Virtual Reality & Intelligent Hardware

•Review•

June 2025 Vol. 7 No. 3: 203–236
10.1016/j.vrih.2025.01.002

Advanced driver assistance system (ADAS) and machine learning (ML): The dynamic duo revolutionizing the automotive industry

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Received 25 June 2024; **Revised** 5 November 2024; **Accepted** 14 January 2025

Abstract: The advanced driver assistance system (ADAS) primarily serves to assist drivers in monitoring the speed of the car and helps them make the right decision, which leads to fewer fatal accidents and ensures higher safety. In the artificial Intelligence domain, machine learning (ML) was developed to make inferences with a degree of accuracy similar to that of humans; however, enormous amounts of data are required. Machine learning enhances the accuracy of the decisions taken by ADAS, by evaluating all the data received from various vehicle sensors. This study summarizes all the critical algorithms used in ADAS technologies and presents the evolution of ADAS technology. Initially, ADAS technology is introduced, along with its evolution, to understand the objectives of developing this technology. Subsequently, the critical algorithms used in ADAS technology, which include face detection, head-pose estimation, gaze estimation, and link detection are discussed. A further discussion follows on the impact of ML on each algorithm in different environments, leading to increased accuracy at the expense of additional computing, to increase efficiency. The aim of this study was to evaluate all the methods with or without ML for each algorithm.

Keywords: Machine learning; Face detection; Advanced driver system

Citation: Harsh SHAH, Karan SHAH, Kushagra DARJI, Adit SHAH, Manan SHAH. Advanced driver assistance system (ADAS) and machine learning(ML):The dynamic duo revolutionizing the automotive industry. Virtual Reality & Intelligent Hardware, 2025, 7(3): 203–236.

1 Introduction

1.1 Introduction to driver assistance system and its importance

Driver assistance systems (DAS) use cameras, radar, and other sensors to perceive the environment and help

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Peer review under the responsibility of Beijing Zhongke Journal Publishing Co. Ltd.

drivers navigate a wide range of driving scenarios on safer roads. DAS features include lane departure warnings, forward collision warnings, and adaptive cruise control (ACC), all intended to help drivers make safe maneuvers in various driving situations.

Thus, DAS reduces the burden on drivers, thereby preventing accidents. Advanced driver-aid technologies, such as lane-keeping and distance-regulating systems, are being increasingly used by human drivers. Haptic-shared guidance control is a popular method for human-machine interfaces in collaborative systems because it allows touch-based communication and interaction with the automated system[1,2].

The modeling of driver behavior has been introduced previously. For many years, research was conducted to mathematically represent driver actions under different road conditions. This is a challenging task because driver behavior is highly intricate. The response of a single driver to threats under different road conditions can vary. Various factors at specific locations and times can significantly affect the driver's behavior[3].

In the current scenario, transportation of goods and essential services is crucial, and mobility plays a vital role. Several measures have been implemented to increase the speed of transportation and decrease the number of accidents. "DAS" is one solution for decreasing accidents and accidental deaths. The goal of DAS is to enable automated driving in all scenarios in the future, with a level of safety that surpasses that of a human driver by collaborating with other road users[4].

1.2 Conventional technology in driver assistance and its limitations

Conventional driver assistance systems collect various data regarding the diverse conditions of the vehicle with the help of sensors. This does not involve making independent decisions, instead collecting information and displaying it to the driver, to make the driver aware of the vehicle's condition, such as displaying the pressure of air in the tire so that the driver can decide to refill the tire.

This study uses AI-based smart perception systems to enhance the ability of driver assistance systems to detect and understand thermal information, providing more genuine data on challenging weather and lighting conditions. The study focuses on enhancing the current system to detect and categorize objects using thermal vision, emphasizing seven essential categories. The development of smart automotive systems has been linked to conventional technologies, including the fusion of data from different sensors and machine learning (ML)-based obstacle detection and tracking systems[5].

Conventional driver assistance systems provide drivers with important information to reduce accidents; however, they do not take action. Advanced driver assistance systems (ADAS) are better but rely on sensors that need to be standardized, making it difficult to trust their reliability. If a sensor malfunctions, then the system may fail. In addition, the algorithms may malfunction in certain scenarios because the research is conducted in limited environments[6].

