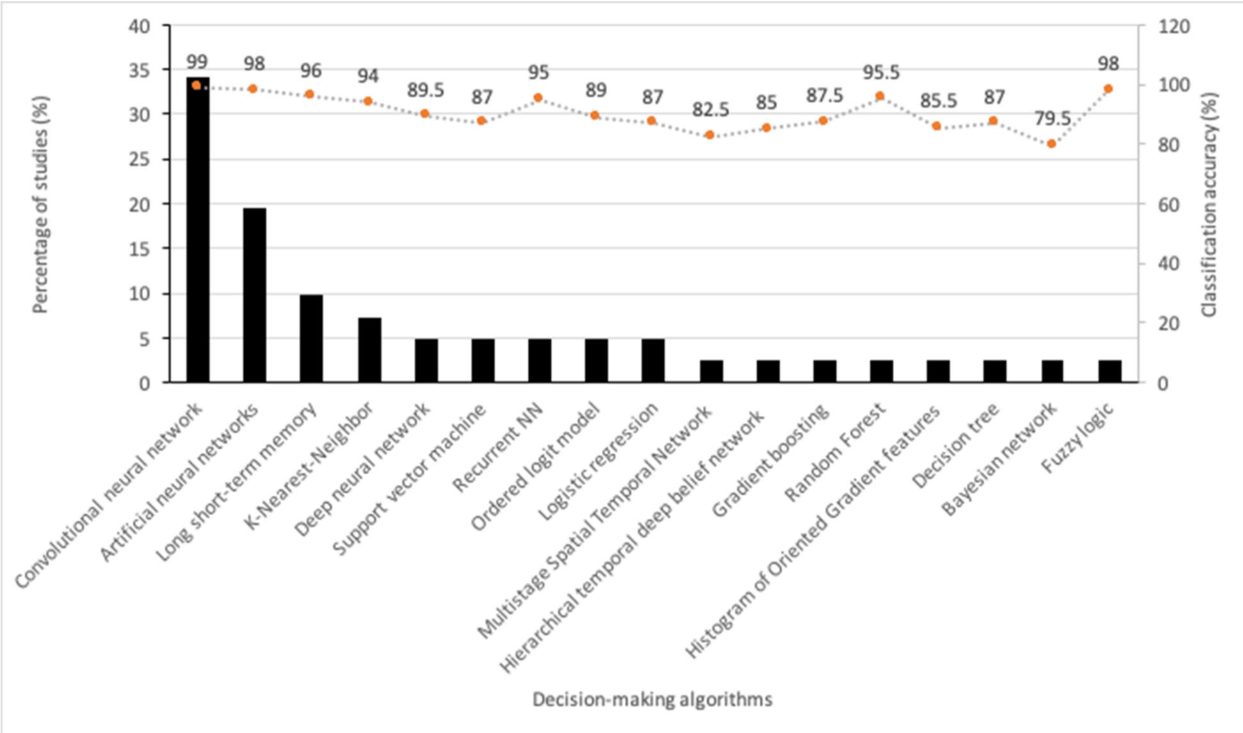

FIGURE 6. Identified decision-making algorithms with associated classification accuracy.

be further eye activity- measures and decision-making algorithms that have not yet been studied. In addition, the number of studies reporting a given ocular parameter or classification algorithm was not necessarily related to its importance. Another common limitation is the possibility of missing relevant studies that were not detected by the keywords or did not match the systematic extraction criteria. To minimize the effects of this problem, the final list of included studies was checked by a colleague involved in a similar study. Moreover, the review excluded books, reports, and unpublished works that could contain important research findings on detecting driver drowsiness using eye activity.

Additional limitations and gaps in the current research are related to the following:

- Prediction vs. detection: predicting how long until a driver becomes drowsy, rather than detecting the drowsiness state itself, can significantly reduce fatalities and injuries related to road accidents. For example, studies that solely used prolonged eye closure to detect drowsiness, i.e. [15], [16], and [29], might not be able to detect a microsleep state, which occurs at earlier stage (before drowsiness). Majority of the included studies focused on detecting drowsiness, except studies [6] and [21].
- Physiological intrusiveness: two studies, i.e. [3] and [4], used electrooculography (EOG) in their methods, which is known to be highly intrusive to drivers.
- Subject diversity: diversity, especially in ethnicity, can affect the classification accuracy in behavioural-based models. Majority of the included studies lack ethnicity variations and some studies do not even report it. Some of the included studies, i.e. [17], [18], [19], [23], [24], [26], [27], [28], [29], [31], [33], [35], [36], [37], used the NTHU dataset, which is considered the most diverse publicly available dataset [96]. However, this dataset has been criticized for its poor generalization for end-to-end learning models, which require large amounts of training data [178].
- Sample size: approximately 25% of the included studies, i.e. [1], [6], [8], [9], [10], [12], [14], [15], [18], [30], have a sample size below 20. Drowsiness detection models developed with such low sample size cannot be generalized to broader populations.
- Experiment protocol: protocols for data collection need to include both daytime and night scenarios to ensure the efficiency of the detection system. Majority of road accidents associated with drowsiness occur between midnight and 6 a.m. [7], yet only 40% of the included studies considered a night driving scenario [15], [16], [17], [18], [19], [23], [24], [26], [27], [28], [29], [31], [33], [35], [36], [37].
- Type of experiment: the differences between real and simulated driving have been reported (e.g., in duration, sensitivity to speed and perception of risk) [177]. Only 17% of the included studies [1], [2], [7], [8], [25], [32], [41], involved real and on-road driving, owing to the complexity of setting real experiments and the difficulty of collecting data and finding participants.
- Drowsiness measure: the review showed that different studies used different drowsiness measures to detect

