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Next-Generation Driver Monitoring Systems: A Review of Multimodal Detection of Distraction, Drowsiness, and Sudden Medical Conditions

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Abstract Driver impairment caused by distraction, drowsiness, and sudden medical conditions remains a major contributor to road traffic accidents worldwide. This paper presents a comprehensive review of recent advances in real-time detection systems targeting these three domains, with the goal of informing the development of effective and deployable driver monitoring solutions. Literature on distraction detection reveals a transition from traditional gaze-based thresholds to efficient deep learning architectures deployable on embedded platforms, including privacy-preserving approaches using vehicle dynamics alone. Drowsiness detection research has progressed toward multimodal and personalized frameworks that integrate physiological, behavioral, and contextual indicators, enhancing detection accuracy and reducing false alarms. Research on sudden medical condition detection, although less extensive, demonstrates promising results through wearable biosensors, in-cabin sensing technologies, and automation fallback strategies capable of executing controlled vehicle stops during acute health events. Across these domains, the review identifies persistent challenges: limited availability of large-scale, diverse, and naturalistic datasets; reliance on controlled laboratory or simulator environments; and the need for adaptive, context-aware, and computationally efficient algorithms suitable for real-world deployment. The integration of multimodal sensing, personalized detection thresholds, and uncertainty estimation is highlighted as a promising direction for improving robustness and user acceptance. By synthesizing findings across diverse methodologies and application contexts, this review provides a consolidated understanding of the state of the art, identifies critical research gaps, and outlines pathways toward next-generation driver monitoring systems capable of reducing crash risk and enhancing road safety. Unlike existing reviews that often focus on a single aspect, this work offers a unified and critical perspective across driver distraction, drowsiness, and sudden medical condition detection, linking technological advances with practical deployment considerations.

Keywords Driver Distraction, Sudden Medical Conditions, Drowsiness

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1. Introduction

Driver impairment caused by distraction, drowsiness, or sudden medical conditions represents a significant and persistent risk to road safety, accounting for a considerable proportion of traffic accidents worldwide[1, 2, 3]. With the increasing adoption of in-vehicle sensors, connectivity, and computational resources, real-time driver monitoring has become an important focus for research and development. Such systems aim to identify hazardous driver states promptly and to initiate alerts or, in advanced setups, initiate partial automation fallback maneuvers [4, 5, 6]. In the domain of distraction detection, early work relied heavily on gaze-based threshold systems that warn drivers when off-road glances exceed safe durations[1]. Recent developments include efficient deep learning architectures optimized for embedded platforms, such as lightweight CNNs and hybrid vision transformers, capable

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of maintaining high accuracy while operating under automotive hardware constraints[6, 7]. Parallel advances have explored privacy-preserving approaches that utilize only vehicle dynamics, demonstrating competitive accuracy without reliance on facial imagery[8].

Drowsiness detection has evolved beyond traditional eyelid closure and blink metrics, incorporating multimodal frameworks that integrate physiological indicators such as electroencephalography, heart rate variability, and respiratory patterns, along with posture analysis and environmental context[5, 9, 10]. These systems increasingly emphasize personalization, adapting detection thresholds to individual baseline behaviors to reduce false alarms and improve user trust[11]. Moreover, environmental factors, such as thermal comfort, have been identified as modulators of drowsiness onset and progression, opening new possibilities for adaptive interventions through cabin climate control[9].

Although less common, sudden medical conditions—including cardiac arrhythmias and other acute health events—pose severe risks due to their rapid onset and potential to completely incapacitate drivers. Detection approaches in this area span wearable biosensors, steering wheel-integrated ECG and grip monitoring, and automation fallback strategies that can bring the vehicle to a safe stop when impairment is detected[12, 6, 13]. Recent reviews emphasize the need for standardized protocols, robust noise handling, privacy preservation, and large-scale real-world validation before such systems can be deployed reliably in consumer vehicles[3]. Despite substantial progress across all three domains, key challenges remain, including the scarcity of representative datasets covering diverse populations and conditions, the scalability of data annotation for naturalistic driving, and the integration of contextual and personalized detection capabilities[2, 14, 11]. Addressing these challenges will require integrated, adaptable, and computationally efficient systems that perform robustly in varied operational environments. Unlike prior surveys that typically address isolated aspects of driver monitoring, this work offers a comprehensive and integrative review spanning distraction, drowsiness, and sudden medical condition detection, with particular emphasis on cross-domain insights, research gaps, and deployment-oriented challenges. Figure 1 depicts the conceptual design of the proposed system, integrating the three primary conditions—distraction, drowsiness, and sudden medical emergencies to convey how the system is intended to function in monitoring diverse driver states. Whereas figure 2 shows the proposed research methodology.

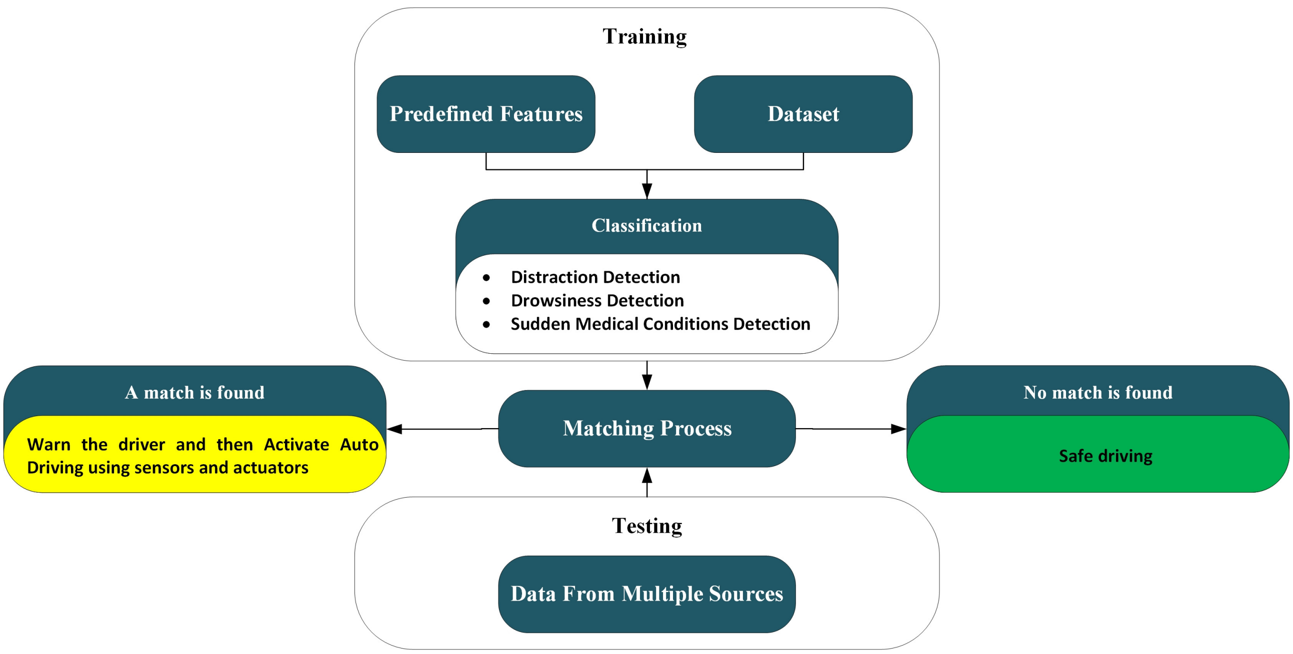

Figure 1. Conceptual system architecture illustrating the driver monitoring process.

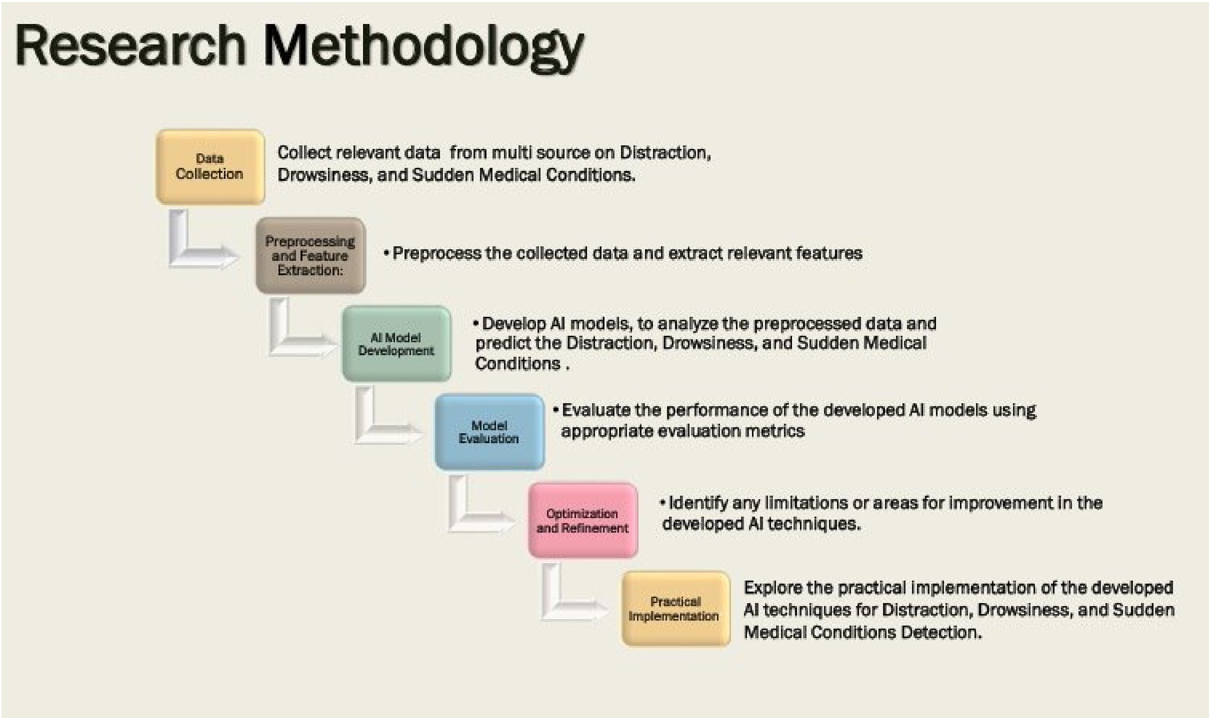

Figure 2. Proposed system methodology outlining the stages of study selection.

