Volume 0 (2025), Number 0 pp. 1–5

Systematic literature review of driver monitoring system, fatigue detection, and accident prevention using AI

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Abstract

Every year, the number of vehicles on the roads continues to rise. As the number of drivers increases, so does the number of accidents. One of the most common causes of road accidents is drowsy or fatigued drivers. To address this, various methods have been developed to detect driver drowsiness. This systematic literature review (SLR) aims to investigate the performance of various methods for driver drowsiness detection, focusing on comparing invasive and non-invasive detection techniques together with artificial intelligence. The initial search identified 652 relevant articles, which were then filtered based on predefined criteria, resulting in 21 articles selected for further analysis. Based on the articles analyzed in this SLR, the optimal solution proposed is a combination of two detection methods, trying to combine minimal driver commitment while maintaining high accuracy.

Keywords: AI, Machine Learning, SLR, Systematic Literature Review, Driver, Car, Vehicle, Fatigue, Drowsiness

1 Introduction

Drowsy driving is a significant road hazard and a common cause of accidents. According to the Foundation for Traffic Safety, between the years 2017-2021, 17.6% of all fatal crashes involved drowsy drivers [Tef]. Due to the severity of this issue, many car manufacturers have implemented safety features designed to detect driver fatigue and notify the driver to take a break. Many different types of sensors are used to detect driver fatigue. The most commonly used sensors, covered in this systematic literature review (SLR) include an electroencephalogram (EEG), Facial Features Analysis, Driving Behavior, Electrocardiogram (ECG), and Electrooculogram (EOG), among others. The collected data from these sensors were then processed by different machine learning algorithms, where neural networks, gradient boosting, decision trees, and clustering algorithms were the most frequently applied techniques.

This article is structured as follows: Section 2 outlines the filtering process used for selecting relevant studies. Section 3 presents the results and key findings, including an overview of the different detection methods. Section 4 provides a conclusion of the results and a proposed optimal solution.

2 Material and Methods

In this study, the chosen research methodology was to apply a systematic literature review. This process involves selecting and analyzing relevant scientific articles and publications from different article databases. For this study, Scopus [SCO] was chosen due to its ability to search through many of the largest article databases. This process focused on filtering out articles relevant to the following research question:

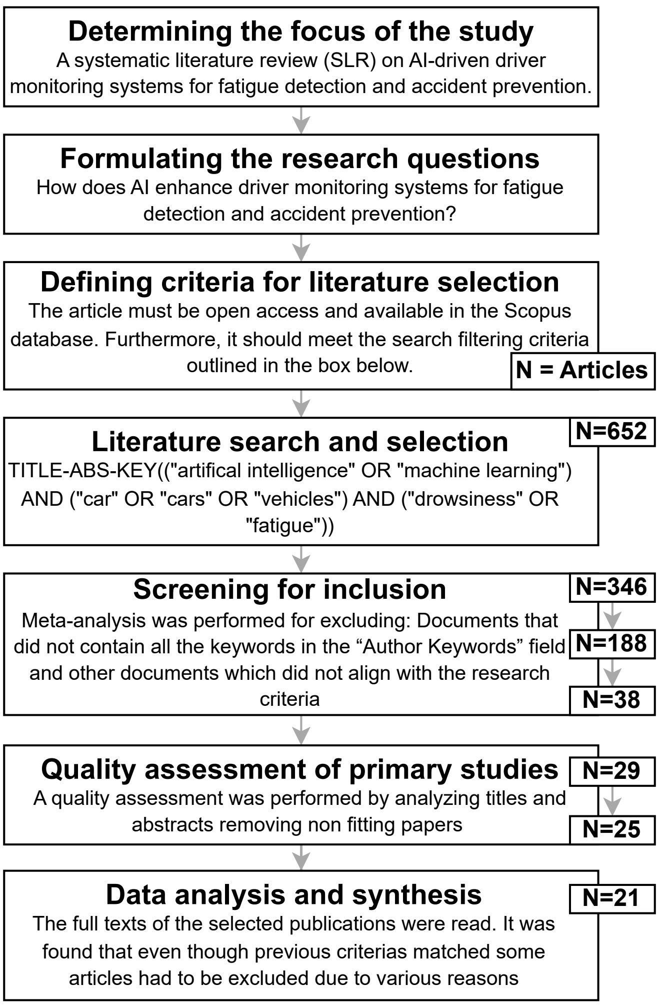
Which sensor technologies integrated with AI, are most suitable for detecting driver drowsiness in real-world driving conditions?

