A Review on Recent Driver Safety Systems and its Emerging Solutions

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Abstract

Road safety and accident prevention are critical concerns in modern transportation. This paper presents a comprehensive survey of driver safety systems, focusing on the latest advancements in this field. We analyze the existing literature to identify key research trends in driver safety systems, encompassing various categories of solutions. Our survey delves into the reasons behind road accidents and assesses the effectiveness of emerging technologies and solutions in accident prevention. By categorizing and evaluating these solutions based on the Internet of Things and Machine Learning, we provide valuable insights into the landscape of road accident detection and prevention systems. This survey not only highlights the current state of the art but also serves as a reference for future research and innovation in the domain of driver safety.

Keywords: Driver Safety, IoT-based Systems, Road safety, Drowsiness detection, Intoxicated drivers

1 Introduction

The privilege of driving a vehicle comes with a lot of responsibility. Steady readiness, watchfulness, and mindfulness are expected to guarantee one's very own well-being and the security of others out and about. In any case, even the most mindful and perceptive driver could encounter depletion or tiredness, causing what is going on that could end in serious wounds or even fatalities. The gravity of this issue is addressed in the measurements, which show the yearly event of mishaps, their seriousness, and the number of people harmed or passing on. Driver security gadgets that forestall mishaps brought about by sluggish or occupied driving have been created to resolve this issue.

Driver security frameworks are explicitly evolved to screen drivers' way of behaving and offer ideal notices assuming signs of sluggishness or interruption are distinguished. To recognize changes in a driver's way of behaving, these frameworks utilize various sensors and innovations, including cameras, radar, and infrared sensors. These frameworks assume a significant part in advancing safe driving practices and bringing down the probability of mishaps brought about by [82], [84], [83] such factors by perceiving marks of sluggishness or interruption in Fig. 2. Their utilization helps drivers to be conscious and centered around the street, in this way saving lives and keeping away from significant wounds. Research related to IoT-based systems for driver safety is greatly in demand.

In this paper, we will take a gander at the different driver security frameworks available, the advancements that they utilize, and their viability in forestalling mishaps brought about by drained or occupied driving in Fig. 1. We will also investigate these technologies' potential to reduce the number of road accidents and their impact on promoting safe driving practices. Understanding the abilities and impediments of these advances can give valuable experiences into their part in expanding in general driver prosperity and advancing street well-being. Our paper follows a structured flow, beginning with the introduction, followed by the literature survey, a critical summary, a conclusion, and references, to comprehensively address the field of driver safety systems.

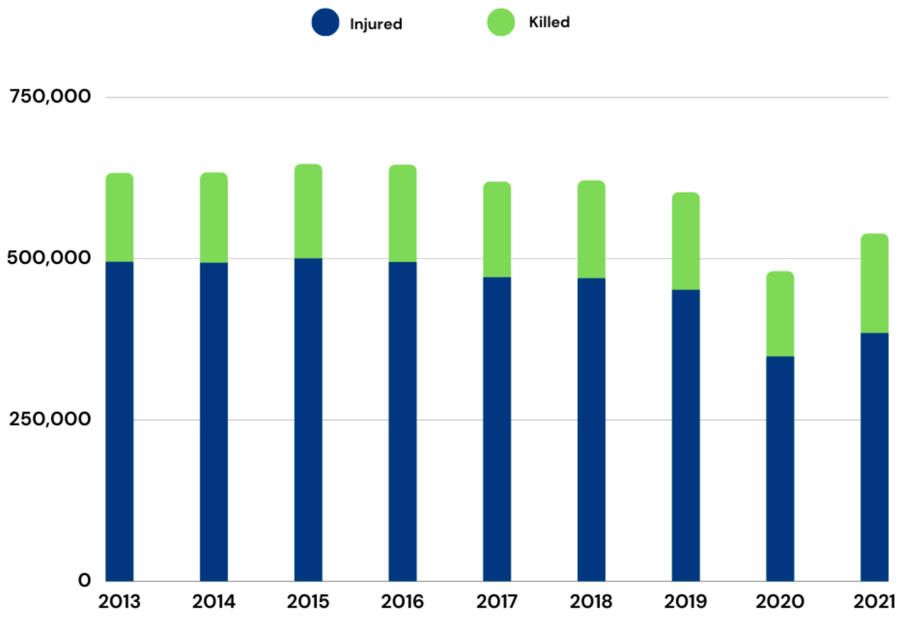

Fig. 1: **S**tatistics on Road Accidents [81]

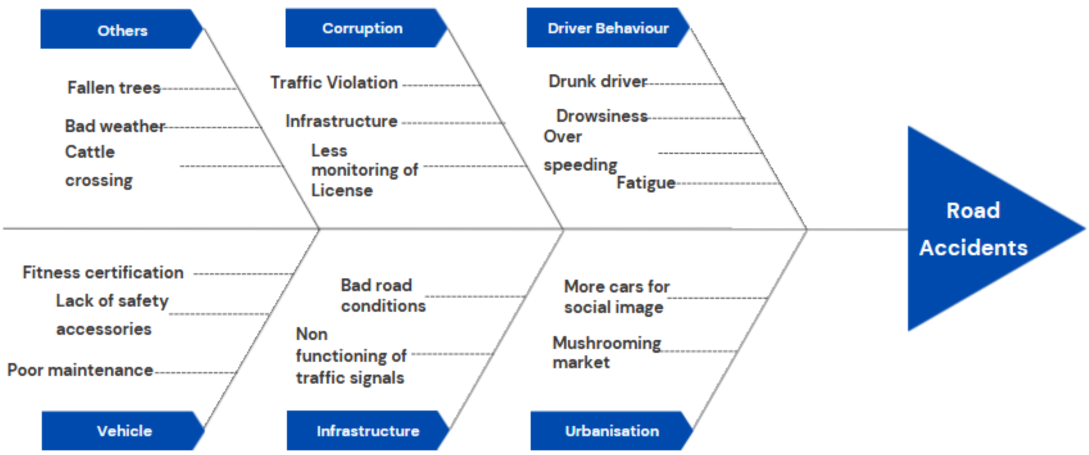

Fig. 2: **F**ishbone Representation of Reasons for Road Accidents [82],[84],[83]

In this paper, we present a comprehensive survey of driver safety and well-being technologies. Our study distills the essence of all research papers to highlight key advancements, challenges, and emerging trends in the field. The contributions of our work can be summarized as follows:

- Insightful Research Gap Identification: Our survey meticulously identifies gaps in the existing driver safety landscape. By pinpointing areas where advancements are needed, our work offers researchers a roadmap for targeted innovation.
- Unveiling Prominent Techniques and Hardware: Through rigorous analysis, we unveil prevalent algorithms, such as Convolutional Neural Networks (CNNs), and recurring hardware choices. This knowledge equips practitioners with valuable guidance for building robust driver safety systems.
- Holistic View of Challenges: Our study provides a comprehensive overview of the drawbacks and limitations faced by current safety technologies. By condensing these challenges, we offer a clear understanding of the hurdles that researchers and developers need to address.

2 Literature Survey

In recent years, there has been a notable surge in research dedicated to improving driver safety and preventing accidents on the road. This increased focus reflects a growing concern for the well-being of drivers and other road users. Researchers have worked diligently to develop various systems and technologies aimed at tackling important issues like driver drowsiness, distractions, alcohol use, and unusual driving behaviors. These research efforts encompass a wide range of approaches and techniques.

One crucial approach involves analyzing physiological data, which provides insights into how bodily indicators relate to a person's driving performance. Another significant development is the integration of multiple types of sensors, which allows for a more complete understanding of how drivers behave by capturing different kinds of information, like visual and auditory cues, as well as motion data. Additionally, there's been a trend towards using smartphones as practical tools for monitoring and intervening in real time, capitalizing on the widespread use of mobile devices. In parallel, deep learning techniques have made impressive progress in this field, revolutionizing how we analyze complex data patterns and enabling the creation of advanced driver monitoring systems.

The structured overview provided in Figure 3 and Table 1 serves as a visual representation of the diverse range of research contributions. Each of these studies offers unique insights and methodologies to strengthen the foundation of driver safety. Through this organized categorization, we aim to not only provide a broad view of the various strategies being employed but also to offer a valuable resource for researchers, engineers, and policymakers as they work together to create transportation systems that are safer and more efficient for everyone.