The remainder of this paper is structured as follows. Section 2 provides a review of related studies on driver distraction, while Section 3 examines research on drowsiness detection, and Section 4 addresses approaches for identifying sudden medical conditions. Each of these sections is organized into subsections that discuss sensing modalities, algorithmic strategies, and the practical challenges of real-world deployment. Finally, Section 5 presents the conclusion, highlighting the limitations of existing technologies and outlining potential directions for future research. Particular emphasis is placed on enhancing the detection of drowsiness and sudden medical emergencies to improve the safety, reliability, and user acceptance of driver state monitoring systems.

2. Driver Distraction Detection

Driver distraction detection research spans a broad spectrum of sensing modalities, algorithms, and interface designs, each aiming to improve road safety by identifying inattention in real time. For clarity, the reviewed literature is grouped into five methodological categories: vision-based detection, physiological signal analysis, deep learning and hybrid architectures, multimodal sensor fusion, and cognitive or auditory interaction-based distraction. This organization highlights the dominant trends in current research and the complementary potential of combining these approaches into integrated driver monitoring solutions.

2.1. Vision-Based Detection

Vision-based detection systems for driver distraction utilize visual cues such as gaze direction, head pose, facial expressions, and posture to monitor driver attention in real time. Recent studies have explored various approaches, including eye-tracking for glance duration measurement, hybrid deep learning architectures for head-pose estimation, multi-feature frameworks combining gaze and facial metrics, and lightweight convolutional models optimized for embedded hardware. These methods integrate a range of visual indicators to improve detection performance across varying driving conditions.

Lachance-Tremblay et al.[1] designed a real-time distraction mitigation system that employs eye-tracking to measure the duration of off-road glances, activating alerts when gaze is diverted from the road for more than 1.6 seconds. Their experiments compared multiple alert modalities in simulated driving, finding that combined audio–tactile alerts significantly improved on-road gaze behavior and reduced violations during secondary task interaction. Visual-inclusive alerts were less effective, likely due to increased visual load that competed with the primary driving task. The authors noted that preventive, gaze-thresholded warnings were more effective than reactive interventions and observed drivers modifying behavior to avoid alert activation. They concluded that optimal alert design should be tailored to the driving context—manual or automated—to ensure maximum safety benefits. Zhao et al.[15] proposed TokenFOE, a hybrid architecture integrating CNN–MLP feature extraction with a dimension-adaptive Transformer and learnable orientation tokens for accurate head-pose estimation. Tested on datasets including 300W-LP, AFLW-2000, and BIWI, the model achieved more than a 20% reduction in mean absolute error compared to leading methods, while maintaining robustness in day and night conditions on the 100-Driver dataset. The system operated between 21 and 75 FPS, indicating suitability for real-time deployment, though the authors acknowledged that self-attention operations increased computational load. They recommended further optimization for low-power embedded systems to improve deployability without compromising accuracy. Alam et al.[16] developed a vision-based monitoring framework that integrates PERCLOS measurement, yawning frequency detection, and gaze direction analysis to detect driver distraction. The system achieved over 92% accuracy in varied low-light urban driving scenarios, demonstrating robustness for night-time operation without intrusive wearable devices. By focusing on non-invasive camera-based sensing, the design promotes driver comfort while maintaining cost efficiency. The authors outlined future enhancements such as modules for cognitive load estimation, biomedical signal monitoring, and alcohol detection to extend its utility. They emphasized that such systems could be deployed effectively in real-world contexts with further validation in diverse environmental conditions.

In the same field of vision based detection, Tang et al.[4] introduced CaTNet, a compact architecture derived from pruning ConvNeXt and enhancing it with a self-attention module to balance local and global feature extraction. Achieving 94.82% accuracy on the AUC dataset and 99.91% on SFD3 with only 2.83 million parameters, CaTNet demonstrated strong performance while remaining efficient enough for real-time use on embedded hardware like the Jetson Nano. Despite these strengths, the authors noted limitations related to small dataset sizes and occasional focus on irrelevant regions in attention maps. They suggested exploring parallel CaT module configurations and expanding applications to other driver monitoring tasks to improve both generalization and robustness. Whereas, Hossain et al.[7] conducted a comparative analysis of four CNN architectures—Simple CNN, VGG-16, ResNet50, and MobileNetV2—applied to posture-based distraction detection across ten different distracted driving postures. MobileNetV2 achieved the highest accuracy at 98.12%, closely followed by ResNet50 at 94.50%, demonstrating that lightweight architectures can match or exceed the performance of heavier models while being more suitable for real-time mobile deployment. The authors emphasized that such efficiency enables practical integration into smartphone or in-vehicle embedded platforms. Future work involves creating an on-road testbed and Android application to validate system performance in operational conditions. Kotseruba and Tsotsos[2] presented a comprehensive review encompassing over 175 behavioral and 100 applied studies on driver attention and monitoring, with particular attention to vision-based systems. They identified gaps in dataset variety, inconsistencies in defining distraction types, and a lack of standardized evaluation metrics, all of which hinder cross-study comparability. The review called for the development of richer, more representative datasets capturing real-world variability and urged greater interdisciplinary collaboration to advance algorithmic robustness and generalizability. Zhao et al.[17] enhanced a ResNet50-based framework for head-pose estimation, evaluating over 20,000 samples from the SF3D dataset. Significant differences in Euler angles between safe and distracted states confirmed the utility of head pose as a distraction indicator. The authors argued for the combination of head-pose and gaze features to strengthen classification accuracy and advocated continuous video-based tracking to capture temporal context. Such an approach, they noted, could improve system responsiveness in real-time applications.

Huang et al.[18] proposed a lightweight visual detection model incorporating context fusion, channel optimization, and saliency distillation, designed to enhance small-object detection relevant to distraction classification. The architecture improved accuracy without sacrificing inference speed, making it suitable for deployment on embedded systems. The authors highlighted the model's scalability to other safety-related visual detection tasks. Gao and Liu[19] sought to improve interpretability and reduce misclassification in deep learning-based distraction detection by constraining attention maps. Their approach minimized ambiguous feature extraction and reduced overlap between classes, improving accuracy on two benchmark datasets without increasing processing time. They recommended extending these constraints to temporal models to better handle dynamic driving conditions. Michelaraki et al.[20] reviewed non-intrusive distraction detection approaches, finding that vision-based methods dominate the field. They noted, however, a lack of standardization in algorithmic evaluation and dataset use, which impedes direct comparison of results. The authors advocated for the creation of unified benchmarks and large-scale, diverse datasets to foster progress in reliable real-world deployments.

2.2. Physiological Signal Analysis

Physiological signal analysis for driver distraction detection uses data such as heart rate, eye movements, and vehicle dynamics to assess attention and cognitive state. Recent studies have applied both multimodal approaches that combine physiological, visual, and vehicular inputs, and single-modality methods relying solely on vehicle dynamics for unobtrusive monitoring. Other research has examined how different types of secondary tasks influence vigilance, providing insights into the relationship between task demands and driver attention.

Chen et al.[21]created a self-powered driver behavior detection system.combining an electromagnetic triboelectric wristband with deep learning. The device harnesses human motion energy through a pendulum magnet generator and triboelectric Nano sensor, producing electrical signals to recognize six distinct driving behaviors with a multi-scale convolutional recurrent neural network. Test accuracy reached 98.21%, demonstrating strong self-sensing performance and real-world potential for IoV and smart transportation. The authors highlighted future work on improving self-powered capability, integrating additional wearable sensors, and employing multi-node fusion for comprehensive driver monitoring networks.

Fresta et al.[22] created a driver distraction detecting system.that combined vehicular dynamics, eye-tracking data, and physiological signals to identify cognitive distraction. Deep time series models, including ResNet-18, were evaluated in both within-subject and between subject settings, with the latter proving more challenging. Vehicular and eye-tracking features contributed most to classification accuracy, achieving 78.1% accuracy in the between subject case. The study highlighted the benefits of multimodal physiological integration but also noted inter individual variability as a limitation. The authors suggested adaptive models that personalize detection thresholds to driver specific patterns. Wang et al.[8] proposed a distraction detection approach using only vehicle dynamics, enabling unobtrusive monitoring without cameras or wearable sensors. A Bi-LSTM network with attention mechanisms was trained on CAN bus data to detect phone-use distraction, achieving 91.2% accuracy. The results demonstrated that vehicle motion patterns can serve as effective proxies for driver state, although sensitivity to driving style differences was observed. The authors recommended hybridizing with visual cues to improve generalizability across varied driving conditions. Wu et al.[23] investigated the effects of different secondary tasks on driver vigilance, comparing visual–manual–cognitive and auditory–cognitive interactions. Using a vigilance task paradigm, they found that visual–manual–cognitive tasks significantly degraded attention more than auditory tasks. Among auditory conditions, language comprehension tasks preserved vigilance better than working-memory tasks. The study provided evidence for task-specific impacts on driver attention, suggesting that system designers should favor auditory interaction for non-critical tasks in vehicles.