2.1 Article Filtering

When searching for articles relevant to this SLR, it was important to filter out irrelevant articles. The initial keywords filtered out were "AI", "vehicles" and "drowsiness". To further expand the search results, similar keywords were added. The OR operator was used between synonyms of each keyword, enclosed in parentheses to define filtering priority. The AND operator was applied between different keyword categories to refine the search. The search term used on Scopus was:
("artificial intelligence" OR "machine learning") AND ("car" OR "cars" OR "vehicles") AND ("drowsiness" OR "fatigue")
artificial

When filtering using the search string above, 652 articles were found, which was too many to analyze manually. Therefore, the search string was further refined.
The first refinement was limiting the subject area to "Computer Science" and the document type to "Conference Papers and Articles," reducing the results to 346 articles. Next, the search was restricted to English-language articles, narrowing the count to 344. Then, only articles containing the exact terms "Machine Learning"

or "Machine-Learning" were included to ensure relevance to the research question, bringing the number of articles down to 188. Continuing, filtering for open-access articles further reduced the number to 38.
The next step was a manual screening of article titles and abstracts, removing those that were not relevant to the study, resulting in 29 articles. Lastly, articles that lacked relevant author keywords were excluded, leaving 25 articles for the final selection. While analyzing the articles, four additional articles were excluded due to irrelevancy.
The complete search term on Scopus including limitations was:
(TITLE-ABS-KEY(("artificial intelligence" OR "machine learning") AND ("car" OR "cars" OR "vehicles") AND ("drowsiness" OR "fatigue")) AND (LIMIT-TO (SUBJAREA, "COMP")) AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE,"English")) AND (LIMIT-TO (EXACTKEYWORD, "Machine Learning") OR LIMIT-TO (EXACTKEYWORD, "Machine-learning")) AND (LIMIT-TO (OA, "all")))



3 Results

Source	Detection Method							Performance
	EEG	ECG	EOG	FF	DB	UWB	O2	
[PASD23]	✓	✓						89.2%*
[MRS*24]			✓					99%
[DSCS*24]				✓				100%
[GKLM23]			✓	✓				84%
[WSZ*23]	✓	✓						96%
[SCP*24]	✓	✓	✓					None
[ASI*23]		✓						83.3%
[MTX*24]				✓				96.5%
[MSK*23]			✓					98.7%
[EET*23]	✓							98.5%
[SAI*24]						✓		99.6%
[KSR20]		✓						92.1%
[TDS21]	✓							100%
[Y22]				✓				92%
[GHS20]				✓	✓			78.7%
[SFCJ21]	✓							60%
[BKKC23]			✓					97.7%
[SSB*21]						✓		87%
[JA20]			✓	✓			✓	None
[AKP*21]		✓	✓	✓				83.3%
[BZB*22]				✓	✓			92%

* Accuracy is measured based on a multiclass prediction with three classes or higher, rather than standard binary classification.

Table 1:
EEG - A test that measures electrical activity in the brain.
ECG - A test to record the electrical signals in the heart.
EOG - Recording of the eye movement.
FF - Facial Features
DB - Driving Behavior
UWB - Ultra-Wide Band
O2 - Oxygen Levels

3.1 Summary of key-findings

The analyzed papers propose different techniques for detecting drowsiness and fatigue while driving. Sensors can generally be classified into two types: invasive and non-invasive. Non-invasive sensors aim not to distract the driver from physical sensors that must be placed on the body, compared to invasive sensors, where one or more sensors must be attached to the driver.

3.2 Invasive Detection Method

3.2.1 Electroencephalogram (EEG)

An electroencephalogram (EEG) is a detection method that measures electrical activity in the brain using small metal sensors placed on the head. EEG sensors are effective for drowsiness detection given that brain activity is measured directly, providing insights into the mental state in real-time. This makes EEG sensors accurate and reliable for detecting drowsiness before any visible signs. With EEG, the accuracy of the classification is largely dependent on how many electrodes are being used. As shown in [PASD23], when using 19 electrodes in a binary classification, an accuracy of 99.5% was achieved. Meanwhile using only four electrodes resulted in 96.83% accuracy. Similarly, in [TDS21], a setup with 32 electrodes achieved a binary classification accuracy of 100%. In contrast, [SFCJ21] reported only 60% accuracy when using six electrodes, which highlights the impact that electrode count has on performance.
According to [WSZ*23], the drawback of EEG is the limited portability of the recording devices, making this detection method less suitable for use in vehicles. Additionally, this detection method becomes more intrusive as the number of electrodes increases, which contradicts the improved performance achieved with more electrodes.

3.2.2 Electrocardiogram (ECG)

Electrocardiogram (ECG) is an invasive test that records the electrical signals from the heart. ECG is most accurately measured on the chest using electrodes, but in recent years even some smartwatches have included this feature. Although ECG detection on the wrist is considered invasive, it is one of the least intrusive among the methods discussed in Section 3.2.
Similar to EEG, more intrusive and professionally used ECG devices yield higher accuracy. This is shown in the following article [KSR20], where both a wristband and a medical-grade ECG sensor were tested. When comparing the results of the best-performing models for each detection device, the wristband achieved an accuracy of 92.13%, while the medical-grade sensor reached 97.37%. Even though medical-grade sensor shows a slight performance improvement, the authors conclude that “the obtained results with data from wristband and ECG are comparable”. One of the main causes for the increased accuracy in professional devices is the higher sampling rate. One study [ASI*23] originally compared a wrist-worn device emulating a smartwatch, and a professional ECG device. The results were 83.3% and 91.3%, reflecting the same difference observed in the previous study. To address this, the final part of the study aimed to close the gap in accuracy between the devices by oversampling the ECG signal of the wrist-worn device using interpolation. By doing so, they managed to increase the sampling rate of the wrist-worn device from 4Hz to 256Hz, matching the sampling rate of the professional device. This yielded an increased accuracy of 89.4% for the wrist-worn device, which was much closer to the professional device. This shows that the sampling rate is indeed one of the crucial factors in an ECG device’s precision.