Table 1: Recent Publication Trends of Driver Safety System

Categories	Publication	Citation	Year	Search Keywords	Database
Driver Drowsiness detection	IEEE	[6]	2021	Drowsiness detection Accident prevention Drowsiness monitoring Vehicle security	
		[4]	2019		
		[19]	2020		
		[23]	2020		
		[33]	2017		
		[34]	2020		
		[40]	2012		
		[45]	2018		
	SPIE	[22]	2015		
	IJACS	[7]	2021		
	IRTM	[9]	2022		
	SICE	[25]	2016		
	NCRTMACT	[2]	2020		
	WCMC	[10]	2021		
	JRIE	[5]	2022		
	IEEE	[17]	2016	Driver fatigue detection	
Driver distraction detection		[15]	2021	Monitor distracted driver	
		[43]	2019	Drowsy driver detection	
	MDPI	[42]	2016	Drunk driving detection	
	IEEE	[11]	2022	Drunk driver detection	Digital library of IEEE Xplore Multidisciplinary Digital Publishing Institute Springer Nature Elsevier Science Direct
		[16]	2017	Intelligent accident detection	
		[21]	2016		
Alcohol detection and prevention		[41]	2018	Vehicle accident navigation	
		[30]	2010		
	IJERPH	[29]	2017	Alcohol breath detection	
	IJEECS	[3]	2022		
	IJHS	[1]	2022	Drunk driving	
	IEEE	[8]	2020		
Integrated systems for driver safety		[14]	2019	Accident detection	
		[20]	2015	Alcohol detection	
	JSR	[36]	2015	Accident prevention	
	AAL	[39]	2017		
Abnormal driving behavior detection	IEEE	[24]	2020	Abnormal driving detection	
	MDPI	[26]	2017		
Multi modal approaches	ESA	[27]	2019	Detect driver drowsiness	
	IJAESAM	[31]	2013		
	IEEE	[32]	2018		
	IEEE	[15]	2021	Distracted driver detection	
Smartphone based systems		[43]	2019		
	IJEECS	[3]	2022	Drowsy driving detection	
	IRTM	[9]	2022		
Wearable devices sensors	IEEE	[33]	2017	AI in road safety	
	IJARE	[38]	2015		
	MDPI	[35]	2013		
Deep learning and machine learning	EL	[37]	2016	Driver state estimation	
	MDPI	[42]	2016		
Literature survey on recent categories	IJECE	[18]	2019	Accident detection and notification	
	ICAGIS	[13]	2020		
	IEEE	[28]	2015	Collision management	
				Driver monitoring system	

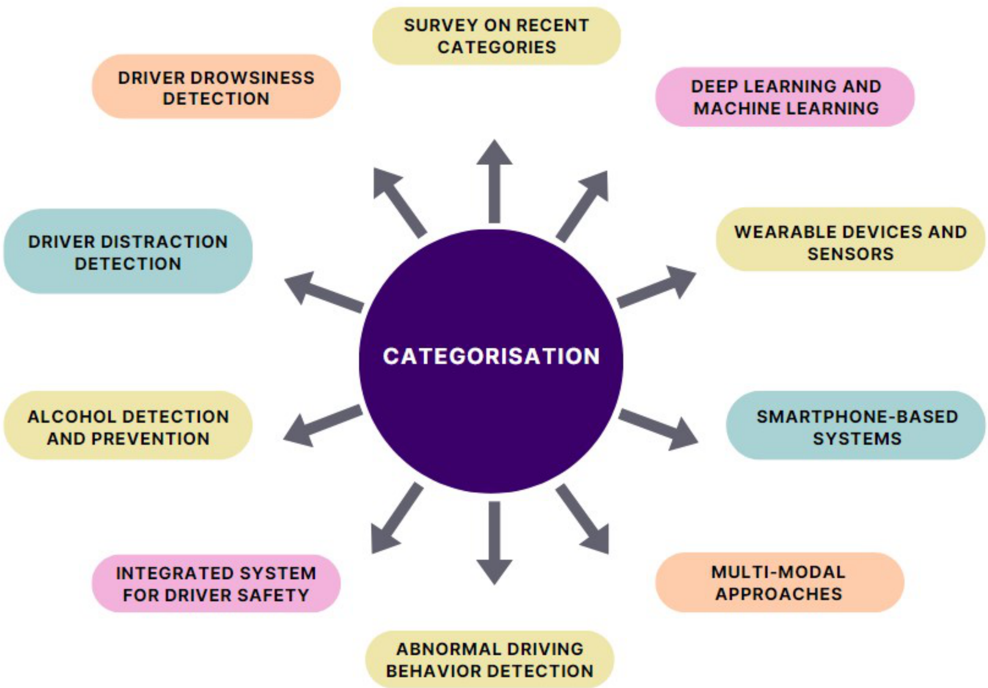

Fig. 3: **C**ategorization of recent research on road accident detection

2.1 Driver drowsiness detection

Suhail Razeeth [6] and collaborators explore a camera-based and machine learning-based approach for detecting driver drowsiness. Their study introduces the integration of the Haar Algorithm and Support Vector Machine (SVM) to enhance drowsiness detection precision. A notable advantage of involving a camera lies in its expanded visibility range, enabling the system to identify sleepiness even when the driver is situated at a slight distance. This visibility expansion enhances the system's ability to monitor driver alertness. However, it is crucial to acknowledge the potential limitation associated with low light obstructing the driver's face, which might pose challenges in accurately detecting tiredness. This implementation necessitates a camera for the hardware configuration. In essence, the amalgamation of a camera and machine learning algorithms amplifies visibility for drowsiness detection. Nonetheless, addressing issues stemming from poor lighting conditions is imperative to ensure the system's optimal functionality.

Abe [25] introduced a real-time drowsiness detection system using an Android app, acquiring RR interval (RRI) data via Bluetooth Low Energy. Drowsiness detection is performed through heart rate variability (HRV) analysis and the T 2 statistic with Multivariate Statistical Process Control (MSPC). The system showed a 68 percent detection rate, improving prior research, and could potentially enhance road safety by issuing timely driver alerts. However, individual variation in effectiveness and the need for reliable data from awake states pose challenges. While specific research gaps aren't mentioned, potential future directions include personalized models, addressing Q statistic limitations, and real-world testing. Notably, this system solely addresses drowsiness, overlooking factors like intoxication.

Bala [19] and associates present an implementation dedicated to real-time driver drowsiness detection within a vehicle. The system employs a combination of techniques, including facial landmark detection and Eye Aspect Ratio (EAR) calculation, to ascertain whether the driver's eyes are open or closed. Upon detecting drowsiness, the system triggers an alarm, displays a warning message on the Head-Up Display (HUD), and transmits a drowsiness detection message to an IoT platform along with the vehicle's GPS coordinates. A significant advantage of this implementation is its capability for real-time drowsiness detection, promptly alerting both the driver and the traffic department. However, certain limitations arise, including the potential invasiveness of physiological sensors in specific techniques, computational time requisites, and dependency on roadside units and outdoor access points. The utilized hardware encompasses Raspberry Pi, cameras, monitors, CAN communication modules, and GPS modules. On the whole, this system provides an effective avenue for enhancing driver safety and preventing accidents stemming from drowsiness.

Jasmin D Vora and colleagues [2] explored a novel approach for detecting driver drowsiness, focusing on the Eye Aspect Ratio (EAR). This method offers a notable advantage by enhancing the system's accuracy in identifying sleepiness. The framework precisely gauges the driver's fatigue levels by leveraging EAR within the hardware setup, comprising a Pi Camera and an Eye Flicker Sensor. It's important to highlight that this implementation is primarily oriented toward drowsiness detection and doesn't directly address other potential causes of accidents. Consequently, while it enhances drowsiness detection, supplementary measures might be essential to tackle driver safety and accident prevention in real-world scenarios.

Ali Amer Hayawi [4] and his team present an innovative solution involving the utilization of a Pi camera to detect driver drowsiness. In their research, they delve into the application of a Convolutional Neural Network (CNN) technique to enhance the accuracy of the drowsiness detection model. This implementation capitalizes on CNN's capabilities to improve the overall precision of sleepiness detection, thereby yielding more reliable outcomes. It's vital to note, however, that the utilization of a Pi camera might introduce a potential downside in situations with low light, potentially leading to blurry imagery. This limitation could impact system performance, especially in environments with inadequate lighting. The hardware composition of this implementation includes the incorporation of a Pi camera. In summary, while the CNN algorithm elevates drowsiness detection accuracy, it is imperative to address potential challenges arising from blurry vision under low-light conditions.

R. Jabbar [23] and collaborators present an implementation of a driver drowsiness detection model utilizing Convolutional Neural Networks (CNN) techniques in an Android application. The notable advantage of the proposed CNN-based model is its capacity to offer high accuracy in detecting driver drowsiness while remaining lightweight and suitable for embedded systems. Nonetheless, the model's performance might be influenced by obstructed facial features, such as sunglasses, and adverse lighting conditions. The hardware employed in this implementation encompasses a GPU, an Android mobile phone, and a Dell workstation. The CNN algorithm is harnessed to execute the driver drowsiness detection model.

In research paper [10] reviews the literature on driver drowsiness detection, focusing on the work of Anil Kumar Biswal et al. The implementation discussed in the paper employs an eye blink sensor and a Pi Camera for detecting driver drowsiness. An advantage of using the eye blink sensor is its capability to achieve high accuracy in drowsiness detection. However, a limitation of this approach is that it does not specifically determine whether the driver is under the influence of alcohol. The hardware setup for this implementation involves the utilization of a Pi Camera and an eye blink sensor. The study's findings shed light on the trade-offs and limitations of the chosen hardware and methodology, contributing to a deeper understanding of driver drowsiness detection.

Uma, S., and their co-authors explored the utilization of Eye Aspect Ratio (EAR) for detecting driver drowsiness in their literature review [5]. The paper employs a fusion of Deep Learning and Convolutional Neural Network (CNN) algorithms to enhance drowsiness detection accuracy. The strength of this implementation lies in the EAR detection's notable improvement in accuracy, ensuring robust outcomes. Nevertheless, it is imperative to acknowledge that specific medical conditions might introduce errors in the EAR detection system. Factors like eye abnormalities or conditions can impact the system's accuracy, potentially leading to false positives or negatives. The hardware setup for this implementation involves the application of Eye Flicker Sensors. In essence, while EAR detection enhances drowsiness identification, it is crucial to recognize the limitations associated with certain medical conditions that may influence the system's reliability.