Driver assistance algorithms are limited by real-time processing requirements, which hinders their development. However, as computing power continues to improve, new opportunities are emerging. Machine vision has been utilized in driver assistance and autonomous vehicles for some time, with video-based object recognition having numerous applications as in monitoring systems, driver assistance systems, and image retrieval[7].

1.3 Introduction to advance driver assistance system and its importance

The main goals of ADAS and DAS are to assist drivers in operating their vehicles safely and efficiently. DAS enhances driver awareness and speeds up driving, whereas ADAS uses advanced sensors and cameras to monitor a vehicle's environment to support drivers in various driving scenarios. Both systems aim to minimize accidents caused by human negligence and improve driving safety. Examples of ADAS include night vision and parking assistance.

In the automotive industry, ADAS is increasingly gaining popularity because of its efficiency in reducing accident rates and enhancing driving safety. It is integrated into automobiles such as Tesla, BMW, Mercedes-Benz, Audi, Ford, Honda, and General Motors. The designers of ADAS ensure that the car remains controlled, stable, and handles dangerous situations well. However, designing and testing ADAS is complex and depends on various factors such as other cars and the environment[8].

Machine vision does not require extensive image processing, is heavily utilized in ADAS to support lateral control functions such as lane departure warning systems and lane-keeping systems[9,10].

However, drivers continue to face visibility issues on the road under foggy conditions, which is a major concern. Recent research based on deep learning (DL) for removing fog from images has shown that an end-to-end system using ADAS is an effective method for improving visibility and performing dehazing and object detection in foggy conditions[11].

Most functions used in self-driving cars are created using ADAS. These advancements aim to increase road safety, and their gradual implementation has had a positive impact. ADAS features contribute to improvements in how cars sense, think, and control themselves. This progress will lead to the development of fully self-driving vehicles in the future[12].

1.4 Introduction to machine learning

Machine learning is a chapter of an open book named “Artificial Intelligence”. It is associated with robotics, system design, neural networks, big data, and computer science. ML concepts have been incorporated into daily life tools, such as Alexa, Siri, Google Assistant, and Google Maps. Machine learning allows machines and computers to mimic human behavior without explicit programming.

Machine learning and artificial intelligence (AI) are gaining popularity owing to an abundance of data and computing power. The concept of computers learning from data emerged as early as the 1950s. There are eight subcategories of machine learning, including unsupervised and supervised learning, which can be further subdivided into clustering, dimensionality reduction & regression, and classification. ML can help solve physical problems such as airflow, weather forecasting, rain prediction, temperature variation, and water quality monitoring[13].

Studies have found ways for machines to learn from data without explicit instruction, known as machine learning. The best examples are the algorithms used by search engines such as Bing, Google, and Yahoo. ML is developing every day. Examples include photo and video editing on social media platforms and product recommendations while shopping on the Internet. Similar content suggestions on social media are also based on ML algorithms[14].

Machine learning employs pattern recognition to differentiate between instances. Recently, significant advancements were made in ML, making precise and effective algorithms accessible to professionals[15].

1.5 Machine learning in ADAS

Machie learning has enhanced the performance of ADAS through algorithm training on massive volumes of sensory data, using neural networks, support vector machines (SVMs), and decision trees. The system makes decisions in real time with regard to the best action toward safe and convenient driving.

Advanced driver assistance systems require a deeper understanding of a myriad of ML and DL techniques to provide optimal deployment. For instance, convolutional neural networks (CNNs) excel in image classification and object detection tasks, making them highly effective for real-time ADAS applications, such as pedestrian detection and lane-keeping support. However, CNNs often struggle to capture long-range dependencies, which are crucial for tasks such as predicting driver behavior over time. In contrast, recurrent neural networks (RNNs) are well-suited for sequential data and can effectively capture temporal dependencies although on long sequences they face limitations because of the vanishing and exploding gradient challenges. Furthermore, advanced architectures, including ResNet, Inception, and DenseNet, have significantly enhanced the training process of deep networks; however, these models typically require extensive computational resources and large labeled datasets, which are constraints in real-world ADAS settings. A thorough examination of these strengths and limitations allows for a more informed implementation of ML and DL methods, enhancing ADAS functionality and contributing to safer driving experiences[16].

