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Driver Drowsiness Detection Based on Drivers' Physical Behaviours: A Systematic Literature Review

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ABSTRACT

One of the most common causes of traffic accidents is human error. One such factor involves the drowsy drivers that do not focus on the road before them. Driver drowsiness often occurs due to fatigue in long distances or long durations of driving. The signs of a drowsy driver may be detected based on one out of three types of tests; i.e., performance test, physiological test, and behavioural test. Since the physiological and performance tests are quite difficult and expensive to implement, the behavioural test is a good choice to use for detecting early drowsiness. Behaviour-based driver drowsiness detection has been one of the hot research topics in recent years and is still increasingly developing. There are many approaches for behavioural driver drowsiness detection, such as Neural Networks, Multi Layer Perceptron, Support Vector Machine, Vander Lugt Correlator, Haar Cascade, and Eye Aspect Ratio. Therefore, this study aims to conduct a systematic literature review to elaborate on the development and research trends regarding driver drowsiness detection. We hope to provide a good overview of the current state of research and offer the research potential in the future.

Keywords: Driver Drowsiness Detection, Behavioural Approach, Facial Features.

1. INTRODUCTION

According to the data from the National Police Department of the Republic of Indonesia in 2017 [1], in one hour, on average three people died due to traffic accidents. The biggest factors that cause traffic accidents in Indonesia are human factors, vehicle factors, and environmental and infrastructure factors. The data also states that 61% of the accidents that occur were caused by human factors.

The human factor is one of the factors that cause traffic accidents, which is related to the ability and character of the driver. One issue related to human error is apparent in drivers who drive in a drowsy state, so they don't focus on the road in front of them. Studies show that some drivers can lose their self-judgement on how drowsy they are after driving for a long period of time. They also show that drowsiness can affect workers' ability to perform their work safely and efficiently [2, 26]. Therefore, fatigue driving can be considered as one of the significant and latent concerns in traffic accidents. It can also endanger both the driver and other people on the street [3].

According to the aforementioned problem, automatic driver drowsiness detection systems can be a beneficial thing to reduce the number of traffic accidents. To implement those systems, there are some kinds of approaches that have been used, but basically, these approaches can be divided into four main approaches: Karolina

Sleepiness Scale (KSS), changes in vehicle driving parameters along with driving area and lane detection algorithms, physiological measurements, and behavioural measurements [4].

Karolinska Sleepiness Scale is widely used to examine drowsiness in various contexts by subjectively measuring the drowsiness level at particular times [27, 28]. The subjects will rate which level describes their psycho-physical state within the last 10 minutes. This scale is originally a 9-point scale that varies from 1 (extremely alert) to 9 (extremely sleepy), but a modified KSS adds the tenth scale, which means extremely sleepy and falls asleep all the time. The longer the subject is awake, the higher the KSS score will be. However, since this scale only measures situational drowsiness, it is prone to fluctuations, and the results may vary depending on the parameters.

Approaches by observing the changes in vehicle and driving parameters, also known as vehicle-based drowsiness detection, is a method that measures the drowsiness level based on in-vehicle sensors and collects several indicator metrics for determining alertness/drowsiness level of the driver through his driving behaviours [23]. The approach's three main aspects include the steering wheel movement, vehicle deviation and position, and vehicle speed and acceleration. The steering-wheel angle and track become irregular, and the deviation range significantly increased when a driver is in a drowsy state [29,30]. Approaches using vehicle deviation and position rely on some metrics such as Standard Deviation of Lane Position (SDLP), which measures the vehicle's position regarding the road's middle lane. It has been shown that the KSS score of the driver can affect the SDLP score as both are closely related. Therefore, the drowsier the driver is, the higher the SDLP score will be, and SDLP will be such a potential indicator in detecting drowsiness [29, 31, 32]. Lastly, the vehicle speed and acceleration might indicate abnormal driving caused by drowsiness since drowsy drivers may accidentally increase or decrease the acceleration of their vehicle [23]. It can also be used to develop a real-time measure of driving context by converting continuous time-series data into discrete symbols called Symbolic Aggregation Approximation (SAX). The result showed that context-based algorithms could perform significantly better in detecting drowsiness than simpler algorithms and Percentage of Eye Closure (PERCLOS) depending on the acceptable false-positive rate [33]. However, measuring drowsiness using vehicle driving parameters requires complex and costly infrastructure [34].