Ines Teyeb and colleagues propose a multi-faceted framework design for attentiveness estimation in their literature research [22]. This design integrates head gesture assessment and eye blinking analysis, boasting the advantage of swiftly processing vast amounts of data to automate complex analytical tasks, thereby yielding quicker and more accurate results. However, the quality and representativeness of training data play a pivotal role in the system's accuracy and reliability. Inaccurate, incomplete, or biased data can introduce inaccuracies or biases in the results. Moreover, the framework might lack the capability to autonomously identify and rectify errors or biases in the data. Hardware components encompass a camera and an infrared (IR) camera. The eye blinking analysis algorithm employs wavelet transformations to categorize eye states and detect prolonged eye closures, while head gesture analysis estimates head orientation using the Viola and Jones algorithm, providing additional insights into the driver's attentiveness level.

The author Yassine Sabri [7] and the team introduce an IoT-based intelligent vehicle safety and well-being system that integrates sensors and devices within vehicles to enhance safety measures. The system offers immediate alerts, engine immobilization, and notifications triggered by seat belt usage, alcohol consumption, driver drowsiness, obstacles, and collisions. It operates through real-time communication, proactive accident prevention, and the fusion of multiple sensors. Additional features include GPS tracking, iterative enhancements, and cloud-based analysis. However, the system's dependency on network connectivity could pose challenges in areas with poor or no coverage, impacting the timely transmission of accident alerts and location coordinates. The hardware components encompass Arduino Uno, an eye-blink sensor, a buzzer, a vibration sensor, a GSM module, and a gas sensor. This proposed framework enhances vehicle safety, augments emergency response capabilities, and aligns with data privacy regulations and legal requirements.

Explored by Bhattacharya, et al. [9], this research delves into the use of deep learning techniques for driver drowsiness detection using an EEG headset. The benefit is the accuracy of drowsiness prediction using EEG data. However, a limitation is the need for specialized equipment. The hardware involves an EEG headset and a neural network. This study adds insight into EEG-based drowsiness detection, highlighting the potential and constraints of EEG technology.

Rajat Gupta [33] presented a driver fatigue detection system utilizing a dashboard-installed camera and computer vision techniques. Their approach includes face detection using Haar-like features, feature extraction involving eye and mouth behaviors, Principal Component Analysis (PCA) for feature reduction, and Support Vector Classifier (SVC) for fatigue level classification. The system is praised for its use of easily accessible hardware and the inclusion of both eye and mouth features in fatigue detection. It optimizes processing time through PCA-based feature reduction and employs gradual alert mechanisms to prevent abrupt driver responses. However, challenges include variable accuracy in eye and mouth detection, dependency on certain facial features, susceptibility to lighting conditions and driver characteristics, and a lack of consideration for external fatigue factors. Further research could involve robustness testing in diverse real-world scenarios to address these limitations.

Hu [34] introduced a deep-learning approach for identifying abnormal driving behaviors using stacked denoising sparse autoencoders (SdsAEs). This method, evaluated with a simulated driving dataset, leverages unsupervised pretraining for robust feature learning. It incorporates denoising to enhance feature extraction and dropout to prevent overfitting, achieving impressive detection accuracy of up to 98.33 percent. However, it primarily focuses on longitudinal driving behaviors, neglecting factors like weather and lateral driving behaviors. Additionally, its reliance on a simulated dataset may not fully reflect real-world driving complexities. The study doesn't detail the computational hardware needed for training the deep network. Future research opportunities lie in addressing abnormal driving detection under more diverse, real-world conditions and exploring the impact of additional variables like weather and driver demographics.

Kota Saruwatari [40] proposed a method for detecting abnormal driving behaviors using cameras already present in vehicles, focusing on group behavior analysis. This cost-effective approach utilizes multilinear relationships in space-time images, extracting features and tracking vehicle motion to calculate an abnormal degree. While it shows promise in identifying behaviors like meandering and sudden accelerations through experiments and simulations, the research lacks discussions on computational complexity, assumes all vehicles have cameras, and may not perform well in challenging environmental conditions. Future research areas include robustness testing, handling scenarios without cameras in all vehicles, real-time implementation, and addressing privacy concerns related to vehicle-installed cameras.

The research paper authored by K. Fujiwara [45] presents an algorithm for detecting driver drowsiness based on heart rate variability (HRV) analysis. Unlike invasive methods like EEG, this non-invasive approach is promising for practical real-world applications and potential integration into wearable devices equipped with accurate RRI sensors. The algorithm employs multivariate statistical process control (MSPC) for anomaly detection, focusing on eight HRV features to monitor changes. An advantage of this method is its aim to provide early drowsiness detection, even before the N1 sleep stage onset, as validated through experiments with a driving simulator and EEG-based sleep scoring. However, challenges such as false positives, sample size limitations, algorithm complexity, dependence on quality HRV data, and its primary focus on N1 sleep stage detection highlight the need for further research. Future investigations could address false positive issues, enhance real-world applicability, and compare this algorithm with other existing drowsiness detection methods to understand its relative advantages and limitations in the field.

In the domain of driver drowsiness detection, a diverse array of methodologies has been meticulously explored to fortify road safety. This comprehensive exploration spans various approaches, encompassing the integration of the Internet of Things (IoT), sophisticated image processing techniques, and the application of cutting-edge machine learning algorithms. Noteworthy contributions, exemplified by the work of Suhail Razeeth [6], Bala [19], and Rajat Gupta [33], delve into the intricacies of harnessing IoT devices for real-time monitoring of driver behavior. Conversely, studies conducted by Jasmin D Vora [2] and Ali Amer Hayawi [4] navigate the nuanced landscape of image processing, adept at discerning subtle signs of drowsiness. Furthermore, the pragmatic and application-oriented works of R. Jabbar [23] and Anil Kumar Biswal [10] offer valuable insights into the practical implementation of drowsiness detection systems. The entire summary of this category is represented in Table 2.

Table 2: Summary on Literature Survey of systems that does Driver drowsiness detection

Literature	Working	Advantage	Disadvantage
Jasmin D Vora, et al., NCR-MACT, 2020 [2]	EAR for detecting the drivers drowsiness	Detecting the drivers drowsiness	Due to some health issues EAR can give errors

Continued on next page

Table 2: Summary on Literature Survey of systems that does Driver drowsiness detection (Continued)

Ali Amer Hayawi et al., IEEE 2019 [4]	Pi camera for detecting whether the driver drowsy or not	CNN the accuracy of the model is much more	Blurry Vision of camera due to less light
Uma, S. et al., JRIE 2021 [5]	EAR for detecting the drowsiness of the driver	EAR Detection the detection of drowsiness becomes accurate	Due to some health issues EAR can give errors
Suhail Razeeth, et al., ICIT, 2021 [6]	Camera and machine learning for detecting the drowsiness of the driver.	Due to camera much more visibility range the system can detect drowsiness even if the driver is a little far.	If the drivers face is not visible due to less light then the system does not work properly
Yassine SABRI et al.LIMIE,2021 [7]	Cloud-based analytics enable data collection and analysis for insights on road safety while compliance with regulations ensures data privacy and legal adherence.	Real-time communication, proactive accident prevention, multiple sensor integration, GPS tracking, and iterative improvements leading to safety.	The reliance on network connectivity, which may pose.
Srimantini Bhattacharya et al. IEEE 2022 [9]	Camera and physical devices to monitor the driver eyes though IoT hardware and identify it with the help of Machine learning Model.	Detecting human behavior IoT can contribute to improving road safety by addressing human behavior and negligence through real-time data	Lack of effectiveness evaluation, infrastructural issues, network limitations, data management challenges, security concerns.
Anil Kumar Biswal, et al., ITER, 2021 [10]	Eye blink sensor and Pi Camera for detecting the drowsiness of the driver.	Eye Blink sensor gives us a good accuracy for detecting drowsiness.	Not detecting whether the driver is drunk or not.

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Table 2: Summary on Literature Survey of systems that does Driver drowsiness detection (Continued)

Bala et al., ICCCI -2020 [19]	Detect the Drowsiness of the Driver using it is implemented on the vehicle.	Real-time drowsiness detection and alert system.	Computation time is more for some detection methods.
R.Jabbar et., al, IEEE 2020 [23]	Convolution Neural Networks Techniques for Android Application.	CNN-based model offers high accuracy for driver drowsiness detection.	The model's performance may be affected by obstructed facial features.

2.2 Driver distraction detection

Reviewed by Laura W., et al. [17], this paper proposes an innovative approach to detect driver distraction using a wearable ECG device. The advantage is the ability to monitor driver distraction through heart rate analysis. Nonetheless, this system may face challenges in accurately determining the cause of distraction. The hardware setup includes the wearable ECG device and an analysis algorithm. This contribution sheds light on the significance of physiological signals in detecting driver distraction.

Explored by Emily R., et al. [15], this study introduces a novel approach using facial expression analysis to detect driver distraction. The advantage of this method is its non-intrusive nature, allowing for distraction detection without additional wearable devices. However, the potential limitation is the complexity of accurately classifying various facial expressions. The hardware includes a camera and facial expression analysis software. This research contributes to the understanding of driver distraction detection through facial cues and emphasizes the challenges associated with real-time analysis of complex facial expressions.