Recent advancements in road safety have used ADAS to focus on detecting risky driver behaviors. A significant development combines powerful machine learning techniques, such as XGBoost, with deep learning to create a system that can identify early signs of driver fatigue or distraction. By utilizing data from the National Tsinghua University driver drowsiness detection (NTHUDD) dataset, this model effectively recognizes behaviors, such as talking or yawning, which are key indicators of potential impairment. To enhance the reliability of the system, explainable AI techniques such as SHapley Additive exPlanations (SHAP) are integrated, providing transparency regarding how the model reaches its conclusions. This transparency not only fosters user confidence but also clarifies the reasons behind specific behavior alerts. By addressing the complex challenges of real-time monitoring, this innovative approach represents a significant stride in ADAS technology, ultimately aiming to reduce accidents and improve road safety for everyone[17].

Machine learning improves ADAS by reducing casualties, preventing accidents, and providing prompt medical treatment. ML can be used to develop systems for driver monitoring, parking assistance, and controlling the vehicle laterally and longitudinally. Adaptive cruise control and collision-mitigating systems can identify hazards for lane changes, and parking assistance technology allows vehicles to park without requiring a driver's presence or action.

There are four major architectural components to ADAS: Driving vigilance monitoring system, lateral control, longitudinal control, and parking assistance. The application of ML techniques has facilitated the development of integrated systems[18].

Convolutional neural networks, which are a more advanced version of artificial neural networks (ANNs), can handle complicated tasks. However, because ML models require significant computational resources, the industry uses processing components that are both resource and cost limited. Consequently, several options exist for embedding memory-intensive models into the various computing systems used in automotive platforms[19].

Demonstrating remarkable accuracy in visual identification tasks, CNNs often surpass human capabilities. However, they encounter difficulties in the presence of visual distortions such as glare and noise, which humans tend to manage more effectively. Similar to other deep learning methods, CNNs depend heavily on the quantity and quality of training data. Current research aims to advance the CNN capabilities by integrating mechanisms such as active attention and online memory, to allow CNNs to analyze and adapt to novel inputs more effectively[16].

1.6 Introduction to advance technologies in ADAS

Face detection is a well-researched area in computer vision. Currently, the most common approaches for face detection rely on two key concepts: Boosted cascade structures and basic features. Although these methods perform well under typical conditions, they tend to be less accurate in challenging situations, such as low lighting, facial expressions, or occlusions. Researchers have developed alternative techniques to overcome these limitations, such as “divide and conquer”, which require training multiple algorithms to detect faces from different perspectives. The overall accuracy of face detection can be improved by combining the results of these algorithms[20].

Head pose estimation is an important form of nonverbal communication used to infer the communicator’s intentions. Humans can easily interpret intentions using head pose; However, head-pose detection is very difficult for machines. Head-pose estimation includes classifying the head pose into discrete orientations identified by the algorithm. The head-pose estimation algorithm can estimate the various degrees of freedom of the head position. The complexity of the algorithm increases with the number of degrees of freedom as the orientation of the head increases[21].

Gaze estimation involves continuously tracing the direction of a person’s gaze. Continuous tracking of the gaze direction provides access into the person’s internal state. Most appearance-based methods require a clear and closed view of the eyes for gaze estimation. All prominent gaze estimation methods require the distance from a person to be less than 1 m or a frontal view. Some methods that use surveillance cameras for gaze estimation from a distance, use head or body orientation. However, this approach reduces the accuracy of the method and cannot be used in real-world scenarios[22].

Blink detection involves detecting the blinking of the human eye in a video frame. Blink detection is used to determine eye location at the start of the algorithm. Numerous methods exist for locating the eye in a video frame if the initial location is provided. The initial location of the eye is then matched in the entire video frame to determine the next location of the eye. Here, the problem is to determine the initial location of the eye, for which blink detection is used. Similarly, in vehicles, the driver's alertness is determined based on the driver’s blinking frequency[23].

1.7 Statistical insights on ADAS effectiveness and challenges

The advanced driver assistance system has great potential for achieving road safety and can avoid almost 90% of accidents and deaths. However, its effectiveness depends on its design and functionality in terms of the human-machine interface (HMI). Poorly designed HMIs can lead to unintended consequences, such as increased driver workload and diminished situational awareness, ultimately reducing the intended safety benefits. For instance, ACC has been shown to distract drivers by lowering their situational awareness and counteracting safety gains. Despite the encouraging potential of ADAS, the current literature provides limited statistical validation of its real-world impact on driver safety, underscoring the need for comprehensive evaluations. Assessing the usability and understanding the cognitive demands placed on drivers in these systems are essential steps for ensuring that they are both effective and user-friendly. To address this issue, tools such as the Utah vehicle technology assessment scale (UTA-S) are essential for rigorously assessing the ADAS interface. By prioritizing a robust and intuitive design, ADAS systems can be ensured to enhance driver safety, thereby bridging the gap between technological potential and real-world impact[24].