2.3. Deep Learning and Hybrid Architectures

Deep learning and hybrid architectures for driver distraction detection employ advanced neural network designs to improve accuracy and efficiency. Recent approaches include semi-supervised Vision Transformer models that leverage unlabeled data, dual-channel frameworks combining CNN-based spatial feature extraction with Transformer-based temporal modeling, and benchmark comparisons of CNN and hybrid CNN–Transformer configurations. These methods have been evaluated on benchmark datasets with a focus on balancing detection performance and real-time processing capabilities.

Aljohani [24] suggested a real-time driver distraction identification system using a hybrid genetic deep network technique. The method integrates convolutional neural networks and machine learning models optimized via a genetic algorithm to improve classification accuracy of distracted driving behaviors. The hybrid model was trained on labeled driving datasets, achieving high accuracy in recognizing multiple distraction types in real time. The genetic optimization refined network architecture and hyper parameters to balance performance and computational cost, indicating suitability for deployment in in-vehicle safety systems. Future directions include expanding dataset diversity and testing under varied environmental conditions to validate robustness.

Mohammed et al.[25] introduced a semi-supervised Vision Transformer framework trained with an exponential moving average teacher–student method. By generating pseudo-labels from weakly and strongly augmented data, the model leveraged unlabeled samples to boost performance. It outperformed comparable architectures on benchmark datasets while maintaining a lightweight profile suitable for embedded systems. The study demonstrated the feasibility of semi-supervised learning for distraction detection, though real-world performance under varied lighting and occlusion remains to be assessed. Mou et al.[26] coupled CNN-based spatial feature extraction with Transformer-based temporal modeling in a dual-channel network to classify distractions.The architecture processed multimodal inputs, with the multimodal configuration outperforming single-modality setups in accuracy. While performance gains were clear, increased computational complexity posed a barrier for real- time edge deployment. The authors proposed exploring pruning and quantization to reduce model size without sacrificing performance. Sheikh and Khan[27] presented a study benchmarked several CNN and hybrid CNN–Transformer models for real-time distraction detection, focusing on accuracy and inference time. The fine-tuned VGG19 Batched model achieved the highest accuracy at 0.98, closely followed by a hybrid CNN–Transformer architecture with similar accuracy but slightly slower processing. Findings underscored the trade-off between accuracy and speed in real-time systems, recommending careful selection based on application constraints such as hardware capability and latency tolerance.

2.4. Multimodal Sensor Fusion

Multimodal sensor fusion in driver distraction detection combines data from multiple sources to enhance system reliability and coverage. Recent studies have integrated inputs such as GPS, accelerometer, camera, and eye-tracking data, as well as visual action recognition, head-pose estimation, and voice commands. Approaches include smartphone-based sensing frameworks, automated dataset annotation pipelines, and fusion of spatial and gaze information using deep learning models. Other work has incorporated complementary safety features, such as pedestrian hazard detection, to broaden monitoring capabilities.

Garfan et al.[28] reviewed 207 studies employing smartphone-based sensing for driver monitoring, covering modalities such as GPS, accelerometer, and camera. They identified validation and standardization gaps, particularly in integrating heterogeneous sensor data. The authors proposed a three-phase research framework to guide future work, emphasizing cross-platform consistency and real-world validation. Elhenawy et al.[14] presented a semi-automated annotation pipeline for naturalistic driving datasets, using CNNs and Random Forests to classify driver behaviors. The approach reduced manual labeling time significantly while maintaining high precision and low false positives. By accelerating dataset preparation, the method supports large-scale training of multimodal distraction detection models. Qiao et al.[29] used dashcam video frames with eye-tracking heatmaps using adversarial learning and Transformer-based temporal modeling. This approach achieved 96.42% accuracy in cognitive distraction detection, demonstrating the benefits of combining spatial and gaze information. The authors highlighted robustness across varying lighting conditions and suggested extending the model to incorporate additional physiological inputs. Abououf et al.[30] integrated visual action classification, head-pose estimation, and voice control into a single distraction detection framework. The system achieved high accuracy with sub-second GPU inference, making it suitable for real-time use. However, certain micro-sleep cases were missed, indicating the need for integration with eyelid closure monitoring. Alias et al.[31] designed a Raspberry Pi–based system to detect sudden pedestrian crossings, issuing audible alerts to the driver. Although primarily focused on external hazards, the system complements in-vehicle distraction detection by addressing peripheral safety risks.

2.5. Cognitive and Auditory Interaction-Based Distraction

Cognitive and auditory interaction-based distraction research examines how in-vehicle tasks, alerts, and communication systems affect driver attention. Recent studies have evaluated phone-use restriction applications, driver monitoring systems aligned with safety protocols, and auditory warning mechanisms in urban driving. Reviews have explored distraction risks among specific driver groups, such as younger drivers, while other work has compared the cognitive demands of voice assistants, highlighting differences in task efficiency and potential implications for safer interaction design.

Kujala et al.[32] evaluated a phone-use monitoring application designed to restrict manual phone interaction in high-demand driving zones. Field tests showed reduced risky touch interactions except in dense urban environments where compliance decreased. The authors recommended enhancing context-awareness and automating restriction enforcement for greater effectiveness. Koniakowsky et al.[33] assessed a driver monitoring system following Euro NCAP protocols, examining its influence on glance behavior during secondary tasks. The system reduced prolonged glances away from the road in complex scenarios, especially for novice drivers. Effectiveness was lower for experienced drivers, suggesting the need for adaptive alert thresholds. Goldsworthy et al.[34] reviewed the effects of distraction on younger drivers, linking increased vulnerability to neurodevelopmental factors affecting attention control. The review emphasized the heightened risks associated with visual–manual tasks in this demographic and the importance of targeted interventions. Lioi and Bassani[35] provided a study tested an audible warning system for distraction in urban driving, finding minimal benefits for drivers engaged in texting. The authors suggested that multimodal feedback, such as combining audio with tactile alerts, and supportive policy measures could enhance impact. Paper 27 — Alexandra Loew et al. Loew et al.[36] compared the cognitive load of texting via Siri, Google Assistant, and Alexa. While all assistants increased cognitive load moderately, speed control was not significantly affected. Google Assistant had the slowest task completion times, indicating potential for optimization in voice interface design for safer use while driving.

2.6. Critical Analysis and Research Gaps

The reviewed literature demonstrates substantial progress in driver distraction detection across diverse sensing modalities and algorithmic strategies. Vision-based approaches dominate the field, benefitting from advances in deep learning, yet remain sensitive to lighting variation, occlusion, and domain shift, underscoring the need for adaptive models and standardized benchmarks. Physiological and vehicle dynamics–based methods offer non-visual alternatives but often struggle with inter-driver variability and require improved personalization techniques. Deep learning and hybrid architectures achieve high accuracy but face deployment challenges due to computational demands, suggesting opportunities for model compression and energy-efficient design. Multimodal fusion holds promise for robustness, though real-world integration demands careful calibration of heterogeneous sensors and resilience to partial data loss. Cognitive and auditory interaction studies reveal that not all secondary tasks impact attention equally, pointing toward task-specific alert strategies. Across all categories, critical gaps include the scarcity of large, diverse, real-world datasets; inconsistent evaluation protocols; and limited longitudinal field testing. Addressing these gaps will require collaborative dataset curation, cross-disciplinary modeling efforts, and validation under naturalistic driving conditions to ensure that detection systems are reliable, context-aware, and adaptable to the complexities of real-world driving environments. Table 1 and Figure 3 illustrates briefly the most recent work and the critical analysis of existing studies on distraction and highlights the corresponding research gaps, respectively.

3. Driver Drowsiness

This section synthesizes recent research on driver drowsiness detection and mitigation, organizing the literature into five complementary lenses: vision-based cues; physiological signals; deep learning and hybrid model innovations; multimodal sensor fusion; and cognitive or interaction-related factors that modulate drowsiness risk. Across the corpus, studies span controlled simulators, partially automated driving, and real-world deployments, and leverage

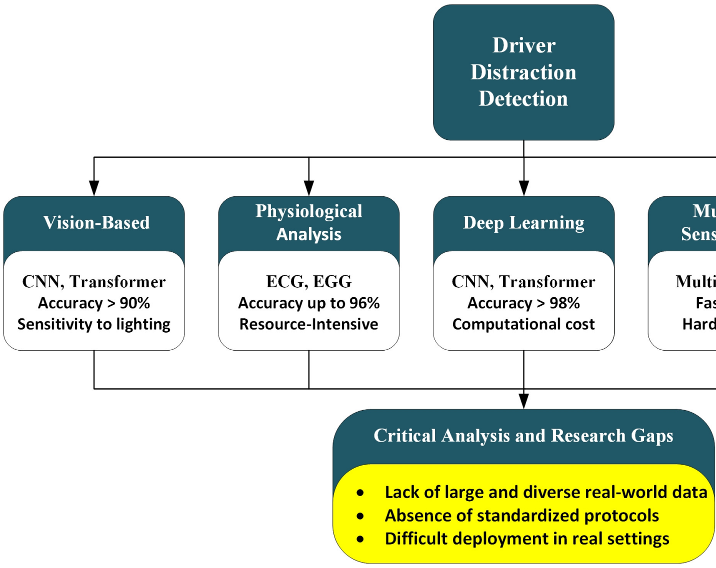

Figure 3. Critical analysis of the distraction domain highlighting the key limitations in existing approaches and the main research gaps that guide future investigation.

signals from faces and posture to EEG, respiration, and fleet telemetry[37, 38]. Below, each subsection situates key papers, articulating their problem framing, data and methods, headline findings, and stated limitations.