Physiological measurements measure drowsiness using physiological signals from the human body such as the brain, eyes, muscles, and heart. The brain signal is captured by electroencephalography (EEG) signal, the ocular eye activity is measured by electrooculography (EOG) signal, the muscle tone is recorded by electromyography (EMG) signal, and the heart rate is monitored by electrocardiography (ECG) signal [23, 35]. EEG signal is known as one of the most reliable measurements for detecting drowsiness. The raw data from the electrodes can be split into different frequency bands after preprocessing, which involves the removal and filtering of the artefacts [36]. EOG signal identifies drowsiness based on eye movements by measuring the electric potential between the cornea and the retina from the electrical field that reflects the eye orientation [37]. EMG signal is associated with the electrical signal produced by muscle contraction and relaxation. The signal is recorded from the driver's forearm position and steering wheel grip while driving [38] or the movement in the driver's eyelid muscles [39]. ECG is a

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non-invasive signal that can read the heart rate and heart rate variability (HRV). It has two lead systems for detecting hypovigilance, which can be easily implemented into wearable devices. Also, several research works indicate the correlation between internal states and ECG signals [40]. Physiological signals can provide an accurate measure of drowsiness because they are strongly correlated with drowsiness. However, it uses invasive techniques and might make the driver uncomfortable due to wearability issues and limited feasibility [34, 36].

Facial features, such as eyeblink, yawn, and gaze direction are captured using a sensor implemented in the car and then observed to detect drowsiness [21]. The parameters used in detecting drowsiness include Percentage of Eye Closure (PERCLOS), Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head position. PERCLOS is the percentage of the total frame where the eyes are detected as closed within a specific frame interval. A predetermined threshold is defined in order to classify whether the eyes are closed or open. Then, PERCLOS is calculated based on the approximated area of the iris to identify driver drowsiness [42, 43]. Meanwhile, the EAR is used to record eyeblink frequency based on the proportion between height and width of the eye [11, 44, 45]. The EAR value is almost constant while the eye is open, goes down to zero when the eye is closed. The MAR is similar to the EAR, but it uses more amount of mouth landmarks to detect yawns, and the scale is opposite to EAR. The more open the mouth is, the bigger the MAR value will be [46, 49]. The MAR can be measured based on the red colour regions of the lips. However, the performance still strongly depends on the light conditions [47]. The change in the head position is one of the typical behaviour phenomena shown by drowsy drivers. It is usually experienced by drivers in the early stage of drowsiness, marked by the increased frequency of head slipping back down [48, 50].

Behavioural measurements, especially facial behaviours, have been used in much research because, unlike the other approaches, it does not require any complicated and invasive components. However, it can still give fairly good results in detecting driver drowsiness in real-time [2, 34, 41]. Therefore, this approach will be the main focus of this research. Even though many researchers have conducted research about driver drowsiness detection, more and more researchers have got more interested in conducting research about driver drowsiness detection. Thus, this topic has been one of the hot research topics and increasingly developing [3, 44]. This study aims to find out about the development and research trends regarding driver drowsiness detection by reviewing and analysing the current state of research and offering some research direction in the future through a systematic literature review.

The remainder of the paper is organized as follows: Section 2 describes the background of this study and explains the methodology of the systematic literature review (SLR). Section 3 discusses the results of the SLR. Section 4 gives the conclusion of the paper.