driver drowsiness. Some of the limitations associated with different drowsiness measures are described as follows. Detection systems based on eye gaze, i.e. [5] and [13], are sensitive to rapid changes in in-vehicle conditions (e.g., lighting conditions) and head movements. In addition, they may give inaccurate results under strong illumination changes or when drivers wear glasses [145]. Detection systems based on saccadic parameters, i.e. [7], [21], and [39], are difficult to measure because they require high sampling rate (500–1000 Hz), which cannot be attained by classical video systems. Detection systems based on pupillary parameters, i.e. [5], [7], [14], [32], and [34], are sensitive to changes in illumination and cognitive demands. In addition, the measurement of pupillary parameters mostly depends on eye image processing, which can be affected by eye blinks and saccadic eye movements [137]. Detection systems based on eyelid closure or PERCLOS, i.e. [2], [3], [4], [5], [6], [8], [9], [12], [14], [15], [16], [21], [22], [29], [30], [33], [34], [39], and [40], cannot be measured easily under special conditions, such as when wearing glasses or sleeping with eyes open [129].

- Performance measures: different studies used different performance metrics to evaluate the efficiency of their classification methods. These performance metrics include: accuracy (in 34 studies), F1-Score (in 7 studies), sensitivity (in 3 studies), Student's t-test (in 3 studies), correlation coefficient (in 3 studies) and RMSE (in one study). The variations of performance measures made the comparison across studies impossible. Although majority of the included studies (83%) used accuracy metric, it is very difficult to compare accuracy measurements across studies. This is because classification accuracy depends on a variety of factors that cannot all be accounted for when comparing between the studies. These factors include: 1) training, testing and validation splits; 2) level of drowsiness used; 3) number of drowsiness levels; 4) number and diversity of participants; 5) differences in the dataset used; 6) differences in the type of experiments (simulator vs. on-road); 7) differences in modelling (per subject vs. cross-subject); 8) differences in acquisition configuration; 9) lighting and environmental factors. All the aforementioned factors contributing to the outcome, make the comparison across studies challenging [177].
- Several studies ([5], [8], and [32]) showed very high classification accuracy ranging from 98-99%. These accuracy results were not validated on independent dataset.

The majority of the identified studies have focused on decision-making algorithms and their accuracy in classifying and predicting drowsiness. Although this component is critical for developing DDD systems, the classification accuracy does not depend solely on the decision-making algorithm. The careful selection of drowsiness measures can also significantly affect the classification and prediction accuracy of drowsiness. In addition, it can aid the early detection of driver drowsiness when it is not too late to implement safety interventions. The next section discusses the main research directions concerning driver drowsiness detection based on ocular parameters.

B. FUTURE DIRECTIONS

The main methods used to identify driver drowsiness include: physiological, behavioural and vehicle-based techniques. Physiological methods (e.g., EEG and EOG) have been shown to be the most accurate in detecting driver drowsiness, but at the same time the most intrusive to drivers [177] and [180]. Behavioural methods (i.e., eye activity based) are considered the second most accurate and less intrusive than physiological methods, but may have some privacy concerns [177] and [181]. Vehicle-based methods are considered the least accurate and intrusive method [177]. Individual methods have their unique strengths and weaknesses, and therefore the integration of these methods may offer the possibility of utilizing the strengths of each method while mitigating weaknesses. Several studies showed that hybrid models (i.e., with multiple drowsiness measure sources) are more flexible and accurate than singular techniques in identifying driver drowsiness [77], [177], and [182]. They also have the advantage of overcoming the drawback of intrusiveness and allowing for data losses [177]. These advantages, however, come at the expense of increased cost and complexity of development [177]. Therefore, future research should be directed toward the development of hybrid drowsiness detection models, with consideration to the complexity they bring.