3.1. Vision-Based Detection

Vision-based drowsiness detection focuses on identifying physiological and behavioral fatigue indicators rather than task-related distractions. Unlike distraction-focused systems, which track secondary activities such as phone use or gaze diversion, drowsiness monitoring emphasizes features like eyelid closure rate, blink duration, head tilt, and yawning patterns. Recent research has explored deep learning models—including CNNs, LSTMs, and hybrid feature selection techniques—to process facial imagery and temporal sequences for early detection. Implementations range from lightweight embedded systems to IoT-enabled modules, highlighting their potential for continuous, real-time fatigue assessment in diverse driving conditions.

Amzar et al.[39] presented a driver drowsiness detection and monitoring system (DDDMS) for detecting driver sleepiness. In brief, this driver sleepiness monitoring system can constantly monitor drivers to prevent accidents in real time. The objective of this study is to create a driver drowsiness and monitoring system that can aid the driver while driving. Then, to increase the system's accuracy, the algorithm should contain a classifier trained on a set of example photos. In the future, this Driver Drowsiness and Monitoring System might be updated even further by adding more systematic features to make it easier for the driver to operate their car.

Deep learning and IOT were used by Phan et al.[40] to build smart alerting and driver drowsiness detection. It may significantly increase the forecast accuracy of sleepiness and assist in resolving practical issues. By creating and refining four adaptable neural networks based on LSTM, VGG16, InceptionV3, and Dense Net, A deep learning-based method for sleepy driver identification and prediction is suggested. This reduces training time, prevents over-fitting, and increases the forecast accuracy of sleepiness. In further study, The Raspberry Pi monitoring system and voice output via an Internet of Things (IoT) module will be used to implement the suggested techniques in a sleepiness warning system.

Table 1. Driver distraction

Authors	Year	Techniques/Approach	Dataset	No. of Classes	Results
J. Lachance-Tremblay et al. [1]	2024	Gaze-based countermeasure with real-time eye-tracking and multimodal alerts (audio/haptic/visual)	Driving simulator with IVIS distraction tasks (eye-tracking)	N/A	Reduced off-road glances; improved attention (no accuracy %)
J. Chen et al. [21]	2024	Self-powered electromagnetic–triboelectric wristband + deep learning (multi-scale CNN-RNN)	Custom time-series dataset (six driving behaviors)	6	Test accuracy 98.21%
X. Zhao et al. [15]	2024	TokenFOE (CNN + Transformer); SO(3) rotation matrix + orientation tokens	300W-LP (train); AFLW-2000 & BIWI (test); 100-Driver dataset	9 (pose categories)	MAE improved 21.2% (AFLW-2000), 9.4% (BIWI) vs SOTA
L. Alam et al. [16]	2021	Active vision-based attention monitoring (PERCLOS, yawning, gaze direction) with decision fusion	Simulator recordings	2 (attentive vs distracted)	Accuracy 92%
X. Tang et al. [4]	2024	CaTNet: lightweight ConvNeXt + Transformer fusion (CaT module)	AUC (American University in Cairo) & State Farm datasets	10	Accuracy 94.82% (AUC), 99.91% (State Farm)
M. U. Hossain et al. [7]	2022	Transfer learning CNNs (VGG-16, ResNet50, MobileNetV2)	State Farm Distracted Driver (Kaggle)	10	Best accuracy 98.12% (MobileNetV2)
I. Kotseruba and J. K. Tsotsos [2]	2021	Survey of behavioral and computational models of driver attention	Review of ∼175 behavioral studies & ∼20 datasets	N/A	Survey only (no accuracy; identifies gaps)
Salem Garfan et al. [28]	2024	Systematic review of smartphone-based driver behavior detection (sensors + ML)	Review of 207 studies (Pervasive & Mobile Computing)	N/A	Review only (no accuracy; summarizes challenges & trends)
Zuopeng Zhao et al. [17]	2020	Head-pose estimator (HPE_ResNet50) combining regression & classification-with-regression	300W-LP (train), AFLW-2000 (eval), SF3D (10 driver behaviors)	10	MAE **6.17°** (AFLW-2000); Euler-angle differences 12.4°–54.9° (SF3D)
Matteo Fresta et al. [22]	2025	Deep learning on multimodal time-series (1D-CNN/ResNet-18) for cognitive distraction	Simulator dataset (42 subjects; vehicular + physiological + eye-tracking)	2 (cognitive distraction vs baseline)	F1-score **78.04%** (ResNet-18, short windows)
Mohammed Elhenawy et al. [14]	2023	Pre-trained CNNs (VGG, ResNet, Inception) + Transfer Learning + Random Forest	Australian Naturalistic Driving Study (ANDS) videos (dashboard & face cameras)	2 (distracted vs. non-distracted)	TPR 60.9% (dashcam) / 74.8% (face cam); Precision 32.5% / 65.1%; FPR 21.8–34.4%

Authors	Year	Techniques/Approach	Dataset	No. of Classes	Results
Yu Qiao et al. [29]	2025	DCDD: Fusion Adversarial Network + Multi-View Space-Channel Network (eye-movement + dashcam fusion)	DCDD dataset (eye-tracker heat maps + dashcam images)	2 (cognitive distraction / normal)	Accuracy 96.42%
X. Huang et al. [18]	2024	FADNet with Context Fusion Enhancement Module (CFEM) + Global Saliency Optimization	LDDB (6 behaviors); StateFarm (10 categories)	6 (LDDB); 10 (StateFarm)	mAP 96.2% (LDDB); mAP 93.6% (StateFarm)
X. Wang et al. [8]	2022	Bi-LSTM + Attention on vehicle dynamics	Shanghai Naturalistic Driving Study (SH-NDS)	2 (phone use vs. normal)	Accuracy 91.23%; F1 91.44%; AUC 97.40%
Adam A. Q. Mohammed et al. [25]	2024	Semi-supervised Lightweight Vision Transformer (ViT) with pseudo-labels	StateFarm (10 classes); 3MDAD (16 classes)	10; 16	Accuracy 95.43% (StateFarm); Avg. per-class 71.09% (3MDAD)
T. Kujala et al. [32]	2024	Context-sensitive smartphone distraction warnings	12-week naturalistic field study (26 drivers)	N/A	Reduced smartphone use in high-demand contexts; no significant change in urban driving
M. Wu et al. [23]	2025	Multi-criteria decision models (TOPSIS, Fuzzy Comprehensive Evaluation, Rank-Sum Ratio)	Driving simulator with ADAS (31 participants)	3 (visual-manual; auditory-cognitive; baseline)	Visual-manual tasks ↓ vigilance; auditory-cognitive maintained vigilance (no % accuracy)
Hang Gao; Yi Liu [19]	2024	Constrained Attention (CA) mechanism with MobileNetV2 backbone	AUC V2; StateFarm (split by driver)	10	Improved accuracy over MobileNetV2 baseline (reported gains, no single % figure)
L. Mou et al. [26]	2023	Dual-channel CNN + Transformer with bilevel hyper-parameter optimization; multimodal fusion	Custom multimodal dataset (vehicle dynamics + eye-tracking + physiological signals)	4 (normal; cognitive; emotional; sensorimotor)	Accuracy 99.80%; F1 99.82%
A. Abououf et al. [30]	2022	Multimodal: CNN for driver actions + head-pose estimation + speech pipeline (ASR + text classification)	AUC Distracted Driver dataset (10 actions) + custom car-command speech dataset	10 (actions) + commands	Driver action accuracy 94.1%; Speech command accuracy 95.19%; Head-pose MAE 6.21°
A. A. Sheikh and I. Z. Khan [27]	2024	CNNs (VGG16, VGG19, custom CNN + transformer)	State Farm Distracted Driver Dataset (Kaggle)	10	Accuracy ∼96–98%; fine-tuned VGG19 gave best performance.
E. Michelaraki et al. [20]	2023	Systematic review (PRISMA-based)	Not applicable	N/A	Eye-tracking & steering sensors most effective; gaps in harmonized distraction definitions.