Recent studies have shown that roads can be safer when ADAS is used. This technology can reduce crashes, fatalities, and injuries, by employing alerting technologies, such as advanced emergency braking (AEB) and forward collision warning, to help the vehicle brake. Studies indicate that AEB can lead to an impressive reduction in crashes by 18–26%, whereas lane departure warning systems lower accident rates by 3–18%. At the core of these systems are advanced algorithms that leverage machine learning for crucial tasks, including face detection, head-pose estimation, gaze estimation, and blink detection. This technology enables ADAS to rapidly analyze data from various sensors and cameras, thereby helping drivers avoid potential hazards. Looking ahead, researchers predicted the future impact of different ADAS technologies on crash reduction by utilizing national crash data from Austria for the years 2025, 2030, and 2040. They emphasize the importance of ongoing research in assessing the performance of these systems in real-world conditions, especially with the new data anticipated for release in 2023. This facilitates more effective comparisons between vehicles equipped with and without ADAS. Overall, this body of work strongly supports the idea that ADAS, enhanced by modern ML techniques, can play a crucial role in improving road safety and minimizing accidents. This represents a significant advancement toward creating safer driving environments and protecting lives on the road[25].

Significant advancements have been made in detecting failures within deep neural network-based lane-keeping systems through the implementation of innovative test generators in the deep framework. The latest generator, deeper optimization method (μ, λ) achieved an impressive success rate of 95.0% in generating effective test scenarios, closely rivaling the previous version, Deeper non-dominated sorting genetic algorithm II (NSGAII) achieved a success rate of 98.0%. This progress highlights the enhanced ability to provoke a variety of failure scenarios, which is essential for assessing the safety and reliability of machine learning-driven systems. Compared to traditional methods such as Frenetic and GABExplore, both achieving 100.0% success in specific instances, the new approach demonstrated greater adaptability and diversity, enriching the overall testing process. This development not only strengthens failure detection capabilities but also promotes a more resilient testing framework, effectively addressing the challenges of validating advanced driver-assistance systems in real-world scenarios[26].

The advanced driver-assistance system has been promising in improving road safety and reducing accidents. According to data from the Federal Statistical Office of Germany, fatality accidents were reduced by 6.9 % in 2016. However, the overall 3.3% increase in road accidents highlights the complex relationship between driver behavior and safety technologies. Interestingly, drivers using ADAS perceive a lower likelihood of being involved in an accident, rating their perception at an average of 3.03 compared to 3.42 for those without these systems. This finding suggests that ADAS not only provides technological support but also positively influences drivers' views on their safety. Furthermore, ADAS users report feeling more in control during risky situations, scoring an average of 3.31, whereas non-users scored only 2.92. These insights indicate that ADAS can significantly boost driver confidence and shape behavior, contributing to a safer driving environment by altering risk perception. As the development and implementation of these systems continue, it is essential to recognize their potential for enhancing comfort and efficiency while fostering a culture of safety on the roads[27].

1.8 Contribution & motivation

The authors have made diverse contributions to the fields of DAS and ADAS, highlighting their significance and limitations. Our research involves analyzing mathematical models of driver behavior under different road conditions, implementing AI-based perception systems to improve the thermal sensing capabilities of DAS and utilizing machine learning and computer vision to enhance ADAS control functions, such as lane departure warnings, lane keeping, and lane assist systems. They also identified challenges in developing and testing ADAS such as the need for standardized sensors and algorithms. The aim was to minimize the number of accidents caused by human negligence and enhance driving safety by making DAS more intelligent and dependable, which requires increasing driver awareness, improving driving speeds, and enabling automated driving in all situations while maintaining high safety standards, recognizing the importance of mobility in delivering goods and essential services, particularly in the current scenario. Therefore, their work is driven by the urgency to reduce accidents and fatalities, to make transportation more efficient and reliable. They believe that their research can help create safer, better, and more efficient roads.

2 Advance technologies

The progress of ADAS has been a significant focal point of the automotive sector in modern times, with advanced classification in ADAS referring to the use of precise, accurate, and refined algorithms based on computer vision techniques, to accurately identify and categorize objects within the driving environment. These include vehicles, pedestrians, road signs, traffic lights, and other objects that may affect the safe operation of a vehicle[28].