3.2.3 Electrooculography (EOG)

"The electrooculogram (EOG) is an electrophysiologic test that measures the existing resting electrical potential between the cornea and Bruch’s membrane" [EYE]. Where the resulting signal is called the electrooculogram. This detection method is very effective, achieving an accuracy of 99% with a detection time of 0.0083 seconds in the following study [MRS*24]. However, a major flaw of this method is the obstruction of vision, which is highly invasive, potentially causing accidents rather than preventing them [AKP*21].

3.3 Non-invasive Detection Methods

3.3.1 Facial Features Analysis

Analyzing facial features is the most common non-invasive method when it comes to the detection of drowsy driving due to its low cost, simplicity of setup, and lightweight in terms of computing resources. [Y22] even managed to achieve drowsiness detection by only using a Haar Classifier. The facial feature method works by pointing a regular or infrared camera toward the driver and then performing a series of facial feature extraction steps on the video feed. Commonly, the method aims to extract eyes, mouth, and head rotation. This is to perform pattern detection on yawning, eye state, or lack of focus on the road. This type of technique gives good results when combined with a CNN as seen in [MTX*24] where the research team achieved an accuracy score of 96.54%

Although drowsiness detection using facial features is promising and can be used as a standalone detection method, it has some challenges that need to be considered. [AKP*21] among others encountered the problem of different eye shapes varying between drivers. Where stature, breadth, and tallness all differ, making it difficult to accurately predict drowsiness. Further, both [GHS20] and [BZB*22] propose the solution of a personalized prediction model. [BZB*22] implements and validates the idea which shows great results. The non-personalized model results in an accuracy of 71.6% meanwhile a personalized model achieves an accuracy of 92%. Even though facial features show promising results on their own, [GHS20] proposes the idea of combining it with other techniques such as EEG and ECG to further improve accuracy.

3.3.2 Driving Behavior

Analyzing driving behavior is a method that comes up briefly in most articles, but not to the extent where it has been used in classification. It works by analyzing acceleration and deceleration patterns, steering angle, and longitudinal and latitudinal position of the vehicle, among many other factors. In [GHS20] and [BZB*22] this technique is used as a complement to facial feature analytics since it cannot be used as a stand-alone method. According to [BZB*22], driving behaviors differ greatly between drivers, thus a personalized model would be needed, making it less versatile. Further, predicting drowsiness based on driving behavior is becoming obsolete due to the rise of self-driving technology implemented in most modern vehicles.

3.3.3 Ultra-Wide Band

Ultra-Wide Band radar (UWB) is a technique presented in [SAI*24] and [SSB*21], where it is used to analyze respiration rate patterns of drivers using radio waves. It works by detecting the reduced frequency of breathing, which occurs right before a human is about to fall asleep. UWB is an effective, non-invasive method that does not require any driver commitment since it can penetrate through multiple materials and still allows for accurate readings. Since the sensors are very sensitive, valuable information such as micro-movements and vibrations can be collected to analyze breathing and heartbeat. Further, when applying a machine learning algorithm such as SVM (Support Vector Machine) seen in both [SAI*24] and [SSB*21], good results are shown with an accuracy of 96.6% and 87%, respectively. These results combined with the simplicity of data collection allow for promising real-world implementation.

3.3.4 Oxygen Levels

Air quality sensors are a non-invasive method that works by measuring the amount of carbon dioxide inside the cockpit of a vehicle in terms of ppm (parts per million). According to [JA20] carbon dioxide sensors are a cost-effective, accurate, and reliable metric for drowsy driving detection. Indicating that once concentration levels of carbon dioxide exceed 1500ppm, drowsiness is expected to occur. Although oxygen sensors are promising, they do not collect enough data to serve as a stand-alone metric. However, combining it with other sensors such as facial features and EOG as done in [JA20] shows promising results.

4 Conclusion

This systematic literature review has explored multiple research papers on drowsiness detection. Including both invasive and non-invasive methods, where each approach has advantages and limitations. Results show that invasive sensors tend to have higher accuracy, at the cost of being intrusive and inconvenient for the driver. In comparison, non-invasive methods offer the convenience of not needing any commitment from the driver. The drawback is dependence on environmental factors, which can slightly affect performance. Since detection methods are easily combinable, based on the results presented in the different methods, we propose that the optimal solution would be to pair facial feature analysis with a form of heart monitoring, either UWB or ECG. The choice depends on the balance between ease of use, driver engagement, and the impact of environmental factors.

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