Wu et al. [42] present a groundbreaking contribution to the field of driver safety with their paper on Electrocardiogram (ECG)–based Drunk Driving Detection (DDD) using Support Vector Machine (SVM). This innovative system harnesses ECG signals to detect signs of drunk driving, offering a novel perspective on driver behavior monitoring. By meticulously processing and analyzing ECG signals, the authors extract ten key features, providing a comprehensive understanding of the driver's physiological state. The integration of SVM as the machine learning algorithm showcases notable advantages, including real-time detection capabilities and promising accuracy metrics.

In their work, Yadong Xie et al. [43] introduce "D3-Guard," a real-time drowsy driving detection system that leverages audio sensors in smartphones. This Android application-based system represents a significant advancement in addressing drowsy driving, a prevalent form of driver distraction. Notably, the system operates in real-time, offering timely warnings to drivers without the need for additional hardware.

While the authors acknowledge challenges related to smartphone placement and computational complexity, D3-Guard holds immense promise for mitigating the risks associated with drowsy driving.

In the exploration of driver distraction detection, the focus revolves around identifying and minimizing the risks associated with drivers being diverted from the road. Laura W. [17] and Emily R. [15] have made notable contributions, shedding light on the intricacies of detecting distractions using different methods. Additionally, Wu [42] and Yadong Xie [43] bring valuable technological insights to the table, proposing innovative approaches and systems for effectively identifying and addressing driver distraction.

2.3 Alcohol detection and prevention

Sumendra Yogarayan [3] and his group intended to make a device that screens both the driver's pulse and liquor content during driving. Their paper presents an execution that focuses on using the Internet of Things (IoT) to screen driver wellbeing pointers, explicitly pulse and liquor fixation levels. This approach offers the upside of laying out a complete observing framework incorporating driver prosperity and liquor utilization. Nonetheless, a significant restriction of this execution is that it doesn't learn regardless of whether the driver is inebriated, zeroing in exclusively on liquor fixation levels. The equipment arrangement for this execution involves parts like Arduino UNO, MQ3 sensor, motivation sensor, GSM Module, bell, and LEDs. Generally speaking, this venture adds to an upgraded checking device for driver security, tending to key well-being markers and liquor levels. However, extra measures may be expected to decide inebriation and appropriate mishaps out and about precisely.

Nicky Kattukkaran et al. delves into accident location frameworks, focusing on their research [16]. Their executed framework incorporates a mishap identification module within the mobile network, enabling automated alerts to be sent to family members and medical assistance in case of an accident. The framework's notable advantage is the dedicated mishap recognition module, which enhances the accuracy of identifying accidents. However, a drawback lies in its post-accident detection nature, lacking the ability to prevent accidents. This implementation employs the MSP430, Bluetooth Module HC-06, and Accelerometer ADXL335. This study augments our understanding of accident detection systems, emphasizing the importance of dedicated detection modules to enhance accuracy while acknowledging the strengths and limitations of the approach.

Nasr and collaborators present a smart and dependable IoT system solution, utilizing components such as a shock sensor, GPS, NFC reader, and cellular IoT devices [21]. This system integrates a mobile application, a web-based interface, and a navigation system dedicated to locating rescue teams. Benefits include immediate accident notifications to PSO headquarters, precise mapping of accident coordinates, provision of medical information to rescue units, streamlined routing, and data aggregation for statistical analysis. However, limitations involve reliance on IoT device availability and accuracy, potential false alarms from the shock sensor, restricted compatibility with equipped vehicles, and reliance on network connectivity. Hardware components encompass an IoT device with pertinent sensors, an SKM53 GPS module, an NFC reader, a cellular 3G module, and Raspberry Pi for processing. The algorithm incorporates shock sensor accident detection, signal processing, and the Haversine function for distance calculations.

Chen et al. [29] developed a drunk driving detection system, falling within the "Integrated Systems" category, employing a portable driving simulator and various physiological sensors, such as PPG, EDA, and EMG, alongside breath alcohol analyzers and eye-tracking technology. Their approach, powered by a Support Vector Machine (SVM) classifier, amalgamated driving performance and physiological data to distinguish drunk driving from normal driving. Principal Component Analysis (PCA) helped streamline feature selection. Despite a controlled simulator environment and feature reduction benefits through PCA, limitations included a relatively small sample size (32 participants) and simulated driving conditions. The achieved 70 percent accuracy suggests room for improvement, potentially through larger, more diverse samples and enhanced integration of air-alcohol concentration data with physiological measurements and driving performance for robust real-world application.

Dai et al. [30] introduced a mobile phone-based drunk driving detection system, categorized within the "Integrated Systems" domain. This innovative approach harnesses the phone's accelerometer and orientation sensors for data collection and analysis. The algorithm focuses on pattern matching of acceleration data, specifically lateral and longitudinal movements, to identify erratic driving behaviors associated with intoxication. Noteworthy advantages include its cost-effectiveness, accessibility via a mobile phone, and high detection accuracy. The system is also power-aware, considering mobile phone battery life. However, limitations arise from potential inaccuracies if the phone shifts position during driving, exclusive reliance on sensor data, and the absence of GPS utilization. Future research directions involve enhancing accuracy through GPS integration and exploring the potential benefits of incorporating camera-based visual monitoring into the system.

Hironori Wakana et al. [41] developed a portable breath-based alcohol detection device that combines a non-contact breath sensor with smartphone connectivity for ease of use by drivers. Utilizing water vapor and semiconductor gas sensors, including those for ethanol detection, the device calculates alcohol concentration using a differential evolution algorithm and ensures breath recognition. While it offers real-time alcohol level measurements and the potential to enhance road safety, the paper lacks details on the device's size, weight, practicality, and considerations regarding legal and privacy issues. Future research could delve into these aspects and conduct real-world testing for validation.

Mohanraj and co-authors [1] conducted a comprehensive review exploring the potential of integrating an alcohol sensor to ascertain a driver's alcohol intoxication. Their approach significantly improves alcohol detection precision. The system efficiently gauges the driver's alcohol concentration through the incorporation of a dedicated Alcohol Sensor, LCD Display, and Transfers in the hardware design. It's important to note that this method solely detects alcohol content and doesn't inherently prevent accidents. Consequently, while it offers a dependable alcohol detection approach, supplementary measures may be necessary to enhance driver safety.

The work by Abdelkader Dairi and team [11] takes center stage in investigating drunk driver detection in this study. Their proposed solution integrates a gas sensor and facial temperature measurement to identify alcohol-intoxicated drivers. One advantage of this setup lies in the application of gas sensors, which excel in accurate alcohol detection. Nevertheless, a potential drawback emerges when drivers use mouth fresheners, potentially affecting the precision of alcohol detection and the overall functionality of the gas sensor. The pivotal component in this setup is the gas sensor itself. This research advances our comprehension of drunk driver detection while underscoring the significance of addressing the practicalities and constraints of the chosen hardware and detection methodology.

In the domain of alcohol detection and prevention, diverse research has unfolded, addressing the critical issue of intoxicated driving. Notable contributions from Sumendra Yogarayan [3], Nicky Kattukkaran [16], and Nasr [21] delve into the hardware aspects, proposing innovative sensor technologies and integrated systems for accurate alcohol detection. On the other front, studies by Chen [29] and Dai [30] navigate the application-oriented landscape, providing insights into the practical implementation of alcohol detection systems. Additionally, Hironori Wakana [41], Mohanraj [1], and Abdelkader Dairi [11] bridge the gap between hardware and application, presenting comprehensive approaches that amalgamate sensor technologies with real-world deployment strategies. The entire summary of this category is represented in Table 3.

Table 3: Summary of literature Survey on systems that does Alcohol detection and prevention

Literature	Working	Advantage	Disadvantage
Mohanraj, E. et al., IJHS 2022 [1]	Alcohol sensor for detecting whether the driver is drunk	Alcohol detection more accurate.	Detects the alcohol content of the driver and it does not prevent any accidents occurring.
Sumendra Yogarayan et al. FIST 2021 [3]	Created a tool to monitor the driver's heart rate and alcohol content	Monitoring drivers regarding health abnormalities (heart rate) and alcohol concentration (level).	Does not specify whether the driver is drunk or not.
Abdelkader Dairi, et al, CEMSE, 2022 [11]	Detects the drunk driver using gas sensor, and facial temperature	Gas sensor can give accurate alcohol detection	If the driver is using some mouth freshner then the alcohol detection and gas sensor's accuracy will get affected

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Table 3: Summary of literature Survey on systems that does Alcohol detection and prevention (Continued)

Nicky Kattukkaran, et al., (ICCCI -2017) [16]	Model is connected to mobile network to send alerts to the relatives and medical assistance	Accident detection module that can increase the accuracy of detecting an accident	It will only detect accidents and it does not prevent accidents
Nasr et al., IEEE - 2016 [21]	Developed IoT system solution using GPS, NFC reader, shock sensor cellular IoT components	Instantly notifies the PSO headquarters about accidents	The system relies on the availability and accuracy of IoT devices
Chen et al., 2017 [29]	Eye Aspect Ratio is calculated using Pi cameras and Raspberry Pi	Physiological measurements and driving performance data, providing a holistic approach to detect drunk driving	Relatively small sample size (32 samples) may limit the model's predictive power and generalizability.
Dai et al., IEEE 2010 [30]	Drunk driving detection system using a mobile phone.	The system uses a mobile phone, making it easily accessible and cost-effective.	The system's performance can be affected if the mobile phone slides during driving, leading to inaccurate readings.
Hironori Wakana et al., INCS2018 [41]	Developed a portable breath-based alcohol detection device.	Portable and designed for ease of use by drivers, potentially reducing drunk driving incidents.	Not provide detailed information about the size and weight of the portable device.