Authors	Year	Techniques/Approach	Dataset	No. of Classes	Results
Abeer A. Aljohani [24]	2023	Hybrid genetic deep network (CNN + ML with GA optimization: VGG19, ResNet50, DenseNet121 + KNN, RF, SVM, XGBoost)	State Farm Distracted Driver Detection Dataset	10	Achieved 99.8% accuracy with GA-optimized CNN+ML; NLP commands 96.9%.
I. Koniakowsky et al. [33]	2025	Euro NCAP-based Driver Monitoring System (eye-tracking warnings)	Driving simulator (57 participants, touchscreen tasks)	N/A	DMS reduced distraction only for complex tasks in inexperienced trials; no effect in familiar tasks.
J. Goldsworthy et al. [34]	2024	EEG neurophysiological measures + simulated distraction tasks	Driving simulator, 24 young drivers (18–25 yrs)	3 (Visual, Auditory, Cognitive)	Visual distraction impacted lane keeping; cognitive distraction showed highest workload (EEG beta/gamma).
A. Lioi and M. Bassani [35]	2024	Auditory Advanced Driver Distraction Warning (ADDW) device	Driving simulator, 30 middle-aged drivers (urban texting scenarios)	N/A	ADDW did not improve urban driving performance, unlike highways; little effect during texting.
A. Loew et al. [36]	2023	Speech-based assistants (Siri, Google Assistant, Alexa) vs. arithmetic OSPAN	Driving simulator, 31 participants	3 assistants + OSPAN + baseline	Baseline hit rate = 98.0%; Siri = 87.5%, Google = 85.3%, Alexa = 88.3%
M. A. Alias et al. [31]	2020	Raspberry Pi + Pi Camera + OpenCV (HOG + buzzer alert)	Custom real-world pedestrian detection dataset	2 (Pedestrian / No Pedestrian)	HOG+SVM: detection up to 9.7 m, notification within 1.2–1.4 s; TensorFlow: detection up to 8.6 m, notification within 4 s; confidence >60%.

Bekhouche et al.[41] suggested a technique for identifying driver sleepiness in video sequences using a hybrid selection of deep characteristics.. The suggested framework is built on the sliding window concept, which allows for real-time performance. Several experiments and performance assessments revealed that the proposed strategy is more effective than state-of-the-art methods. The output is then subjected to temporal aggregation, followed by feature selection, to produce the final feature vector, which is subsequently fed into a binary SVM classifier for decision-making. The proposed system analyzes the driver's face by leveraging the dynamics of succeeding image frames and combining them with deep feature-based operators. In addition,The proposed feature selection strategy, which is based on feature clustering, increased the framework's accuracy and speed. The system recognizes the driver's face, extracts deep characteristics from the facial image, then combines these features with those from earlier frames to form an observation matrix.

Hernandez et al.[42] studied real-time driver tiredness and distraction detection using a convolutional neural network with different behavioral features. Future research initiatives could include improving the system's hardware components in terms of size and performance, using additional features or combining other detection features, expanding the dataset, testing the device in different settings, and including more participants. To identify tiredness and distraction, the system uses non-intrusive video sensors and convolutional neural networks (CNN) to monitor the driver's behavior, such as facial expressions, eye movements, and lane location. The findings emphasize the system's impressive performance in detecting tiredness and distractions, with high accuracy rates and an effective alarm system that activates when potential threats are detected. This study lays the groundwork for future advances in proactive driver safety systems, highlighting the crucial relevance of tackling driver sleepiness.and distraction on the roads.

3.2. Physiological Signal Analysis

Physiological signal–based drowsiness detection leverages biosignals such as respiration patterns, heart rate variability, and brain activity to identify early signs of fatigue. Recent research has explored wearable sensors, smart garments, and EEG-based systems to provide non-invasive, real-time monitoring. Techniques range from statistical modeling of respiration variability to deep learning and transfer learning applied to multi-channel EEG data, aiming to improve detection accuracy, adaptability, and robustness in both simulated and real driving conditions.

Yuda et al.[5] investigated the feasibility of using respiration signals from a Hexoskin smart shirt to detect driver drowsiness. Traditional ECG-based heart rate variability (HRV) methods face challenges in real-world driving due to motion artifacts and intrusive electrodes. The study explored respiratory rate variability (RRV) as a less invasive alternative. Nine healthy participants (7 males, 2 females; mean age 45 ± 9 years) drove either on a track or a personal vehicle while respiration, ECG, and acceleration were continuously recorded. Drowsiness was assessed via the "Dip & Waves" heart rate pattern, a known surrogate marker. Results showed no significant change in respiratory rate during drowsiness, but RRV increased steadily starting 4 minutes before Dip & Waves, peaking at the event, then declining. HRV measures did not show a comparable predictive trend. The findings suggest that RRV may offer early warning of drowsiness before overt signs appear, making smart-shirt monitoring a promising, non-invasive tool for driver safety systems. Limitations include the small sample size and reliance on a surrogate drowsiness marker. Further research is needed to confirm the predictive power of RRV in broader driving conditions.

Lin et al.[43] investigated driver sleepiness detection using eeg in a simulated driving scenario. Extensive tests were carried out on both public and self-built datasets to evaluate the efficacy of the suggested technique. Second, a convolutional neural network (CNN) is used to integrate the attention mechanism with multi-anchor attentive fusion technology. The experimental findings show that the technique can successfully simulate real-world driving scenarios, properly capture drivers' EEG signals, and identify drowsiness. In the future, the research is intended to be expanded into real-world road conditions in order to capture more realistic driving data in an ethical manner.

Puspasari et al.[44] proposed predicting tiredness in young Indonesian drivers using eeg signals for driver drowsiness detection.. Thus, the study's goal is to develop a sleepiness indicator based on EEG signals under simulated driving scenarios. The SVM outperformed logistic regression in classification, with the linear kernel coming out on top. The EEG signals, together with sleep state and driving time parameters, yielded a model accuracy of 77.1% in data training and 90.2% in data testing, with 90.5% sensitivity and 90% specificity.

Feng et al.[45] developed a pseudo-label-assisted subdomain adaptation network with coordinated attention to identify driver sleepiness using eeg data.. Extensive studies on two publicly accessible driver sleepiness datasets show that the proposed framework beats state-of-the-art baselines in overall performance. To overcome these challenges, a pseudo-label-assisted subdomain adaptation network with coordinate attention (PASAN-CA) is presented for detecting driver sleepiness using EEG data. In this paper, the focus is placed on enhancing the accuracy and generalization of the deep transfer learning approach for detecting driver sleepiness using EEG. In the future, an EEG-based driver drowsiness detection technique that takes privacy into account is planned to be investigated.

Latreche et al.[46] developed an optimal deep hybrid learning for multi-channel EEG-based driver drowsiness detection.. The study used a publicly available dataset with twelve healthy subjects. As a result, as a first step and for the first time in our knowledge, an optimization technique was used to establish the ideal preprocessing parameter values using a CNN model, with accuracy as the objective function. The constraints of the proposed study include a small amount of data (the utilized dataset comprises only 12 individuals), and more data are required to generalize and confirm the results.

Chen & Xie [47] presented eeg-based tsk fuzzy graph neural network for driver drowsiness estimation for driver drowsiness detection The performance of TSKG on the fatigue-driving dataset (RMSE and CC) is much better than that of the comparison algorithms, and the improvement is especially noticeable for samples that performed poorly in the comparison algorithms. TSKG uses mutual information minimization to extract the invariant features from the original features, and then GCN to construct the affinity matrix while keeping the structure unchanged, transferring as many sample characteristics as possible to rule construction, learning more effective rules, and achieving better results. However, the noise problem and non-stationary EEG data make it difficult for BCI to maintain adequate accuracy in the real world. In future research, the algorithm for calculating the affinity matrix and the method of information migration will be further optimized to improve the performance of TSKG.

3.3. *Deep Learning and Hybrid Architectures*

Deep learning and hybrid architectures have been employed to improve drowsiness detection by capturing complex, non-linear relationships in driver state data. Approaches such as multi-aware graph convolutional networks leverage spatial–temporal dependencies to enhance accuracy on public datasets, while CNN–DNN frameworks integrate multiple input features to achieve robust, real-time performance under varying conditions. These models demonstrate strong potential for adapting to diverse driving environments and operational scenarios.

Lin et al.[48] studied a multi-aware graph convolutional network for driver drowsiness detection. Experiment findings reveal that the proposed MAGCN outperforms state-of-the-art drowsiness detection techniques on two public datasets. The research proposes a CNN model for detecting drowsiness called MAGCN. Different lighting conditions (e.g., bright or low light) might alter the accuracy of drowsiness detection. In the future, the influence of light intensity and direction on the performance of drowsiness detection algorithms will be investigated to optimize detection under changing lighting situations.

Pattarapongsin et al.[49] investigated real-time tiredness and attention detection for drivers by combining computer vision and deep learning. Real-time identification of early indicators of tiredness or driver attention has not yet shown to be the most reliable. The DNN used for face identification and the CNN used to extract facial land-marks outperform Haar and HoG in all occlusion, frontal and non-frontal face detection scenarios.

3.4. *Multimodal Sensor Fusion*

Multimodal sensor fusion approaches integrate diverse physiological, behavioral, and spatial data streams to improve the reliability of drowsiness detection. For instance, CNN–LSTM architectures have been applied to datasets encompassing both manual and automated driving modes, achieving up to 96% accuracy in distinguishing rested from fatigued states. Other research has combined electroencephalography with spatial driving metrics, revealing that model performance is more strongly influenced by feature selection and algorithm type than by dataset size. Personalization has emerged as a key focus, with “driving fingerprinting” methods tailoring detection thresholds to individual driver patterns to address inter-individual variability. Additional studies have demonstrated the value of combining postural and physiological indicators—such as pressure distribution, cardiac activity, and respiration—to capture distinct signatures across drowsiness stages. While these fusion methods show promise in enhancing detection robustness, future research should prioritize adaptive, personalized systems validated in real-world driving environments, with sufficient sample diversity to ensure generalizability.