2. REVIEW METHODS

This study uses the SLR procedure from Kitchenham [24], [25] for writing the reporting mechanism and creating the research framework. The main steps of this procedure consist of the planning step and the review step. The planning step is the construction of the research question, which will be explained in sub-section 2.1. Meanwhile, the review step is divided into three phases: article search methodology (sub-section 2.2), article selection (sub-section 2.3), and data extraction (sub-section 2.4).

2.1 RESEARCH QUESTIONS

These research questions (RQ) are proposed to maintain the focus while conducting an SLR. The research questions of this study will be shown in Table 1.

TABLE 1
Research Questions

ID	Research Question
RQ1	How is the behavioural approach better than the other approaches in detecting drowsiness?
RQ2	What are the recent gold standards in behaviour-based automatic driver drowsiness detection?

To formulate the research questions, the population, intervention, comparison, outcome, and context (PICOC) criteria from Kitchenham [24], [25] was used. They identified 'population' as the application area of the study and 'intervention' as technology that addresses specific problems. Meanwhile, 'outcome' is quite clearly defined, 'comparison' is defined as the concept to be compared, and 'context' is the niche of the problem. The PICOC criteria will be presented in Table 2.

TABLE 2
PICOC Criteria

PICOC Aspect	Criteria
Population	Driver drowsiness detection
Intervention	Automatic drowsiness detection, behavioural approach
Comparison	Behaviour-based automatic driver drowsiness detection methods vs other methods
Outcome	The advantages of driver behavioural approach and the recent gold standard in the behaviour-based automatic driver drowsiness detection
Context	Behaviour-based automatic driver drowsiness detection

The application area of the articles reviewed in this study is driver drowsiness detection. Therefore, that topic is used as the population criteria of this SLR. The driver drowsiness detection problem can be addressed by some interventions such as automatic drowsiness detection. Since this study focuses on driver behaviour-based drowsiness detection, behaviour-related technology can also be the intervention criteria. This SLR also compares the behaviour-based automatic driver drowsiness detection methods and other methods to show the advantages of the behavioural approaches and the recent gold standards regarding the problem as the outcome. Lastly, this SLR will mainly discuss behaviour-based automatic drowsiness detection, which is the context criteria of this SLR.

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2.2 ARTICLE SEARCH METHODOLOGY

Research articles from journals and conference proceedings in five online databases (Scopus, Science Direct, ACM Digital Library, IEEE Xplore, and SpringerLink) were collected in October 2020. This article search was done by using the Boolean search query: "Drowsiness Detection" AND ("Behavioral" OR "Facial") AND "Measurement", which was derived from the PICOC criteria presented in the previous sub-section.

The initial step of the article search retrieved a total of 133 articles from all databases. Specifically, the number of articles obtained from each database will be shown in Table 3. Then, these articles would be selected according to the article inclusion and exclusion criteria and literature quality assessment checklist, which will be explained in the next two subsections.

TABLE 3
Article Search Result from Each Database

No.	Database	Number of Articles
1	Scopus	8
2	Science Direct	69
3	ACM Digital Library	17
4	IEEE Xplore	13
5	SpringerLink	26
Total		133

2.3 ARTICLE SELECTION

The stages of the article selection process include selecting articles based on inclusion and exclusion criteria, then assessing the quality of the articles based on the article quality assessment checklist.

A. Article Inclusion and Exclusion Criteria

The first stage of the article selection process is selecting the articles based on the inclusion and exclusion criteria that will be described in Table 4. These criteria were constructed considering the language, domain, relevancy, recency, and accessibility aspects in the articles. First, these inclusion and exclusion criteria were applied to the article titles and abstracts. Next, they were applied to the full text of the articles. By only applying the criteria on the first level, the number of candidate articles can be reduced from 133 to 36. Meanwhile, the full-text selection selected only 20 out of 36 articles obtained from the previous level. The number of articles obtained from each database by using the inclusion and exclusion criteria will be presented in Table 5.