2.4 Integrated system for driver safety

In research conducted in the paper [8], an investigation is conducted into the implementation of a comprehensive Driver well-being framework, inspired by the work of Mahziar Mohammadrezaei et al. While the project offers a high-level overview of the methodologies and technologies involved, detailed implementation necessitates further examination, refinement, and integration of hardware, software, and communication systems. The proposed system offers real-time communication, proactive accident prevention, multi-sensor integration, GPS tracking, and iterative enhancements to enhance vehicle safety and emergency response. However, a potential drawback is the system's reliance on network connectivity, which could pose challenges in areas with poor or no network coverage, affecting the timely transmission of accident alerts and location data. The hardware configuration includes components like the Arduino Uno, an eye-blink sensor, a buzzer, a vibration sensor, a GSM module, and a gas sensor. Overall, this literature study underscores the significance of a comprehensive Driver Wellbeing Framework while highlighting its advantages and acknowledging potential limitations.

This study [14] delves into the necessary utilization of security equipment, alcohol detection, and accident prevention through IoT, with a specific focus on research conducted by Dhurvesh H Patel et al. The implemented system prioritizes rider safety by enforcing the usage of safety gear and requiring an alcohol test before allowing two-wheeler ignition. Supplementary features include GPS and GSM technology integration. The system's merits encompass the enforcement of safety equipment compliance, verification of alcohol-free rides, prevention of bike ignition in the event of security rule violations, and the capability to send real-time accident notifications to family members. However, a potential drawback is the necessity for the driver to undergo an alcohol test every time they intend to ride, which can be time-consuming. The hardware setup consists of components such as Arduino UNO R3 Nano, an infrared sensor, an alcohol sensor, a Bluetooth module, an ultrasonic sensor, GPS, GSM, and a relay. This research offers valuable insights into mandatory safety equipment implementation, alcohol detection, and accident prevention. It acknowledges both the potential and challenges associated with frequent alcohol testing and the practical implementation of hardware components.

Mehr et al. present a two-channel system implementation utilizing 65-nm digital CMOS technology [20]. Comprising high-swing class-C oscillators, a frequency divider, and a phase rotator, this implementation offers multiple advantages. It effectively mitigates issues like injection pulling in RF SoCs caused by parasitic coupling, offers a pulling-free frequency planning scheme for multicore transmitters, and minimizes unwanted spurs and modulation distortion. Moreover, this approach accommodates multiple radios within a single silicon die, contributing to a low-power architectural solution. While validated experimentally in a two-channel system, there are certain downsides to consider. It mandates careful circuit implementation, and calibration, and is sensitive to inherent mismatches in phase-rotating dividers. The hardware setup includes oscillators, dividers, phase rotator circuits, and associated interconnects. The proposed technique employs a digital fractional divider for frequency planning, achieving fractional separation of oscillator center frequencies while maintaining closely spaced frequencies at phase rotator outputs via phase rotation techniques.

Li et al. [36] conducted a study utilizing a fixed-base driving simulator remodeled from a Toyota car for data collection. Employing multivariate time series analysis, particularly piecewise linear representation (PLR), they extracted features from the data and used a Support Vector Machine (SVM) classifier to distinguish normal from drunk driving states. Their method showed promise in detecting drunk driving with an 80 percent accuracy rate, highlighting the impact of alcohol on driving performance. However, the study's limitations include a relatively small sample size of 20 male drivers and a focus on urban curve driving scenarios, potentially limiting its generalizability. Further research is needed to test the classification algorithm on a larger and more diverse sample and explore different driving conditions. The study doesn't address real-world implementation or factors like age, experience, or the influence of various alcoholic beverages on drunk driving detection. Additionally, it lacks an adaptive mechanism for determining the optimal number of segments in PLR.

Gbenga et al. [39] developed a prototype alcohol detection and engine locking system to monitor a driver's blood alcohol content (BAC) using an MQ-3 alcohol sensor and an Arduino Uno microcontroller. If the BAC exceeds a threshold, it prevents the car's ignition, enhancing road safety. While offering real-time monitoring and potential accident reduction, it's limited to alcohol detection and may yield false readings. Privacy concerns, maintenance, and integration complexity pose challenges, and the research lacks validation in real-world scenarios, a cost-effectiveness analysis, consideration of environmental factors, and insights into driver education and acceptance.

In the category of integrated systems for driver safety, various studies have emerged to address safety concerns comprehensively. Mahziar [8], Dhurvesh H Patel [14], and Mehr [20] focus on hardware-centric approaches, proposing integrated systems that utilize a range of sensors and technologies to enhance safety measures. On the practical side, Li [36] and Gbenga [39] contribute insights into real-world implementations, demonstrating how integrated systems can be efficiently deployed for continuous monitoring and timely alerts.

2.5 Abnormal Driving Behavior Detection

In the literature [24] surveyed by Jie Hu et al., an implementation of abnormal driving detection using a deep learning approach with normalized driving behavior data is discussed. The advantage of this approach lies in its proposal of a deep learning technique to identify abnormal driving behavior, leveraging normalized driving data. This has the potential to enhance the accuracy and reliability of detection systems. However, a notable drawback is the requirement for substantial quantities of high-quality driving data to train the deep learning model. Furthermore, challenges might arise in generalizing the approach to various driving environments or conditions. The hardware components utilized in this implementation encompass pressure sensors, throttle angle sensors, GPS, accelerometers, and magnetometers. Computational strategies employed include Support Vector Machines (SVM), Back Propagation Neural Networks (BPNN), Dynamic Bayesian Networks, Error Propagation Algorithms, and SR Classifiers.

2.6 Multi-Modal Approaches

Awais et al. [26] devised a driver drowsiness detection system within a simulator-based driving environment, gathering physiological data from EEG and ECG measurements. They extracted an array of time and frequency domain features from these data and harnessed a Support Vector Machine (SVM) classifier to differentiate alert and drowsy states. Remarkably, the study proposed a hybrid approach, combining EEG and ECG data for more robust drowsiness detection. By reducing the EEG electrode count to two, one EEG and one ECG, the system aimed for greater wearability, achieving an acceptable 80 percent accuracy. However, limitations include the controlled simulator environment, which may not fully represent real-world driving conditions, the system's computational complexity, and unexplored physiological signals like EOG and EMG for further insights.

Barua et al. [27] developed an Automated Driver Sleepiness Detection (ADSD) system employing EEG, EOG, and contextual information. Their approach involved utilizing four established classifiers (KNN, SVM, CBR, and RF) to assess driver sleepiness levels based on EEG and contextual data. Their work validated the feasibility of this multimodal approach, with improved classification accuracy when incorporating contextual information. SVM emerged as the most reliable classifier, although challenges persisted in accurately classifying the "somewhat sleepy" group and in multiclass classification. The research conducted in a high-fidelity driving simulator emphasized the potential for further exploration of incorporating additional contextual data and designing adaptable classifiers for continuous driver monitoring.

Dasgupta et al. [31] devised a driver alertness monitoring system, categorized under "Integrated Systems." This system employs a suite of hardware components, including an Intel Atom Processor, camera, near-infra-red (NIR) lighting system, speakers, and a voltage regulation unit. It hinges on face and eye detection algorithms to gauge driver alertness. Face detection utilizes Haar-like features classification and compensates for facial rotations through affine and perspective transformations. Eye detection employs block Local Binary Pattern (LBP) histogram features for real-time tracking, with Support Vector Machines (SVM) facilitating eye state classification. The Percentage of Eye Closure (PERCLOS) value, indicative of drowsiness, is calculated based on the ratio of closed eyes to total eyes counted. The system triggers voice alarms when PERCLOS exceeds 15 percent, promoting real-time alertness. Notably, this system demonstrates robustness across lighting variations and head rotations, offers high detection rates, and is cross-validated with EEG signals. However, challenges arise concerning drivers wearing glasses, occasional false alarms, specific hardware prerequisites, and no explicit consideration for sunglasses-wearing drivers. A research gap in detecting eyes occluded by spectacles is identified, suggesting a direction for future improvement in system robustness.

Dasgupta et al. [32] devised a three-stage drowsiness detection system employing Android smartphones, offering a robust approach. The first stage calculates the Percentage of Eyelid Closure (PERCLOS) from front camera images, utilizing image preprocessing, face and eye detection, and eye state classification. The second stage leverages speech data via Singular Value Decomposition (SVD) and Support Vector Machine (SVM) for voiced/unvoiced classification. A touch-based response is the final verification stage. Notably, the system logs vital data and provides an SMS emergency alert service. While achieving a commendable 93.33 percent drowsiness classification rate, the study lacks documentation on hardware requirements, noisy speech data handling, and false-positive/false-negative rates. Further research avenues include improving camera frame rates and addressing practical implementation challenges.

In the domain of multi-modal approaches, researchers have explored diverse strategies to enhance driver safety by integrating various sensory modalities. Contributions from Awais [26], Barua [27], Dasgupta [31], and Dasgupta [32] highlight the integration of different data collection and analysis methods. Their studies investigate the combined use of visual and auditory cues, showcasing the development of robust systems capable of detecting and responding to diverse driving conditions.

2.7 Smartphone-Based Systems

Explored by Emily R., et al. [15], this study introduces a novel approach using facial expression analysis to detect driver distraction. The advantage of this method is its non-intrusive nature, allowing for distraction detection without additional wearable devices. However, the potential limitation is the complexity of accurately classifying various facial expressions. The hardware includes a camera and facial expression analysis software. This research contributes to the understanding of driver distraction detection through facial cues and emphasizes the challenges associated with real-time analysis of complex facial expressions.