Shanthi et al.[10] investigated data fusion for driver drowsiness recognition using a multimodal approach to driver drowsiness detection. The suggested approach tackles the difficulty of identifying driver sleepiness by utilizing a WACHSens dataset gathered from both manual and automatic driving modes, including rested and tired states. A unique strategy that uses Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to detect drowsiness in drivers with a 96% accuracy level. Future research should focus on building adaptive drowsiness detection methods that can tailor alerts and treatments to individual driver traits and preferences.

Farhangi et al.[50] proposed driver drowsiness modeling based on spatial parameters and electroencephalography utilizing machine learning methods: a simulator research for driver drowsiness detection. Twenty adult subjects took part in the simulator tests, and based on their self-reports of drowsiness, the first and last minutes of driving were labeled as wakeful and drowsy, respectively. EEG signals were modeled using 35 signal features and 2800 train data records, while spatial drowsiness was modeled using four spatial criteria and 8320 train data records. According to the authors, in ML modeling, the type of data and method have a greater effect on output accuracy than sample size of previous studies.

Sun et al.[11] claimed that driver fingerprinting improves sleepy driving detection by adapting to individual driver characteristics. To begin, 24 participants (with a 2:1 male-to-female ratio and diverse ages and occupations, including professional taxi drivers and graduate students) participated in simulated driving experiments, and data on their driving behavior, facial expressions, and Karolinska Sleepiness Scale (KSS) scores were gathered. Drowsiness identification is a long-standing issue in reducing drowsiness-related accidents. Individual variations have a significant impact on the precision with which sleepiness may be detected. There were several limits and problems, such as the need to extend face measurements, increase sample size, and distinguish between virtual and actual cars.

Perrotte et al.[51] developed a method for monitoring driver drowsiness in partially automated vehicles by combining postural and physiological indicators. In this study, 22 volunteers drove for 100 minutes in a static simulator with level-2 automation on a 2 x 2 motorway. Physiological markers (e.g., pressure, movements, and cardiac and respiratory) were continually collected, and PERCLOS70 was used to diagnose sleepiness. The findings show that the various sleepiness phases have distinct physiological and postural fingerprints.

Pondit et al.[52]introduced a real-time driver monitoring system based on visual signals to identify driver drowsiness To evaluate the system, we utilized our own datasets. Many of these incidents are caused by driver distraction and microsleep. The system achieves 97% accuracy in detecting eye blinks, 96% in detecting yawns, and 63.4% in estimating head poses. The technology will be evaluated in the future with a real-world dataset.

Chai [53] conducted research on a driver monitoring system based on vital signs and behavior detection for driving sleepiness. The MTCNN model is primarily utilized to capture the driver's face picture in real time. The research proposes a fatigue algorithm that can increase monitoring efficacy and accuracy. In the future, new health monitoring technologies and real-time monitoring of driving status will be investigated to continuously improve the system and give more accurate services.

3.5. Cognitive and Auditory Interaction-Based Distraction

Drowsiness in drivers can be influenced by thermal comfort, work schedules, vibration exposure, and human–automation interaction. Studies highlight how environmental conditions and operational demands affect alertness, while crash analyses link fatigue severity to roadway, vehicle, and temporal factors. These findings underscore the need for adaptive in-vehicle systems and continuous monitoring strategies to address diverse drowsiness triggers.

Sunagawa et al.[9] investigated the influence of thermal comfort on driver sleepiness progression with anticipated mean vote, an experiment employing real highway driving circumstances for driver drowsiness detection. These findings were derived from genuine highway driving data and hence give insights into driver situations in a realistic setting. These findings were derived from genuine highway driving data and hence give insights into driver situations in a realistic setting. More driver data is needed to generalize our findings in future investigations.

Saito et al.[12] investigated the efficacy of a dual-control strategy for detecting driver drowsiness. Regardless of whether the suggested system was present or not, the frequency of blinks decreased one minute after moderately sleepy individuals (level 3) were exposed to the test events. Furthermore, two minutes after the events, those who were very tired (level 4) showed an increase in the percentage of eyelid closing time. Participants exhibited indicators of tiredness when driving with partial automation. Two-way communication was seen to increase blink frequency and decrease eyelid closure time under extreme tiredness (level 5), but it was not regarded beneficial for boosting alertness. The study proposes a strategy to bring the vehicle to a controlled stop if the driver fails to supervise the partial driving automation. For extremely drowsy participants (level 5), responding to system information was difficult. Without the proposed system, driving automation continued to control the vehicle even when participants were extremely drowsy. In contrast, with the proposed hands-off safety control, the system could execute safe control through human interaction. To evaluate the effective- ness of driver state identification via the dual-control scheme, four performance metrics were considered: accuracy = 0.78, precision = 1.0, recall = 0.71, specificity= 1.0. Among 23 instances where first-stage control was implemented, the system successfully determined that the driver failed to supervise partial automation in 12 cases. In 8 of these 12 cases, the vehicle was brought to a complete stop.

Al-Bdairi et al.[54] introduced injury severity of sleepy drivers involved in single vehicle collisions by accounting for temporal instability and unobserved variability in driver drowsiness detection. Drowsy driving has received very little attention in road safety literature when compared to other safety concerns, despite its catastrophic impact on society in terms of human life loss and related economic costs. According to the estimation results, the influence of factors on injury severity varies with time. Using four years of collision data from the state of Washington from 2013 to 2016, a variety of parameters were investigated, including driver traits, highway conditions, crash characteristics, vehicle conditions, lighting conditions, and temporal variables.

Soleimanloo et al.[55] suggested a method for detecting driver tiredness by combining schedule features of heavy truck drivers with continuous eye-blink measurements. In real-world operations with a variety of work conditions, driving a heavy vehicle at night between 9 p.m. and 2 a.m., after 18 hours of driving, during shifts beginning early in the morning, and shifts with break durations shorter than 7 hours significantly increases hourly rates of drowsiness events in HVDs. The study's findings highlight the need of continuous drowsiness monitoring using ocular metrics in evaluating the influence of scheduling on naturalistic driving studies and developing a national framework for collecting and analyzing tiredness data in HVDs. Results: The combined effects of time of day (10 pm-2 am), shift start time (2 pm-3 pm), hours into the shift (16-21 h), break duration (7-9 h), and sleep time could determine the likelihood or rate of drowsiness events. Future studies should use larger cohorts of HVDs and long-term protocols to examine the association of total sleep time, shift type, shift length and shift order with real-time drowsiness event rates in HVDs.

Fard et al.[56] investigated the effect of vibration frequency on driver drowsiness, reaction time, and driving performance for driver drowsiness detection. Fifteen participants each completed six 1-hour sessions of simulated driving while exposed to WBV at 0 Hz (no vibration), 1-4 Hz, 4-8 Hz, 8-16 Hz, 16-32 Hz, or 32-64 Hz. The two lowest frequency ranges significantly reduced reaction time, a measure of attention and alertness. These findings were supported by subjective reports of drowsiness.

3.6. Critical Analysis and Research Gaps

Several cross-cutting limitations recur across the reviewed work. First, many models report high accuracy on modest or homogeneous samples (e.g., $N \leq 30$, single-lab datasets), or within simulators, leaving generalization to diverse drivers, vehicles, occlusions, night conditions, and long-haul operations underexplored. Second, personalization is often implicit or absent—yet multiple studies show strong inter-individual variability; methods that adapt thresholds and features per driver (e.g., driving fingerprinting, domain adaptation) deserve wider adoption and benchmarking. Third, physiology-only or vision-only pipelines struggle under real-world noise; the strongest signals of drowsiness (and even early prediction) emerge when fusing complementary modalities (posture + cardio-respiratory; EEG + spatial/temporal context), but there is a scarcity of standardized, multimodal, open datasets captured in real vehicles. Fourth, few systems close the loop with calibrated, context-sensitive interventions (thermal or HMI strategies, dual-control safety maneuvers), and almost none evaluate safety impact beyond ML metrics. Lastly, deployment constraints—compute on embedded platforms, privacy-by-design, and robustness monitoring—are sporadically addressed. Future work should therefore prioritize (i) large-scale, longitudinal, multimodal datasets with shared benchmarks; (ii) adaptive, privacy-preserving personalization (on-device learning, federated and domain-adaptive techniques); (iii) early-warning models tied to interpretable physiological and behavioral mechanisms; and (iv) human-centered evaluation of alerts and fallback control in partially automated driving. Table 2 and Figure 4 provides briefly the most recent work and a synthesis of the critical analysis on drowsiness detection, drawing attention to the key research gaps that warrant further investigation, respectively.