Another future direction is related to data collection protocols for identifying driver drowsiness with special focus on: collecting real diving data with appropriate ethical considerations (to improve reliability), recruiting larger number and diverse range of participants (to improve generalizability), and conducting both day and night studies (to improve efficiency of the detection system).

New DDD systems should focus more on drowsiness prediction rather than detection in order to warn the driver in time before an accident occurs. Future research should explore how far early drowsiness can be predicted and which method is suitable for predicting drowsiness. In this context, physiological and behavior-based methods are highly effective in predicting the onset of driver drowsiness [177]. Therefore, the integration of these methods can be used by big automobile manufacturers to minimize drowsiness related accidents. Further research can also explore the impact of future driving conditions (i.e., semi/fully automated driving) on driver behavior and drowsiness, which may reveal new measures of drowsiness.

Future research should utilize the significant technological developments in artificial intelligence (AI), the Internet of Things (IoT) and sensor miniaturization. For example, the

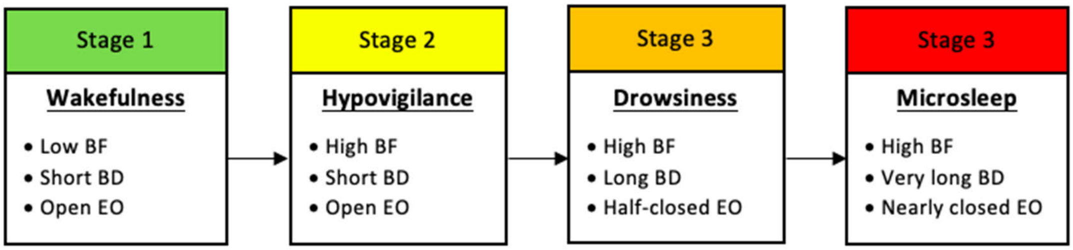

FIGURE 7. Blinking behavior during different driver vigilance stages (Note BF: Blink frequency; BD: Blink duration; EO: Eyelid opening).

5G technology may help in conducting real driving scenarios, where data can be obtained from actual drivers and factors with consideration to factors, such as light conditions, individual differences, road vibrations, noise. Moreover, research should investigate the application of deep learning techniques in identifying driver drowsiness. The 5G connectivity may allow for the use of multi-access edge computing power for deep learning, which improves the accuracy of real-time decisions [183]. In addition, vehicles can operate in networks, where the network can warn the drowsy driver, take control of the vehicle and contact other vehicles in the network to stay at a safe distance [183]. These technological advancements will help in developing accurate and reliable driver drowsiness detection systems and hence pave the way for their practical implications in smart cities.

Several studies have shown that blinking behavior is one of the most experimentally examined drowsiness detection and prediction indicators [14], [92], [94]. However, few studies have investigated the intercorrelation between these indicators and their independent correlation with the level of induced drowsiness. A simulation study conducted by Hargutt [44] showed that different driver sleepiness levels can be determined using different blinking behaviors. Four levels of sleepiness were determined according to the collected blinking parameters: awake, hypovigilant, drowsy, and microsleeping. The results showed that light fatigue (the transition from awake to hypo-vigilant) was indicated by an increase in blink frequency, whereas the transition to severe fatigue was accompanied by an increase in blink duration. In 2004, Galley and Schleicher conducted a study that investigated the relationship between various ocular parameters and drowsiness levels as indicated by subjective indicators. They concluded that sleepiness while driving involves three partially independent processes: decreasing attention (indicated by blink interval), decreasing alertness (indicated by blink duration and blink amplitude), and pronounced effort to maintain the required level of alertness (indicated by the velocities of saccades and lid movements). This result was supported by [46], who concluded that blink frequency and blink duration may have to be considered independent aspects of blinking behavior. Another study conducted by [47] supported the fact that hypovigilance is an early stage of drowsiness that occurs before microsleeping. This indicates that driver drowsiness can be predicted in earlier stages (i.e., hypovigilance) by detecting an increase in blinking frequency, which will later be accompanied by an increase in blinking duration. These findings can shift the attention of researchers, engineers and policy makers of the transportation industry to the hypovigilance state of the driver, which is an early stage of drowsiness.

Fig. 7 illustrates the blinking behavior during different vigilance stages and how it can help in predicting drowsiness. For example, a signal can be initiated if an increase in blinking frequency occurs (yellow). This signal turns into an alarm when an increase in blinking duration and half-closed eyelid opening are detected (orange). This mechanism provides a great opportunity to detect drowsiness before reaching the microsleep state, which provides drivers with sufficient time to react safely before falling asleep. The proposed research direction may help road safety researchers develop reliable DDD systems that can detect drowsiness at an early stage.

Several studies, as well as practical experience, have shown that not all drowsy drivers experience a long blink duration or high blink frequency at the wheel, but some manage to keep their eyes open during an episode [47], [56], [179]. This phenomenon is known as ''highway hypnosis'' or ''driving without awareness (DWA),'' wherein drivers are seemingly unaware of impending driving errors or road accidents, even with their eyes open.