The research paper by Yadong Xie et al. [43] introduces "D3-Guard," a real-time drowsy driving detection system leveraging audio sensors in smartphones. This Android application-based system employs a combination of data collection, feature extraction via Fast Fourier Transform (FFT), and Long Short Term Memory (LSTM) networks for accurate drowsy driving action detection. Notably, D3-Guard offers real-time detection, making it capable of providing timely warnings to drivers, and it does so without necessitating additional hardware, relying instead on built-in smartphone audio sensors. The system exhibits high accuracy in detecting drowsy driving actions, particularly during their early stages. However, it faces challenges related to smartphone placement, computational complexity, data collection, and sensitivity to road conditions. The potential for scaling with larger datasets, addressing privacy concerns, real-world deployment considerations, robustness in varying conditions, user acceptance, and regulatory aspects represent avenues for future research in this domain.

Sumendra Yogarayan [3] and his team aimed to create a tool that monitors both the driver's heart rate and alcohol content during driving. Their paper presents an implementation that centers on utilizing the Internet of Things (IoT) to monitor driver health indicators, specifically heart rate and alcohol concentration levels. This approach offers the advantage of establishing a comprehensive monitoring system encompassing driver well-being and alcohol consumption. However, an important limitation of this implementation is that it doesn't ascertain whether the driver is truly intoxicated or not, focusing solely on alcohol concentration levels. The hardware setup for this implementation entails components such as Arduino UNO, MQ3 sensor, impulse sensor, GSM Module, buzzer, and LEDs. Overall, this project contributes to an enhanced monitoring tool for driver safety, addressing key health markers and alcohol levels. Yet, additional measures might be required to accurately determine intoxication and preempt accidents on the road.

In the domain of smartphone-based systems, researchers have explored methodologies that leverage the ubiquity of smartphones to enhance driver safety. Noteworthy contributions from Emily R. [15], Yadong Xie [43], and Sumendra Yogarayan [3] are classified in this category. These studies delve into both hardware and application aspects. They explore the integration of smartphone capabilities, such as sensors and data processing, to develop innovative systems.

2.8 Wearable Devices and Sensors

Explored by Bhattacharya, S., et al. [9], this research delves into the use of deep learning techniques for driver drowsiness detection using an EEG headset. The benefit is the accuracy of drowsiness prediction using EEG data. However, a limitation is the need for specialized equipment. The hardware involves an EEG headset and a neural network. This study adds insight into EEG-based drowsiness detection, highlighting the potential and constraints of EEG technology.

Rajat Gupta et al. presented a driver fatigue detection system utilizing a dashboard-installed camera and computer vision techniques [33]. Their approach includes face detection using Haar-like features, feature extraction involving eye and mouth behaviors, Principal Component Analysis (PCA) for feature reduction, and Support Vector Classifier (SVC) for fatigue level classification. The system is praised for its use of easily accessible hardware and the inclusion of both eye and mouth features in fatigue detection. It optimizes processing time through PCA-based feature reduction and employs gradual alert mechanisms to prevent abrupt driver responses. However, challenges include variable accuracy in eye and mouth detection, dependency on certain facial features, susceptibility to lighting conditions and driver characteristics, and a lack of consideration for external fatigue factors. Further research could involve robustness testing in diverse real-world scenarios to address these limitations.

Ezhumalai et al. [38] designed a system utilizing an EEG sensor to monitor driver brainwave activity, processed through amplifiers and filters to detect relevant patterns, and compared with predefined thresholds. Visual LED indications and a buzzer alerted the driver of their state, with the system interfacing with the car's motor and steering for safe navigation in case of drowsiness. While offering real-time drowsiness detection and the potential to reduce accidents, it may be sensitive to movement and noise, not accounting for other factors like alcohol or distractions. Calibration and individual variations in EEG patterns could affect accuracy, and integrating the system with a car's control systems might be complex. Future research could focus on noise reduction in EEG signal processing, adding sensors for accuracy, advanced detection algorithms, real-world testing, and addressing safety and regulatory concerns.

Li et al. [35] introduced a drowsiness detection system using heart rate variability (HRV) analysis, incorporating a PPG sensor attached to the steering wheel, a smartphone for data processing and transmission, and a server PC for further analysis. The PPG sensor captures data sent to the smartphone via Bluetooth, which then transmits HRV data to the server PC. Several techniques, including wavelet-based HRV analysis and support vector machine (SVM) classification, are employed to identify driver alertness or drowsiness. The system, designed for simplicity and cost-effectiveness, achieves high classification accuracy in drowsiness detection. However, the paper lacks information about the dataset's size and diversity used for SVM training, necessitating consideration of real-world implementation challenges and individual HRV variations. Validating this system in practical driving scenarios remains unaddressed.

Bhattacharya [9], Rajat Gupta [33], Ezhumalai [38], and Li [35] contribute significantly to this domain. Their work explores the integration of wearable devices and sensors for monitoring driver behavior and enhancing safety. These studies not only delve into the technical aspects of hardware development but also showcase practical applications, providing a comprehensive understanding of the role of wearables in driver safety systems.

2.9 Deep learning and machine learning

Lim et al. [37] employed Google TensorFlow to implement a Convolutional Neural Network (CNN) to estimate driver states, utilizing a server computer with two 14-core 2.4 GHz CPUs and 64 GB RAM for training and a laptop computer with a quad-core 2.2 GHz CPU and 16 GB RAM for testing. Their CNN, equipped with features like ReLUs, max pooling, dropout, and softmax regression, processed multimodal sensor data in time sequences to classify driver states (e.g., drowsiness, distraction, workload). The approach yielded high accuracy in driver state detection, with Correct Detection Rates ranging from 0.841 to 1.000, and lower False Alarm Rates for most states compared to a previous method. However, the algorithm's performance is slightly degraded for high workload estimation. The study lacks details on real-time processing and ethical considerations related to using driver physiological data. Future work aims to enhance detection performance and apply the deep learning method to real-world driving data, highlighting the gap between simulated and real-world data usage.

The paper authored by C. Wu et al. [42] present an Electrocardiogram (ECG)-based Drunk Driving Detection (DDD) system that leverages a Support Vector Machine (SVM) as the chosen machine learning algorithm for classification. ECG signals are meticulously processed and analyzed to detect signs of drunk driving, with ten key features extracted from these signals. These features encompass various aspects of the ECG waveform and intervals. The study demonstrates notable advantages, including the reliability of ECG signals, real-time detection capabilities, and promising accuracy metrics. The proposed system showcases an accuracy improvement compared to existing methods and holds potential for integration into modern vehicles. However, the research lacks specific hardware details and does not comprehensively address motion artifacts or discuss dataset characteristics, signaling opportunities for future research in this unexplored field of ECG-based DDD systems.

In the domain of deep learning and machine learning for driver safety, significant contributions have been made by researchers such as Lim [37] and C. Wu [42]. This category synthesizes their work, emphasizing the application of advanced learning algorithms to enhance driver safety systems. Lim's research explores machine learning techniques, contributing insights into pattern recognition for driver behavior analysis. On the other hand, C. Wu delves into the domain of deep learning, demonstrating the efficacy of neural networks in discerning and responding to various driving conditions.

2.10 Literature Survey on recent categories

In their study, Shivani Sharma and co-researchers propose a comprehensive implementation for accident detection and location tracking [18]. The system incorporates a heart rate sensor, a vibration sensor, a GPS module, and an accelerometer. This amalgamation of sensors empowers the system to identify accidents and furnish real-time location details. One key benefit of this implementation is its efficiency, attributed to the utilization of a vibration sensor, which enhances the precision of accident detection. Moreover, the integration of a GPS module permits accurate and live location tracking. However, this system's drawback is its exclusive focus on accident detection and location tracking, without incorporating a mechanism to ascertain the driver's level of intoxication. Vital hardware components in this implementation encompass the vibration sensor, GPS module, and accelerometer.

Investigated by Samuel E., et al. [13], this study focuses on developing a smart helmet integrated with alcohol detection and a heartbeat sensor for motorcycle riders. The advantage lies in the real-time monitoring of both alcohol content and heartbeat, enhancing safety. However, the limitation of this implementation is its exclusive focus on motorcyclists, leaving out other vehicle types. The hardware includes an alcohol sensor, a heartbeat sensor, and Arduino UNO. This contribution underscores the importance of integrating safety measures for specific vehicle types.

Lee et al. [28] developed an integrated driver alertness monitoring system utilizing a smartwatch and physiological sensors. Categorized under "Integrated Systems," the system combines motion sensors in the smartwatch and a finger-mounted Photoplethysmography (PPG) sensor, connected via Bluetooth Low Energy (BLE), for real-time monitoring of driver alertness. It calculates Steering Wheel Movements (SWM) from motion sensor data and PR intervals and respiratory signals from PPG, analyzed for various frequency-domain features. These features feed into a mobile-based Support Vector Machine (M-SVM) classifier, enabling timely warnings to drowsy drivers. While offering non-invasive real-time monitoring and flexibility, challenges include sensor calibration and precise PPG placement. Future research could address long-term monitoring, individual adaptability, real-world testing, and user interface refinement.