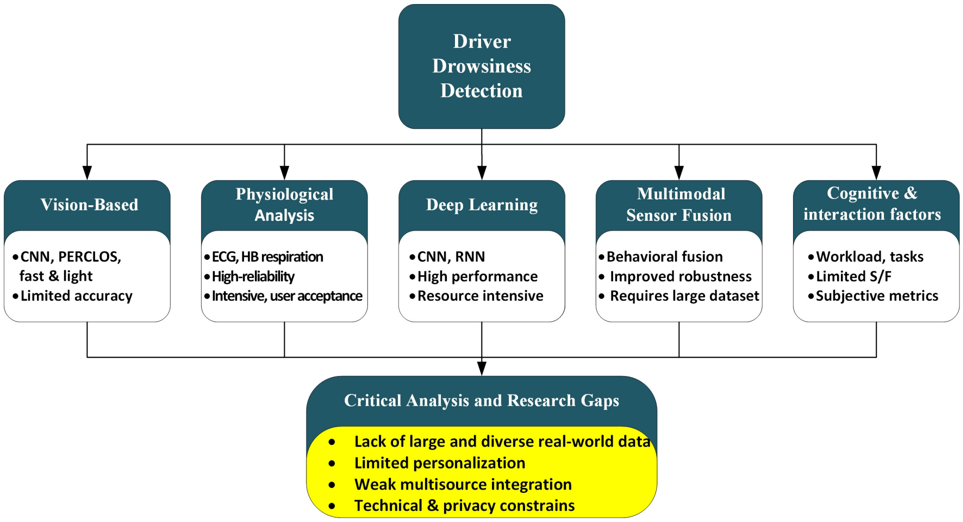

Figure 4. Summary of identified weaknesses in drowsiness detection studies and the corresponding research gaps requiring further investigation.

4. Sudden Medical Conditions

This section reviews research dedicated to detecting sudden medical conditions that may impair driver performance and compromise road safety. While less common than fatigue or distraction, these events can have severe consequences, necessitating rapid detection and intervention. The reviewed works encompass wearable sensors, physiological monitoring, in-vehicle sensing systems, and algorithmic frameworks for detecting conditions such as cardiac anomalies, seizures, and other acute impairments. Each study is summarized with attention to its objective, methodology, main findings, and stated limitations.

Badawi et al.[57] proposed cardiac arrhythmia detection while driving for sudden medical condition detection in drivers. This was accomplished by attaching a heart beat sensor to the earlobe to assess heart rate. High performance was demonstrated, indicating practical possibilities. Hollósi et al.[58] developed capsule networks for bus driver head position detection under dynamic driving conditions in order to detect sudden medical conditions in drivers. To monitor bus driver behavior and posture in the dynamic and unpredictable environment of urban public transportation, strong real-time analytics solutions are required. Our investigation covers four different neural network architectures, including two variations of convolutional neural networks (CNNs) that serve as the comparative baseline. The results indisputably show that the suggested routing algorithm surpasses the current method in terms of accuracy across all investigated cases. These findings have far-reaching consequences, opening up a viable route for future study and practical applications in driver monitoring systems, particularly in terms of public transportation safety.

Table 2. Driver drowsiness

Authors	Year	Techniques/Approach	Dataset	No. of Classes	Results
E. Yuda et al. [5]	2021	Smart shirt respiratory monitoring (Hexoskin) using respiration, ECG, and acceleration; Dip & Waves analysis	9 subjects, 2,359 min driving	2 (Alert vs. Drowsy)	Reliable detection of drowsiness from respiratory patterns
L. Lin et al. [46]	2024	Multi-Aware Graph Convolutional Network (MAGCN): CAAE for global/local facial features, CTAE for temporal features, GCN for region correlations	DROZY, UTA-RLDD	Binary	Accuracy 95.79% (DROZY), 96.76% (UTA-RLDD)
I. Latreche et al. [44]	2025	Optimized deep hybrid learning for EEG-based detection; CNN-SVM hybrid	Public EEG dataset	Binary	Accuracy 99.9%
M. Sunagawa et al. [9]	2023	Analysis of thermal comfort (PMV) on drowsiness under highway driving	29 drivers, real highway	N/A	Model accuracy $\sim$83% (drowsiness detection); Drowsiness prediction improved with PMV (MSE reduced from 0.198 $\rightarrow$ 0.147, $\approx$25.8% improvement)
S. Priyanka et al. [10]	2024	Multimodal fusion (vehicle, facial, biosignals) with CNN+LSTM	WACHSens dataset	Binary	Accuracy 96%
R. A. F. Rozali et al. [37]	2022	Raspberry Pi + computer vision detecting blinks, yawns, head pose	Custom dataset, real-time	Binary	Blink detection 80.9%, Yawn detection 96.3%, Gaze detection 69.6%
A. C. Phan et al. [38]	2023	Deep learning + IoT (LSTM, VGG16, Inception-V3, DenseNet) with Jetson Nano	Custom video dataset	Binary	Accuracy up to 98%
F. Farhangi et al. [48]	2023	EEG + spatial criteria; ML classifiers (BDT, RF, MLP, SVR)	20 subjects, 108 km virtual road	Binary	BDT (EEG): 92.5%, RF (EEG): 91.9%, MLP (EEG): 80.7%, SVR (EEG): 70.6%; MLP (Spatial): 92.1%, BDT (Spatial): 91.8%, RF (Spatial): 91.7%, SVR (Spatial): 89.6%
S. E. Bekhouche et al. [39]	2022	Video-based detection; ResNet-50 + temporal aggregation + SVM	NTHU-DDD dataset	Binary	$\sim$86–87% accuracy across scenarios and subjects
Y. Sun et al. [11]	2024	Driving Fingerprinting (IDDM model) with RBFNN; personalized models	24 drivers	Binary	Accuracy = 95.58%, Sensitivity = 96.50%, Specificity = 94.70%
X. Lin et al. [41]	2025	EEG CNN with attention, fusion, focal loss, Gumbel channel selection	Public + self-built EEG	Multi-class	SADT (public dataset): 87.83%
H. Chen; J. Xie [45]	2024	EEG-based TSK fuzzy GNN	Fatigue-driving EEG	Continuous	RMSE = 0.1681, CC = 0.7118 ($\sim$71.18% correlation)

Authors	Year	Techniques/Approach	Dataset	No. of Classes	Results
Y. Saito et al. [12]	2023	Dual-control L2 automation (detect low arousal, safe stop)	Simulator, 26 drivers	N/A	78% accuracy (Precision: 100%, Recall: 71%, Specificity: 100%)
N. S. S. Al-Bdairi et al. [52]	2024	Crash-data modeling of drowsy single-vehicle crashes	WA crash data 2013–16	Severity levels	Serious 16–21%, Moderate 19–23%, No injury $\sim$60%
G. Perrotte et al. [49]	2024	Posture + physiology monitoring (HR, respiration)	Simulator, 22 drivers	Multiple	Accuracy +10–15% vs posture-only
M. A. Puspasari et al. [42]	2023	EEG + SVM statistical features	Simulated EEG (Indonesia)	Binary	Accuracy 90.2%; Sens. 90.5%; Spec. 90%
X. Feng et al. [43]	2025	PASAN-CA: subdomain adaptation + coordinate attention	SAD, SEED-VIG	Binary	85.85% (SAD), 94.65% (SEED-VIG) average accuracy of 94.65% with a standard deviation of 4.60
J. S. Hernandez et al. [40]	2024	CNN on EAR, MAR, gaze, lane departure	On-road testing	Multi-class	Accuracy $\sim$95%
A. Pondit et al. [50]	2020	Eye aspect ratio, yawn, head pose + XGBoost	Custom dataset	3 states	Blink 97%; Yawn 96%; Head pose 63.4%
P. Pattarapongsin et al. [47]	2020	Mobile deep learning system (EAR/MAR, 3D head pose)	Experimental dataset	Multi-class	$>$90% accuracy; robust lighting; mobile app
L. Chai [51]	2023	Multi-sensor fusion: MTCNN+PFLD (face), LSTM (posture), PPG+ECG (steering wheel)	Prototype tests	Multi-class	Accuracy 93.3%
S. S. Soleimanloo et al. [53]	2022	Naturalistic study: Optalert + actigraphy; logistic regression	10 truck drivers; 2430 h	Binary	Accuracy 81.96%; Spec. 84.03%; Sens. 50.67%
N. Zhang et al. [54]	2024	Simulator study with whole-body vibration	15 drivers	N/A	Low-frequency WBV impaired performance; reaction times slowed $>$100 ms; SDLP worsened $\sim$25–30%

Dan [6] proposed a driver status monitoring and early warning system based on multi-sensor fusion to detect sudden medical conditions in drivers. This system employed a wearable terminal to capture and communicate the driver's heart rate, pulse, alcohol content, and three-axis acceleration data in real time to a server. Furthermore, the heart rate sensors are utilized to accurately determine the driver's state if the driver becomes fatigued as a result of any serious medical problems. The results suggest that this system may successfully avoid tired driving, improve driving safety, and serve as a benchmark for other intelligent driving systems.

Mateos-García et al.[59] used a virtual reality simulator to identify driver stress from physiological signs, perhaps indicating a sudden medical issue. Stress detection using DT yielded an accuracy of 90.34% for eight subjects. Data acquired by sensors in VR simulations is fed into numerous models previously trained by machine learning (ML) algorithms, resulting in a system capable of real-time driver stress detection and high-precision categorization. The method suggested in this research is a machine learning model capable of assessing whether users are stressed with high accuracy and in real time utilizing physiological signal data derived from the HRV acquired by routinely used low-cost portable watches.