Advanced classification systems use ML techniques such as decision trees, neural networks, and SVMs to analyze images and data from various sensors and make predictions about the environment. In the context of advanced classification, ML algorithms use large datasets to learn the patterns and relationships present in the data. This training allows the algorithms to predict new data such as objects in the driving environment. The goal of advanced classification in ADAS is to provide more precise and accurate information to the vehicle's control systems, thereby making cars safer and more efficient. The collision avoidance system is also an example of this field, whereby the vehicle identifies other vehicles or pedestrians and provides either a warning or takes the necessary actions to avoid a collision[29].

As part of this field, ADAS relies on various fields and technology for classification and implementation, including ML, augmented reality/virtual reality (AR/VR), big data, computer vision, Internet of Things (IoT), and AI as shown in Figure 1. Overall, advanced classification in ADAS is a rapidly evolving field and is expected to be an important part of making fully self-driving cars and future vehicles a reality.

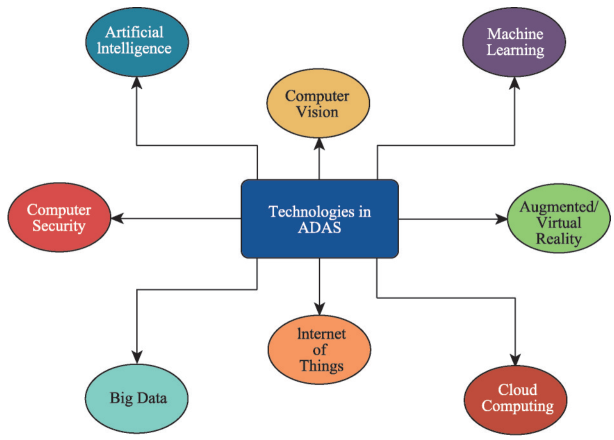

Figure 1 Classification of technologies.

2.1 Artificial intelligence & machine learning

The aim of AI is to bestow machines with human intelligence. These machines are designed to think and act like humans. The opportunities are vast, as AI can be helpful in every field, whether it be automobile, medicine, finance, education, or science among others, as it can process large amounts of data and perform tasks automatically.

The ADAS technology has its roots in AI, and several initiatives are underway to integrate AI into it. One such project involves the development of a video management system (VMS) prototype using ML techniques[30]. Another implementation of AI in an ADAS that applies a combination of DL and ML algorithms[31]. AI is useful in ADAS for tackling advanced tasks and making quick and smart decisions. By analyzing data from sources such as cameras, sensors, and global positioning systems (GPS), AI can assist ADAS in accurately detecting and responding to road conditions, driver behavior, and other driving scenarios. This improves the safety of vehicles and passengers, decreases the risk of accidents, and improves driving comfort. It also makes ADAS technology more efficient and dynamic.

The ADAS technology is being rapidly developed for autonomous vehicles. Machine learning and embedded computing are the two driving forces behind these efforts. The ADAS system can detect obstacles, objects, other vehicles, pedestrians, and lanes through advanced ML algorithms, to estimate object trajectories and intents[32].

2.2 Computer vision

Computer vision involves understanding various images and videos using computers, similar to humans. It includes various methodologies such as text and object recognition. This is a way to teach computers how to understand and see things as humans do.

Computer vision is also used to identify the text written on signboards, which AI eventually uses to make decisions regarding a vehicle's trajectory. Therefore, computer vision is used to determine and evaluate a vehicle's surroundings, such as other vehicles, road turns, and road obstructions. Computer vision and ML technologies have led to more precise detection of road hazards and potential collisions, resulting in greater road safety and fewer accidents. This technology can be used in traffic-signal recognition systems. Correct evaluation of the collected information and immediate decisions made accordingly are essential because their failure can cause severe accidents and damage to human lives. Therefore, various studies have been conducted to decrease the response time and increase system accuracy[30].

2.3 Internet of things

The IoT includes physical devices embedded with electronic chips and connected to the Internet, whereby physical devices can communicate with each other, resulting in interconnections. For example, a mobile phone can operate a fan equipped with IoT.

The ADAS can be integrated with IoT technology to track the driver and car surroundings. In addition, information gathered from various parts of the vehicle can be shared, which is helpful for better decision-making because it provides a better view of the surroundings and conditions of the vehicle.