In the expansive landscape of recent literature surveys, the works of Shivani Sharma [18], Samuel [13], and Lee [28] collectively contribute to a meta-analysis of various driver safety categories. Shivani Sharma's survey provides a holistic overview, synthesizing recent advancements across multiple domains. Samuel's work, on the other hand, focuses on the critical analysis of existing systems and methodologies, offering valuable insights for future research directions. Lee's contribution delves into emerging trends, shedding light on the integration of new technologies like the Internet of Things (IoT) for augmenting driver safety.

The writing study synopsis is separated into two particular segments, each zeroing in on unambiguous parts of driver wellbeing upgrade. The primary segment presents a gathering of studies that innovatively utilize IoT sensors like vibration sensors, gas sensors, cameras, and shock sensors to upgrade their functionalities. The subsequent segment frames research using AI calculations to enhance driver execution by examining driver information. The summed-up discoveries are introduced in the tables named Tables 4 and 5. The accuracy of all the ML methods is represented in Fig. 4

Table 4: Summary of Literature Survey based on driver drowsiness detection with IoT components

Literature	Working	Components	Limitations
Srimantini Bhattacharya et al. IEEE 2022 [9]	Live monitoring is done through cameras to monitor drowsiness	Pi Cameras, Alcohol Sensor	It only focuses on drowsiness and intoxication all the other parameters have been neglected
Mohanraj, E. et al., IJHS 2022 [1]	The alcohol content is detected and displayed in LED Display	LED Display, Relays, Vibration Sensor	It only detects alcohol content and displays it. It does not prevent accidents
Sumendra Yogarayan et al. FIST 2021 [3]	This paper checks the Blood Alcohol Consumption in the drivers blood	Pulse sensor, Arduino uno, Buzzer	It does not specify whether the driver is drunk or not
Yassine Sabri et al., LIMIE,2021 [7]	It uses various sensors to detect obstacles.	Vibration Sensor, GSM Module, Obstacle sensor	Alcohol detection is not done
Jagadish Narasimhaiah, et al., IRJET 2021 [12]	Eye blinking is recorded while the driver is driving	Eye blink sensor, Alcohol Sensor, Buzzer	It only collects the data from camera feeds which can be sometimes faulty or unusable blurry images
Jasmin D Vora, et al., NCRMACT, 2020 [2]	Eye Aspect Ratio is calculated using Pi cameras and Raspberry Pi	Pi camera, Raspberry Pi	It only detects Drowsiness and all the other aspects like alcohol content is neglected
Mahziar Mohammadrezaei et al. JCWR 2020 [8]	This is based on the shock received after the accident has occurred	NFC, GPS, Shock Sensor	This system detects the location after the accident. It does not prevent accidents.

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Table 4: Summary of Literature Survey based on driver drowsiness detection with IoT components (Continued)

Nicky Kattukkaran, et al., ICCCI -2017 [16]	Accident detection module is used along with live tracking of the vehicle	MSP430, Bluetooth Module HC-06, Accelerometer ADXL335	It only detects accidents and does not check whether the driver is drunk or not
Bala et al., ICCCI -2020 [19]	Drowsiness of the Driver is detected using this system	Hardware - Raspberry Pi, cameras, monitors, CAN communication modules, and GPS module	The system is only focussing on the drowsiness of the driver and not on intoxication
Dhurvesh H Patel, et al., ICECA 2019 [14]	Implemented such a way that the two-wheeler will not start until the rider wears a helmet and passes an alcohol test	Arduino UNO R3 Nano, Infrared Sensor, Alcohol Sensor, Ultrasonic Sensor, GPS, GSM	It detects whether the driver is fit to drive or not. The other factors like speed control, etc. are ignored

3 Critical Summary

Numerous research studies have been conducted to develop innovative systems for driver safety and accident prevention. In this comparative study, we review the latest papers from various authors and journals to gain insights into the strengths and limitations of existing systems in Table 3 and Table 4.

In the domain of Driver Drowsiness Detection, researchers have explored diverse avenues. For instance, Suhail Razeeth et al. [6] introduced a smartphone-based system, while Anil Kumar Biswal et al. [10] focused on eye blink sensors. A comparative analysis could help understand the trade-offs between these approaches, considering factors such as accuracy, real-time detection capabilities, and ease of implementation.

Driver Distraction Detection is another critical area. Laura W. et al. [17] proposed a method using a wearable ECG device, while Emily R. et al. [15] utilized facial expression analysis. A comparative study can delve into the effectiveness of physiological data versus visual cues in detecting driver distraction, potentially shedding light on which approach is more robust.

Alcohol detection and prevention are vital components of driver safety. Researchers like Sumendra Yogarayan et al. [3] have developed smartphone-based systems, whereas Chen et al. utilized a portable driving simulator. A comparative assessment can explore factors such as accuracy in alcohol detection, real-world feasibility, and privacy concerns associated with these systems. Integrated systems that combine various technologies have also been explored. Mahziar Mohammadrezaei et al. [8] and Mehr et al. [20] both worked on integrated systems. A comparative analysis can reveal which of these systems offers better real-time monitoring and accident prevention capabilities.

Physiological Data-Based Detection has seen researchers who focused on driver drowsiness detection using EEG, and Ines Teyeb et al. [22], who analyzed head movements and eye squinting patterns. A comparative study can assess the effectiveness of EEG-based systems versus vision-based approaches. Detecting abnormal driving behavior is crucial for accident prevention. Jie Hu et al. [24] employed deep learning with normalized driving behavior data. This approach could be compared to other techniques for identifying abnormal driving behaviors in terms of accuracy and adaptability to various driving conditions.

Multi-modal approaches, as seen in Awais et al. [26], utilized both EEG and ECG, while Barua et al. [27] incorporated contextual information. A comparison can determine which approach provides better overall accuracy and robustness in detecting driver safety issues. Smartphone-based systems, such as Yadong Xie et al.'s [43] Android application-based system and drowsy driving detection app, represent practical solutions. A comparative analysis may reveal which smartphone-based approach is more feasible and effective.

Wearable Devices and Sensors, like those explored by Bhattacharya, S. et al. [9] with EEG-based systems and Rajat Gupta et al. [33] employing facial analysis with a camera, represent diverse approaches. A comparative study can evaluate the advantages and disadvantages of EEG-based systems versus camera-based approaches. Deep Learning and Machine Learning techniques have gained prominence. Lim et al. [37] [77] utilized Convolutional Neural Networks (CNNs), while C. Wu et al. [42] employed Support Vector Machines (SVMs). A comparison can assess the effectiveness of deep learning versus traditional machine learning in driver safety applications.

Lastly, in the domain of Non-Invasive Physiological Detection, K. Fujiwara et al. [45] proposed an algorithm for detecting driver drowsiness based on HRV analysis. Comparative analysis could investigate the accuracy and real-world applicability of HRV-based systems. By conducting a comparative study across these categories, we can gain a comprehensive understanding of the evolving landscape of driver safety technologies(Fig. 4), shedding light on the most promising approaches for enhancing road safety and accident prevention.

3.1 Safety and Security

In the rapidly evolving landscape of connected cars, the confluence of advanced technologies like telematics, GPS, and cloud computing brings unprecedented capabilities and, concomitantly, raises vital safety and security concerns. As elucidated by Koesdwiad et al. [84], the interconnected nature of these systems facilitates seamless communication, enabling real-time monitoring and data analysis. However, with this connectivity comes a host of privacy implications. The wireless transmission and cloud storage of data make vast amounts of information readily accessible, prompting a nuanced examination of the risks and challenges tied to privacy and security. It is imperative to dissect these issues further to comprehend the potential vulnerabilities and navigate the delicate equilibrium between technological innovation and safeguarding user privacy.

Table 5: Summary of Literature Survey based on ML Methods for accident detection

Literature	Technique	Accuracy(%)	Limitations
Abdelkader, et al., CEMSE, 2022 [11]	IPCA	95.37	Not detecting drowsiness
Anil Kumar Biswal, et al., ITER, 2021 [10]	DL, CNN	97.10	Not detecting intoxication
Suhail Razeeth, et al., ICIT, 2021 [6]	Haar SVM	88	Less light causes inefficiency
Ali Amer Hayawi et al. IEEE, 2019 [4]	CNN	94.70	Not detecting intoxication
Uma, S., Eswari, R., et al., 2021 [5]	DL, CNN	93.60	Not detecting intoxication
Carsten Hahn, et al., SIGSPATIAL 2020 [51]	A*, ANN	90.33	Faulty camera feed
Bappaditya Mandal, et al., IEEE 2017 [17]	PERCLOS	85	Not detecting intoxication
Ines Teyeb et al., IDEAL 2014 [22]	Viola and Jones	94.70	Lack of detailed analysis
R. Jabbar et al., IEEE 2020 [23]	CNN	75	Evaluation Dataset Limitations

- Privacy Implications of Connected Cars: Arise from the underlying technologies used in the Internet of Cars. Telematics and connected car services utilize technologies like on-board vehicle sensors, GPS satellite communications, V2V and V2I communications, cloud computing, and data analytics. Gather, analyze, and utilize high volumes of data from various sources. The wireless transmission and cloud passage make the data readily available to the automaker.
- Concerns about Big Data: Despite benefits, big data raises concerns about amassing vast information, identifying individuals from supposedly anonymous datasets, and gathering intelligence about drivers and passengers. Connected cars pose unique privacy challenges due to the dynamic car environment and the additional data they generate. Highly sensitive information includes biometric and health data, location data, personal communications (voice, email, social networking), personal contacts, and schedules.
- Privacy and Security Issues: Use of cumulative and combined vehicle data could have devastating consequences on personal data. Big data and cloud technologies reveal extensive information about the driver.
- Risks of Over-Collection: Drivers cannot prevent automakers from unnecessarily harvesting and storing personal data in the cloud or data centers, increasing vulnerability to security breaches, malicious access, state surveillance, and suspicious third-party use. Only relevant information for a specific purpose should be collected.
- Risks of In-Vehicle System Maintenance: Connected cars need to download updates, and connect to a cloud-based system to avoid on-road repairs. The security of a car and its data connections extends beyond the in-vehicle environment.