TABLE 4
Inclusion and Exclusion Criteria

Inclusion Criteria	1	The article is written in English
	2	The article is published between 2016-2021
	3	The full text of the article can be accessed
	4	The article is related to the search keyword query
	5	The article can answer the research question
	6	The article includes the application of the behavioural approach in detecting
Exclusion Criteria	1	The article is not written in English
	2	The article is not published between 2016-2021
	3	The full text of the article can not be accessed
	4	The article is not related to the search keyword query
	5	The article does not answer the research question
	6	The article does not include the application of a behavioural approach in detecting drowsiness

TABLE 5
Article Selection Result by Applying the Inclusion and Exclusion Criteria

No.	Database	Title and Abstract Selection	Full-Text Selection
1	Scopus	4	4
2	Science Direct	14	7
3	ACM Digital Library	4	0
4	IEEE Xplore	7	3
5	SpringerLink	7	6
Total		36	20

B. Quality Assessment of Articles

After applying the inclusion and exclusion criteria to the candidate articles, the quality of selected articles is then assessed using the article quality assessment checklist. This checklist can be seen in Table 6.

The scores that can be obtained from each checklist range from 0 to 1. Therefore, the highest score that can be obtained by an article is 8. The articles that will be selected from this assessment stage are those with a score above 4.5. All of the articles from the previous stage were selected since there is no single article that scores below the minimum standard. Out of 20 articles selected, 4 articles were obtained from Scopus, 7 articles were obtained from Science Direct, 0 articles were obtained from ACM Digital Library, 3 articles were obtained from IEEE Xplore, and 6 articles were obtained from SpringerLink. Meanwhile, out of 20 articles, 6 articles were published in 2021, 7 articles were published in 2020, 3 articles were published in 2019, 3 articles were published in 2018, 0 articles were published in 2017, and 1 article was published in 2016.

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TABLE 6
Article Quality Assessment Checklist

Checklist	Research Question
C1	Does the article clearly describe the research objectives?
C2	Does the article include a literature review, research background and context?
C3	Does the article include the related works from previous research to show the main contribution of the research?
C4	Does the article describe the proposed architecture or methodology used?
C5	Does the article have results?
C6	Does the article provide conclusions that are relevant to the research objectives/concerns?
C7	Does the article recommend future works or improvements for the future research?
C8	Is the article indexed by Scopus? (Q1/Q2/Q3/Q4)

2.4 DATA EXTRACTION

The data extracted from each article are the advantages of the driver behavioural approach compared to the other approaches and the recent gold standards in behaviour-based automatic driver drowsiness detection. These extracted data are then put into a comparison table.

3. RESULTS AND DISCUSSION

Based on the literature study that has been conducted in 20 articles, it can be found out that the construction and development of behaviour-based automatic driver drowsiness detection have mostly been conducted using some of the methods such as Vander Lugt Correlator [5], Haar Cascade [6, 12, 17], Eye Aspect Ratio [11, 12, 18, 22], and even machine learning methods [11] such as Support Vector Machine [11, 13], Neural Networks [4, 6, 7, 8, 10, 14, 15, 16, 18, 20, 22]. Recurrent Neural Networks like Long Short Term Memory have also been used in some of the research [4, 16, 22].

As for the features used for detecting drowsiness, most of the behaviour-based automatic driver drowsiness detection used eyes as the main features of their models. Head movements [7, 8, 10, 11], other basic facial features such as mouths [4, 8, 9, 12, 19, 21] and facial expressions [6, 7, 9], and some other features such as hand gestures [7], respiration signal [13] or even machine-generated features [14] can also be used as well. However, even though it can be as non-intrusive as using basic facial features, detecting drowsiness using respiration signals requires more sophisticated tools such as a thermal camera.