This technology along with ML techniques can be used to develop a variable message sign (VMS) reading system[30]. An advanced technique based on DL and IoT can also be implemented to monitor the driver and the car's surroundings. The IoT and AI are used extensively in ADAS, with the AI algorithms helping with better and more precise decision-making based on the data collected by various physical devices connected to the Internet[33].

2.4 Augmented & virtual reality

The most promising future technologies revolutionizing the digital age are AR and VR. AR enhances reality by overlaying digital information such as images and text, whereas VR creates a completely immersive digital environment that replaces the real world. These technologies have various applications, in automobiles, entertainment, education, and medicine among others. VR can be used for interactive gaming experiences, and AR can enhance live performance. These technologies can be used to experience the real world virtually, thereby enhancing our experience.

Some applications of AR technology include head-up displays (HUDs), which can project crucial data, such as seatbelt indicators, speed warning, temperature (inside and outside of the vehicle), and navigation maps onto a windscreen. As a result, driver distraction can be reduced, which enhances passenger safety and makes driving more interactive. These technologies can also help deliver real-time alerts and information. Driving simulations using VR can be useful in developing an individual's driving skills. An ongoing project is focused on how 5G can be utilized to make vehicles safer and improve the driving experience. This can also be used to improve the infotainment experience within the vehicle[34].

2.5 Big data

The lifeblood of ADAS technology is big data. ADAS can organize, optimize, and search data from traffic, GPS, object mapping, weather, and other connected automobiles. Self-driving cars are the next big thing in terms of transportation and the force that propels this revolution. Autonomy in cars can provide the security needed to reduce the occurrence of accidents in traffic congestion, decrease congestion and fuel use, and subsequently add value to people's lives. Security and privacy issues are expected to be resolved for the comfort of the drivers, insurers, and automobile manufacturers[35].

2.6 Cloud computing

Cloud computing utilizes global networks to connect hardware-filled data warehouses and to provide data storage and processing power. ADAS applications require GPUs to process data in near real-time; however, this work may be offloaded to the cloud where 5G speeds are available. In the future, the focus will be to include more elements such as network latency and various benchmarks for computer vision performance[36].

2.7 Computer security

A hierarchical-level system is offered to separate threats and attacks into three distinct layers: sensor, communication, and control. Vehicle manufacturers are incorporating AI techniques to modernize communication, but this can lead to risks. Modern architectures should prioritize safeguarding important units, such as powertrain electronic control units (ECUs), using cryptographic and non-cryptographic methods, registration, and authentication procedures[37].

3 Our approach

Figure 2 illustrates the fundamental components of our driver-monitoring system (DMS). Applications can use these outputs to execute solutions and ensure driver safety. We chose to use CNNs to implement the building blocks of our DMS, and the results were superior to those of conventional image processing and computer vision-based implementations[38].

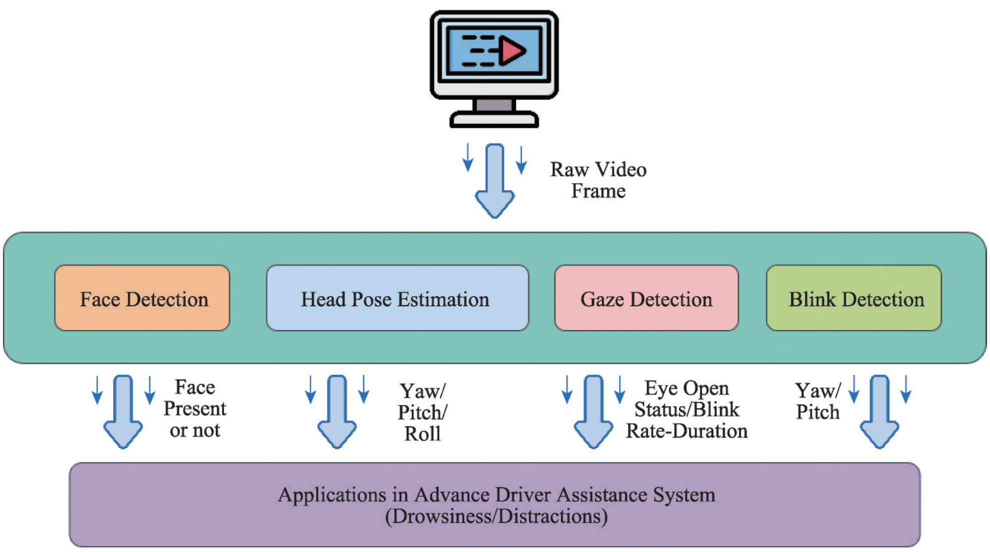

Figure 2 Block diagram of driver monitoring system.