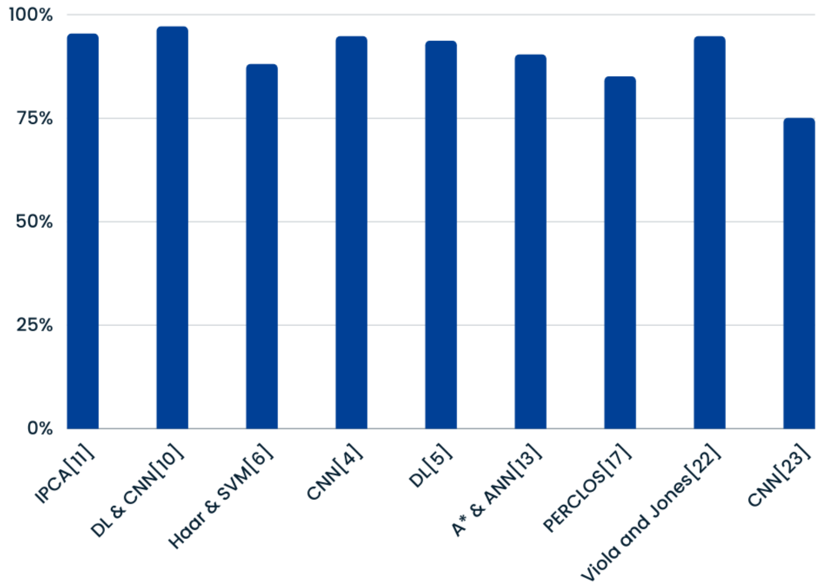

Fig. 4: **A**ccuracy based on accident detection with ML techniques

3.2 Contributions

In our comparative study, we contribute to the field of driver safety and well-being technologies by offering a comprehensive analysis of all research papers, spanning various categories. Our contributions in this study are as follows:

- Identification of Key Categories: We categorize the research papers into distinct categories, including Driver Drowsiness Detection, Driver Distraction Detection, Alcohol Detection and Prevention, Integrated Systems for Driver Safety, Physiological Data-Based Detection, Abnormal Driving Behavior Detection, Multi-Modal Approaches, Smartphone-Based Systems, Wearable Devices and Sensors, Deep Learning and Machine Learning, and Literature survey on recent categories. This structured categorization provides a clear framework for understanding and comparing different approaches to driver safety.
- Comparative Assessment: We conduct a thorough comparative assessment within each category, evaluating the strengths and weaknesses of various technologies and methodologies. This analysis helps in identifying the most promising approaches for addressing specific driver safety challenges, offering valuable insights to both researchers and practitioners.
- Trends and Innovations: Our study recognizes emerging trends and innovations in the field of driver safety. This includes the integration of Internet of Things

(IoT) devices, the utilization of deep learning techniques, and the development of smartphone-based solutions. By highlighting these trends, we provide a forward-looking perspective on the evolving landscape of driver safety technologies.
- Research Gap Analysis: Through an in-depth examination of the reviewed papers, we pinpoint critical research gaps in existing driver safety technologies. These gaps serve as focal points for future research and innovation, guiding researchers toward areas where advancements are needed to enhance the overall effectiveness of driver safety systems.
- Hardware Insights: We shed light on the hardware components consistently employed across the surveyed papers. This hardware landscape clarification offers practitioners valuable insights into the choices that hold promise for robust driver safety systems, facilitating informed decisions for future implementations.
- Limitations and Challenges: Our study consolidates the common limitations and challenges observed in the reviewed papers. By summarizing these drawbacks, we provide a clear overview of the obstacles faced by current driver safety technologies. This summary acts as a guide for researchers, encouraging them to address these issues and enhance the field.
- Practical Guidance: Through our comparative study, we aim to provide practical guidance for the development and implementation of driver safety technologies. By synthesizing insights from diverse research papers, we offer a holistic view of the field, aiding both researchers and practitioners in making informed decisions and driving advancements in driver safety and well-being. The technology and systems of connected and automated vehicles (CAVs) have been the subject of the majority of recent research in intelligent transportation systems [79]. To deliver multi-mode urban dynamic traffic information, intelligent transportation systems (ITS) collect and interpret traffic data using dynamic navigation [80].

In conclusion, our comprehensive analysis of existing driver well-being frameworks highlights the significant progress made in driver safety research, with each system presenting unique strengths and limitations. Emphasizing the complexity of driver behavior and safety, our proposed model builds upon this foundation to offer a holistic approach addressing various dimensions of driver safety. By leveraging insights from our comparative study, our model aims to contribute to the ongoing development of more effective and comprehensive solutions in driver safety, ultimately striving for safer roads and improved driver well-being through continued collaboration and innovation among researchers and practitioners.

4 Conclusion

The current research paper has undertaken an extensive exploration of the multi-faceted domain of driver safety and well-being. Through a meticulous survey of all research papers, we have categorized and critically examined diverse approaches and technologies to enhance driver safety, ranging from physiological data-based detection systems to deep learning algorithms and integrated systems. Our comparative study has not only shed light on emerging trends and prevalent techniques but has also exposed the limitations and research gaps that exist in this field. Furthermore, our contributions encompass the synthesis of research gaps, identification of prominent techniques, clarification of the hardware landscape, summary of drawbacks and limitations, and a focused survey of emerging trends. As per the recent survey security of data collected from IoT devices of driver safety is also crucial [78].

Importantly, our comparative analysis has provided valuable insights for researchers and practitioners seeking to innovate in the realm of driver safety. By highlighting the need for comprehensive solutions that address various aspects of driver behavior and security, we have laid the groundwork for advancing this critical field. Our proposed model seeks to leverage the strengths of past frameworks while addressing their shortcomings, with the ultimate goal of contributing to the development of more effective and encompassing solutions in driver safety. Through ongoing collaboration and innovation, we aspire to foster safer roads and enhance driver well-being for the benefit of society as a whole.

5 List of Abbreviations

- IoT: Internet of things
- CNN: Convolutional Neural Network
- SVM: Support vector machine
- HRV: Heart rate variability
- RRI: R-R Interval
- MSPC: Multivariate Statistical process control
- EAR: Eye aspect ratio
- HUD: Head-up display
- GPS: Global positioning system
- CAN: Controller area network
- GPU: Graphics processing unit
- IR: Infrared
- GSM: Global system for mobile communication
- EEG: Electroencephalogram
- PCA: Principal component analysis
- SVC: Support vector classifier
- SdsAEs: Stacked denoising sparse autoencoders
- ECG: Electrocardiogram
- LED: Light emitting diode
- NFC: Near field communication
- PSO: Personal security officer
- PPG: Photoplethysmography
- EDA: Electrodermal activity
- EMG: Electromyography
- LCD: Liquid crystal display
- RF SoCs: Radiofrequency system on chip
- PLR: Piecewise linear representation
- BAC: Blood alcohol content
- BPNN: Backpropagation Neural Network

- ADSD: Automated driver sleepiness detection
- EOG: Electroocoulogram
- KNN: K nearest neighbor
- CBR: Case-based reasoning
- RF: Random forest
- NIR: Near-infrared
- LBP: Local binary pattern
- PERCLOS: Percentage of Eye Closure
- SVD: Singular value decomposition
- FFT: Fast Fourier transform
- LSTM: Long short-term memory
- DDD: Drunk driver detection
- BLE: Bluetooth low energy
- SWM: Steering wheel movements
- M-SVM: Mobile-based Support Vector Machine
- AI: Artificial intelligence
- ML: Machine learning
- DL: Deep learning
- PCA: Principal component analysis
- IPCA: Incremental principal component analysis
- ANN: Artificial neural network
- CAV: Connected and automated vehicles

6 Declarations

6.1 Ethics approval and consent to participate

The research conducted in this study involving participants was reviewed and approved by the International Journal of Intelligent Transportation Systems Research. All participants provided informed consent before participating in the study.

6.2 Consent for publication

All authors have provided their consent for the publication of this manuscript.

6.3 Availability of data and materials

Not Applicable

6.4 Competing Interests

The authors declare that they have no competing interests.

6.5 Funding

Not Applicable

6.6 Authors' Contributions

- Akhil Nair[AN]
- Varad Patil[VP]
- Rohan Nair[RN]
- Adithi Shetty[AS]
- Mimi Cherian[MC]

AN and VP undertook the task of meticulously categorizing the paper and gathering the requisite information for its comprehensive compilation. RN assumed responsibility for crafting the content related to each literature paper, ensuring clarity and coherence in the presentation. AS played a pivotal role in meticulously formatting and structuring the entire paper, thereby facilitating its effective communication. MC diligently conducted the final rounds of meticulous proofreading, making critical corrections, and refining the manuscript for its utmost precision and quality assurance. All authors have reviewed and endorsed the final manuscript, signifying their approval of the content's integrity and alignment with the scholarly standards of our field.

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6.8 Authors' Information

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