The advantage of these behavioural approaches is that it is easy to use and more acceptable to users due to the less cost and intrusiveness. These approaches also do not require too much sophisticated hardware since it has been able to be implemented by only using a single basic camera. Therefore, it can be implemented more practically and comfortably by the drivers. According to [23], behaviour-based driver drowsiness detection is much less intrusive and user friendly. Additionally, it can also be mounted comfortably in various areas inside a vehicle for real-time monitoring. However, in terms of accuracy, this approach is still not so good as the physiological approach in detecting drowsiness. Big computational costs are still needed for making a precise behaviour-based drowsiness detection method even though the current researches have shown fairly good scores in accuracy and time. The summary of the result will be presented in Table 7.

TABLE 7
Result Summary

Ref.	Methods	Features	Advantages
[4]	Convolutional Neural Network (spatial) Time Skip Combination-Long Short-Term Memory (temporal)	• Eyes • Mouth	• Does not depend on external factors such as road conditions or driving skills. • Can measure the slight changes of drowsiness because it does not rely on the answers given by the driver. • Drowsiness factors can be easily identified using the facial expressions like abnormal blinking (eyes) or even yawning (mouth).
[5]	Vander Lugt Correlator (VLC)	Eyes	The simulated optical correlation via the VLC has shown its good performance in terms of the eye detection and state estimation.
[6]	Haar Cascade (face detection) Convolutional Neural Network (classification)	Facial expression	• Does not require computionally expensive data collection and fusion. • The sensors are generally low cost and can be non-intrusive. • The system can be implemented using one low-cost conventional camera that can be installed inside the vehicle, and thus, it does not rely on wearable devices.
[7]	Convolutional Neural Network (AlexNet, VGG-FaceNet, FlowImageNet and ResNet)	• Hand gesture • Facial expression • Behavioural features • Head movements	Requires minimal hardware, is very cost-effective and also, does not interfere with the driver's driving ability.
[8]	Yawn Detection Somnolence Detection 3D Head Pose Estimation	• Eye • Mouth • Head angle rotation	Appears easier to exploit under real conditions insofar as they have fewer technical constraints during the deployment.

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[9]	Dlib (library for acquiring facial expressions) Eye Inclination Value (digitise blinks) Frequency analysis (drowsiness detection)	• Facial expression • Eyeblink • Mouth movement (yawn)	Does not require placing the electrode in the vicinity of the eyelid, so it will not cause discomfort to the driver.
[10]	Artificial Neural Network	• Driving performance • Head and eyelid movements • Physiological data	• Less intrusive and constraining. • Unlike physiological features, Physical features vary less with other states such as stress, emotions, workload, etc. • Indicates drowsiness more specifically compared to driving behaviour and performance.
[11]	Eye Aspect Ratio (blink classification) Machine Learning model (MLP, RF, and SVM) with time dimension + Karolinska Sleepiness Scale (real-time drowsiness detection)	Eyeblink	Does not require intensive signal and computer processing (such as EEG and EOG).
[12]	Haar Cascade (face detection) Eye Aspect Ratio (drowsiness detection) OBD-II (vehicle details)	• Eyeblink • Mouth (yawn) • On Board Diagnosis data from the vehicle	• Advantageous due to the live stream of the driver provided such that any mishap due to negligence is averted. • Non-intrusive as it doesn't affect or compromise driver comfort in any way.
[13]	Support Vector Machine K-Nearest Neighbour	• Facial thermal imaging • Respiration signal	• Thermal imaging does not require contact (intrusive) nature. • Has the ability to extract vital signs of drowsiness. • Contact-free, non-intrusive, and robust against driver's movement.
[14]	3D Neural Networks	Implicitly deciced by the machine	• Reduces the need for specialised hardware and hence, enables a cost-effective roll-out of the technology across the driving population. • Can achieve a balance between high prediction accuracy and real-time inference requirements.
[15]	Convolutional Neural Network (face + eye detection)	• Face • Eye openness and closure	Has good deployment capacity and accuracy ratio while analysing the environmental constraints.