Melders et al.[3] investigated current advancements in vehicle driver health monitoring systems for detecting unexpected medical conditions in drivers. In contrast, Wi-Fi is distinguished by its ability to offer high data transmission rates, making it a perfect alternative for processing large datasets. A sensor-based health monitoring system provides an integrated mechanism for real-time diagnosis and management, allowing for the detection, prediction, and referral of therapy, as well as illness prevention. To increase sensor data accuracy, noisy and missing data should be filtered out before processing. Its goal is to identify knowledge gaps that need to be filled and to propose future research initiatives that will help to address these gaps.

Lee and Liu [13] investigated the creation of a real-time driver health monitoring system based on a smart steering wheel for detecting sudden medical conditions among drivers. The study proposes a collection of real-time health detection systems embedded into a driver-controlled smart steering wheel. A created program detects the driver's health status (drowsiness) by monitoring biological data such as breathing, hand grip force, photo platysmogram (PPG), and EKG. The precision and reliability of the system, particularly the arrhythmia detection algorithm, are being tested using more accurately measured data. The proposed smart steering wheel may increase predictive health management for drivers, promoting vehicle intellectualization in the near future.

4.1. Critical Analysis and Research Gaps

Across the reviewed studies on sudden medical condition detection, a common limitation lies in the scarcity of real-world, large-scale datasets, with most validations carried out in controlled environments or on limited participant groups. There is also an over-reliance on single-modality sensing, which can be vulnerable to noise, motion artifacts, and false positives. Furthermore, system latency and integration with vehicle control systems are seldom evaluated, leaving questions about the practical deployment of these solutions unanswered. Few studies address the personalization of detection thresholds, despite clear inter-individual variability in physiological baselines. Future research should focus on multimodal, real-time systems validated in diverse driving conditions, seamless integration with advanced driver-assistance systems, and privacy-preserving, adaptive algorithms capable of early warning and automated intervention. Table 3 and Figure 5 presents briefly the most recent work and a critical evaluation of studies on sudden medical condition detection and highlights the key research gaps in this domain, respectively.

Table 3. Sudden Medical Conditions

Authors	Year	Techniques/Approach	Dataset	No. of Classes	Results
H. A. R. A. Badawi et al. [55]	2021	Real-time arrhythmia detection while driving using heartbeat sensor (earlobe PPG), Arduino, GPS/GSM, and alert system.	Simulated driving with ECG/PPG data	2 (Normal vs. Arrhythmia)	System alerts driver with buzzer; if no response, vehicle stops and GPS/GSM alerts emergency contacts.
G. Hollósi et al. [56]	2024	Capsule Networks (CapsNet) for bus driver head position detection under dynamic conditions, compared with CNNs.	Real-world bus driver video dataset	Multiple head positions	CapsNet achieved 97.8% accuracy (hold-out validation); lower accuracy in leave-one-subject-out validation.
Liu Dan [6]	2020	Multi-sensor fusion system using wearable devices (heart rate, alcohol sensor, 3-axis acceleration). Real-time monitoring with family alert system.	Real-time physiological signals from drivers	Driver states (fatigue, alcohol-influenced, normal)	Effective early-warning system for fatigue and medical issues; generated alerts in abnormal conditions.
N. Mateos-García et al. [57]	2023	Stress detection via VR driving simulator + smartwatch PPG sensor; ML algorithms for classification.	15 drivers, simulated VR driving scenarios	Stress vs. Non-stress	Achieved up to 87% accuracy (AUC 0.98) for stress detection; VR proved effective for safe stress simulation.
L. Melders et al. [3]	2025	Systematic review (scoping review, PRISMA-guided) of advances in driver health monitoring using wearable and remote biosensors.	Literature review (351 screened $\rightarrow$ 66 included)	N/A	Comprehensive overview of health monitoring systems; highlighted gaps in biosensor integration for drivers.
J.-C. Lee and H. Liu [13]	2018	Smart steering wheel with sensors (respiration, grip force, ECG, PPG). Algorithm for drowsiness and arrhythmia detection.	Simulated and on-road driver trials	2 (Normal vs. Abnormal)	Successfully detected driver drowsiness and arrhythmia in real-time; effective preventive safety system.

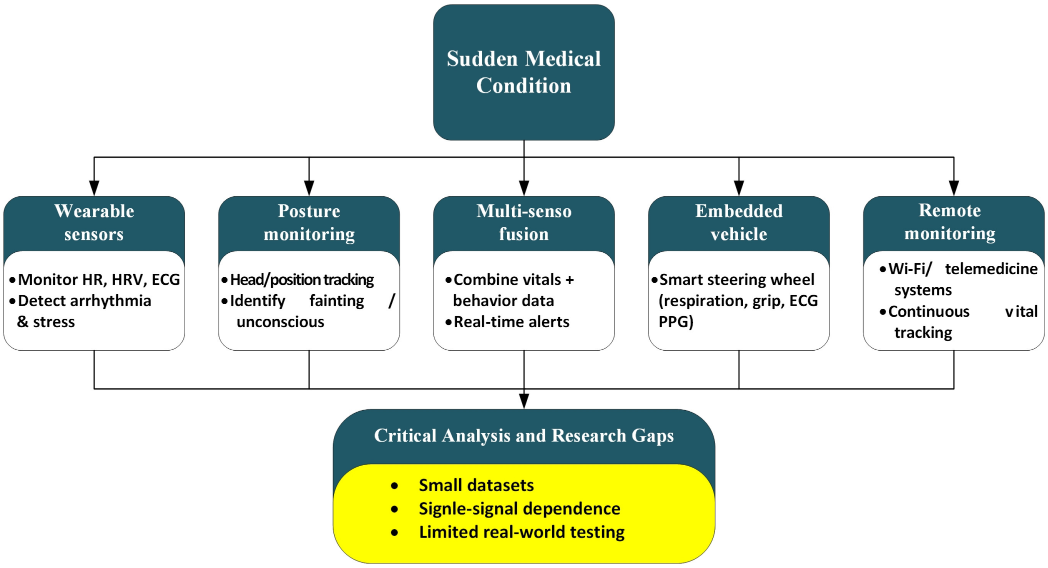

Figure 5. Critical evaluation of studies on sudden medical condition detection, highlighting existing methodological limitations and the significant research gaps that hinder practical deployment.

5. Conclusion

This review has examined the development of real-time driver monitoring systems for detecting distraction, drowsiness, and sudden medical conditions, with the objective of enhancing road safety through timely intervention. Across the three domains, advances in sensing technologies, algorithmic modeling, and system integration have demonstrated considerable potential for accurately identifying driver impairment under controlled and, increasingly, real-world conditions. Vision-based approaches, particularly those leveraging deep learning architectures, have demonstrated high accuracy in detecting visual-manual distraction. Ongoing efforts to reduce computational complexity and address privacy concerns further enhance their suitability for deployment in embedded automotive environments. Building on these advantages, from a real-world deployment perspective, vision-based sensing approaches emerge as the most promising across driver distraction, drowsiness, and medical condition monitoring. These techniques enable the simultaneous extraction of rich behavioral and physiological indicators—such as gaze patterns, facial expressions, eyelid dynamics, and head posture—using a single sensing modality. Moreover, vision-based systems are generally non-intrusive and align well with the growing integration of high-quality in-cabin cameras, particularly those equipped with night-vision capabilities, which enhances their robustness under varying illumination conditions. Drowsiness detection has progressed toward multimodal and personalized frameworks that integrate physiological, behavioral, and contextual data, improving robustness and reducing false positives. Research on sudden medical condition detection, though less extensive, has produced promising wearable and in-cabin sensing solutions capable of supporting automation fallback strategies and emergency interventions.

Despite these achievements, the literature reveals persistent challenges that must be addressed before such systems can be widely deployed. The scarcity of large, diverse, and representative datasets limits the generalizability of existing models. Many studies rely on laboratory or simulator data, which may not capture the variability of real-world driving conditions, populations, and environments. The scalability of annotation processes, the integration of multimodal inputs, and the development of personalized detection thresholds remain critical research frontiers. Furthermore, the seamless integration of these systems into advanced driver assistance frameworks, while ensuring user acceptance, privacy, and reliability, will require careful interdisciplinary collaboration.

Future research should prioritize multimodal sensing strategies that combine vision, vehicle dynamics, and unobtrusive physiological monitoring, validated in large-scale, naturalistic driving studies. Emphasis on adaptive, edge-efficient algorithms will be crucial to meeting the latency and energy constraints of in-vehicle platforms. Additionally, advances in context-aware personalization, uncertainty estimation, and user interface design will help ensure that monitoring systems not only detect impairment but also deliver timely, actionable, and trusted feedback to drivers. By addressing these gaps, the next generation of driver monitoring systems has the potential to substantially reduce crash risk and improve road safety outcomes.

The roadmap for next-generation systems has been organized as short, medium, and long terms. The short-term focus on improving the robustness and accuracy of multimodal detection of driver distraction, drowsiness, and medical conditions through better sensor fusion and real-world validation. Collaboration with automotive engineering and human factors is essential for system integration and effective driver feedback. Whereas the second-term includes developing reliable and adaptive driver monitoring systems capable of accurately detecting critical states and triggering appropriate in-vehicle responses. The efforts should emphasize robust real-time monitoring and effective integration with intervention mechanisms to enhance safety and user trust. Finally, the third-term involves translating these monitoring and intervention capabilities into fully integrated systems within modern and next-generation vehicles. This includes embedding reliable real-time detection and response functions into vehicle platforms to support proactive safety, health-aware operation, and seamless interaction with advanced driving and control systems.

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