The majority of DDD systems focus on detecting microsleep situations without considering that drivers may sleep with their eyes open (Fig. 8). Therefore, investigating the DWA phenomenon, its risk factors, and their relationship with drowsiness is critical for the development of DDD systems. In 2004, Galley and Schleicher investigated the relationship between various ocular parameters and drowsiness levels as indicated by subjective indicators. They concluded that sleepiness while driving involves three partially independent processes: decreasing attention (indicated by blink interval), decreasing alertness (indicated by blink duration and blink amplitude), and pronounced effort to maintain the required level of alertness (indicated by the velocities of saccades and lid movements). Moreover, a simulation driving experiment was conducted by Karrer et al. [179] to investigate DWA and its relationship to driver drowsiness. The results showed a notable correlation between DWA and

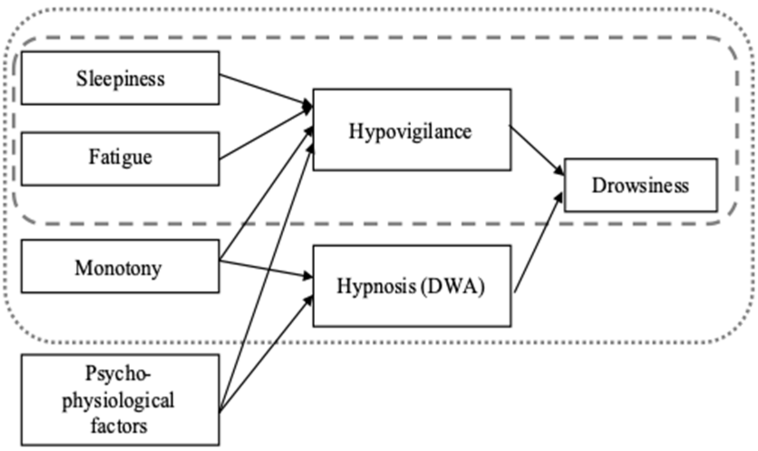

FIGURE 8. Factors causing driver's hypovigilance, DWA, and drowsiness (Note Dashed line: Current technology; Dotted line: proposed technology).

saccadic parameters, such as mean saccadic amplitude and mean saccadic duration. Another study conducted by Desai and Haque [47] supports the fact that DWA occurs in the early stages of drowsiness (hypovigilance). These results highlight the need to carefully investigate DWA situations in field driving and emphasize the use of saccadic parameters to improve the accuracy and reliability of drowsiness detection devices.

There are some potential challenges to implementing eye activity-based DDD systems in real-world settings. One of the main challenges is the difficulty of tracking and recognizing high-quality data of driver's head and face, due to the dependency on the driver, environmental conditions and quality of the equipment [183]. In addition, the difficulty of tracking and recognizing the eyes in the presence of accessories, such as sunglasses, beard and mustache. Another challenge is related to the difficulty of measuring saccadic parameters as they require high sampling rate (500–1000 Hz) [56]. Variations in skin colors, face structure and lighting conditions [185], random head movements [150], distance from the camera, and the need for powerful computing equipment for real-time video analysis [184] are all among the potential challenges that may result in the reduction of detection accuracy or failure of DDD systems.

V. CONCLUSION

Eye activity-based DDD systems have the advantage of being reliable, non-intrusive to drivers and able to detect drowsiness at early stage. Therefore, it was extremely important to provide researchers and practitioners with in-depth information on eye activity measures of drowsiness, current technologies to measure the eye activity and decision-making algorithms to predict drowsiness.

The current review differs from previous literature reviews in several respects. First, to our knowledge, the current review is the first to systematically review empirical studies that develop driver drowsiness detection (DDD) system based on eye activity measures and assess its performance. Second, it identifies the common eye activity measures of drowsiness and classifies them based on the moving part of the eye. Third, it identifies the current technologies used to monitor and measure eye activities and classifies them based on their functional properties. Fourth, it explores decision-making algorithms used to predict drowsiness from eye activity measures. Fifth, it sheds light on new research avenues that emphasize predicting driver drowsiness at an early stage and considering the driver's hypnotic state when developing DDD systems.

This study forms the basis for future research and the development of driver drowsiness detection methods using ocular parameters. The findings will help researchers better understand the various eye activities that indicate drowsiness and different decision-making algorithms.

The outcome of this literature review could help practitioners improve existing DDD systems by incorporating measures of blinking behavior in conjunction with head position or yawning to detect drowsiness in the early stages. It is also expected to help practitioners improve existing DDD systems by incorporating deep learning algorithms such as convolutional neural networks to increase prediction accuracy.

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