[16]	Multitask Cascade Convolutional Neural Network (MTCNN) 1-Dimensional Regular Long Short Term Memory (R-LSTM) and Convolutional Long Short Term Memory (C-LSTM)	Eye	• Non-intrusive and are more suitable for practical reasons. • Very attractive in terms of balance between accuracy and practical aspect • The accuracy is not affected by several factors, including road and weather conditions, driver experience level as well as type of vehicle.
[17]	Haar Cascade (facial landmark deection) Eye Closure Ratio (drowsiness detection)	• Facial landmarks • Eye closure	• Serves as a non-intrusive technique of determining the driver's drowsiness • Does not require any placements of sensors on the driver's body • Does not interrupt the driver while driving.
[18]	CNN-based classifier (facial landmark detection) Eye Aspect Ratio	• Facial landmarks • Head pose • Eye landmarks • Blink rate and duration	Easier to corporate into vehicles.
[19]	Skin tone detection (face detection) Blob histogram analysis (yawn detection)	Lower parts of the face (yawn)	Computationally less complex, robust and has less reaction time.
[20]	Dlib (facial landmark extraction) Multilayer Perceptron (classifier)	Facial landmarks	• Less dependent on vehicle characteristics, road conditions, and driving skills. • Does not require a lot of sensors to be attached to the driver's body, which could be uncomfortable. • Much less price.
[21]	Root Scale Invariant Feature Transform (RootSIFT)	• Eyeblink • Yawning	Invariant to scale, rotation, illumination, viewpoint and translations
[22]	Convolutional Neural Networks (feature extraction) Eye Aspect Ratio (blink detection) Bidirectional Long Short Term Memory (classification)	Eyeblink rate	• Yields excellent results on images with varying backgrounds and lighting. • Has been shown to work effectively in low- resolution images for many eye postures.
[23]	Eye blinking rate, Slow Eye Movements (SEM), and eye closure activities including PERCLOS metric and the Average Eye Closure Speed (AECS).	• Eye movement • Facial expression • Head position	• Non-intrusiveness and user friendly. • Can be mounted comfortably in various areas inside a vehicle for real-time monitoring.

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4. CONCLUSION

In recent years, many methods have been proposed for behaviour-based driver drowsiness detection. These methods involve Neural Networks, Multi Layer Perceptron, Support Vector Machine, Vander Lugt Correlator, Haar Cascade, and Eye Aspect Ratio. Several types of Neural Networks, such as Convolutional Neural Networks, Artificial Neural Networks, and 3D Neural Networks, have been used in many current works, which is an example of machine learning application in this domain.

As machine learning is used in many research works on driver drowsiness detection, it can be one of the gold standards in behaviour-based automatic driver drowsiness detection. These behaviour-based drowsiness detectors mostly use head movements and facial features especially eyes to detect drowsiness, making it less intrusive than the physiological approaches because this approach does not require attaching sensors to the driver's body and is more reliable than the vehicle-based approach because it does not depend on external factors.

The machine learning approaches used are constantly evolving, including automatic driver drowsiness detection using computer vision and deep learning. One of the advantages of the machine learning approach is its ability to learn and improve on its own so it does not require too much human intervention. It also has a wide range of applications and improvements and can also handle a lot of data types. However, these approaches also have some drawbacks, such as requiring a lot of train data and resources to get an ideal model. It will likely be prone to error if the dataset is not sufficient enough for the machine to learn. Additionally, machine learning also requires a lot of computational time to learn and improve the algorithm.

There are still a lot of fields that can be explored in machine learning, including improving computational time and accuracy in behaviour-based automatic driver drowsiness detection. Therefore, as for future works, it will be an interesting point to explore. Research about dataset development will likely improve the accuracy of the machine learning model since it requires a lot of data yet research related to dataset development is still not done much. By developing some new datasets, the data that can be used for training the machine learning model will be more variable. Thus, the model will be able to learn better. As for improving the computational time, merging the facial feature detection and classification step into one machine learning model will likely reduce the computation time in detecting drowsiness. Therefore, the driver drowsiness detection system will hopefully be able to detect the drowsiness without having to use sophisticated computer hardware.

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