3.1 Face detection

3.1.1 Machine learning for face detection

Face-detection systems use ML to detect faces, which makes these systems more efficient in extreme environments. These systems detect faces by identifying 68 facial landmarks. The algorithm was trained on images from various viewpoints to recognize these landmarks and ensure accuracy during testing. Additional images were required during the training process to improve accuracy. Upon detecting a face, the system identifies and centralizes the facial landmarks without distorting the image. The image is then converted into Euclidean space to produce 128 bytes of data per face for classification using trained datasets. For small datasets, SVM is used for classification. The accuracy of the face detection systems is highly dependent on the lighting conditions. To enhance accuracy, gradient transformations are applied to the face images.

The ML algorithm can also be retrained on high-accuracy images to improve its performance. In summary, face detection systems based on machine learning are valuable for increasing security in challenging environments. The 68 facial landmarks are essential for a system to accurately detect faces. More training images are required to improve accuracy. The system identifies facial landmarks, centralizes them, and converts the images into Euclidean space. SVMs are used for classification when the dataset is small. Gradient transformations are applied to facial images. Retraining using high-accuracy images can boost the accuracy of the algorithm[39].

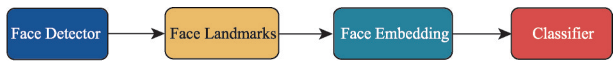

Figure 3 Machine learning for face detection.

Figure 3 depicts the face detection process using ML algorithms. The first step is to detect the face in a given image. The second step detects the faces among the 68 known facial landmarks and centralizes them. The third step involves embedding the centralized image of the facial landmarks into Euclidean space, generating 128 bytes of data per image for embedding. The fourth step checks the data against the training dataset and classifies the data points according to their similarity to facial landmarks.

For face detection, the goal is to reliably identify driver faces even in tricky situations involving low light, shadows, or when wearing sunglasses. Different methods such as the Haar Cascade technique or more modern DL models, can achieve this; however, each has trade-offs. Our focus was to find a method that is both fast and accurate, ensuring responsiveness without missing important details under complex lighting conditions.

3.1.2 Case studies

A new approach by Krishna et al. was introduced for recognizing driver drowsiness by incorporating vision transformers and YoloV5 architectures. This study aimed to enhance road safety by developing an efficient drowsiness detection algorithm. The framework was trained using the public University of Texas at Arlington real-life drowsiness dataset (UTA-RLDD) and evaluated using a customized dataset of 39 participants under different lighting conditions. You only look once (YoloV5) obtained a mean average precision score of approximately 95%, whereas the vision transformer displayed high precision, sensitivity, and F1 score with an accuracy of 95.5% during testing. This framework holds great potential for smart transportation systems but requires a large amount of data, including labeled scene conditions, for training. The authors intend to enhance the network configuration and expand the size of the training data in future endeavors to enhance model performance[40].

In a recent study by Baker et al. on real-time tracking of non-rigid head movements for assessing a driver's mental state, active appearance models (AAMs) were utilized to monitor both fixed head motion and flexible facial expressions. A real-time gradient descent fitting algorithm that operated at over 200 fps was designed for AAMs to handle occlusions. The development of 3D non-rigid face tracking was also explored, creating a structure-from-motion algorithm to convert 2D AAMs into 3D models, along with a fitting algorithm for the 3D model that ran at more than 250 frames per second. The feasibility of these algorithms was demonstrated on standard PCs, emphasizing the possibility of their implementation on low-power devices[41].

Another study by Saini et al. focused on the crucial aspect of driver drowsiness detection in car safety technology to avoid road accidents caused by fatigue-related driving. This study addresses the technologies used in devices that are capable of detecting or preventing drowsiness-related driving accidents. This is realized by means of real-time face video processing from a front-facing camera to measure the degree of driver fatigue, and in the event that drowsiness is detected, to sound an alarm prompting the driver to awaken. Emerging technologies were assessed to determine the best method for avoiding fatal vehicle crashes. The study points out the drawbacks of the current market leader, a reed switch that detects head tilt, and the shortcomings of the product developed by BMW, which is better at detecting drowsiness but needs to warn the driver properly[42].

A study by Shen et al. aimed at enhancing the visibility of driver faces in images captured at night focused on creating an adaptive attenuation quantification retina (AAQR) technique to increase the accuracy of driver face detection under low-light conditions. A dataset of the driver face images captured at night was collected and divided into three groups based on lighting to conduct the study. The AAQR method was executed in three phases: restriction of attenuation, prediction of attenuation, and adaptive quantification. The findings indicate that the AAQR approach demonstrated an 86% detection rate, which is 2-36% better than that of earlier algorithms. The AAQR was found to be especially effective under mixed nighttime lighting conditions and had a faster computing time for a single nighttime image (640 × 480 pixels) than most other sophisticated methods. Thus, the AAQR method can be a new and promising technique for use as driver assistant during nighttime in ADAS and autonomous vehicle systems in the future[43].

A group of researchers recently conducted a study by Abbas et al. in which they introduced a DL method called residual SVM (ReSVM) to detect driver distraction. It merges features from the SVM classifier with ResNet-50. This was compared to six leading techniques using four datasets. The results revealed that ReSVM outperformed the other methods, achieving an accuracy of 95.5%. We intend to improve the model by adding features such as car motion, driver emotions, and tics for distraction detection. Currently, this study only deals with spatial features for classification; future work will focus on temporal aspects. The aim is to develop a vehicle distraction detection system to monitor dangerous driving behaviors and prevent accidents. The plan is to implement the system and increase the amount of data available for DL architectures[44].

A study by Krizhevsky et al. was conducted to classify high-quality images from the ImageNet Large Scale Visual Recognition Challenge (LSVRC)-2010 competition into 1000 diverse categories by applying a deep convolutional neural network. This network includes five convolutional, three fully layers, and several max-pooling layers. The findings revealed a significant improvement compared with previous state-of-the-art results, with error rates of 17.0% and 37.5% for the top 5 and top 1, respectively. This study employed a dropout regularization method to reduce overfitting in the fully connected layers. Moreover, an efficient graphics processing unit (GPU) implementation was used to accelerate the training process. The large deep CNN delivered record-breaking results through pure supervised learning. The study also highlighted the significance of network depth, as the network performance decreased when a single convolutional layer was removed. In the future, researchers should utilize more supervised pretraining and explore larger and deeper networks for video sequences[45].

A novel head-tracking system designed by Zhao et al. specifically for use in Level 3 autonomous vehicles comprised two integrated devices and proprietary software for data collection and calibration. The system was validated through four experiments, obtaining average errors of 0.36°, 1.57°, and 0.38° for the nodding, rolling, and shaking axes, respectively, on a static platform. Household studies showed that the system's measurements for shaking and nodding were very similar, with an average difference of less than 2°, suggesting that the system may be better suited for detecting large head movements during nondriving activities[46].

A group of researchers developed a real-time detection system by Shang et al. for driver fatigue and emotions based on time-series analysis. The updated residual multiscale (RM) -Xception algorithm incorporates a depth-separable convolution component and a residual component, resulting in faster processing and lower training computation requirements while effectively capturing emotions. On the facial emotion recognition (Fer 2013) dataset, the model achieved an accuracy of 73.32%. In the future, the algorithm will undergo further testing in more complex driving environments, using multiple sensor data, to further explore the relationship between facial expressions and emotions while tired[47].

A study by Ulrich et al. conducted on driver attention using 3D cameras and FER indicated that drivers are often distracted by events; however, ADAS only interfered with the focus of one user in one scenario. This study employed an Intel RealSense SR300 and an RGB-D camera to monitor the driver's facial expressions. The use of RGB-D images and deep learning techniques was found to be an effective and noninvasive way to assess driver concentration. However, the correlation between ADAS activation and inattentive facial expression was weak. Future research should explore the efficacy of ADAS and level of feedback received from the user[48].

Table 1 Summary of papers on face detection

Algorithm	Accuracy	Speed	Method	Reference
Convolutional Neural Network, Face Feature Triangle	94.32%	< 20 fps	Appearance- and feature-based	[49]
Haar and Viola-Jones	90.80%	> 5 fps	Feature- and knowledge-based	[50]
Multitask Convolutional Neural Network	YAWDD Dataset: 98% Personal Dataset: 97%	2 fps	Feature- and knowledge-based	[51]
Random Forest, Convolutional Neural Network	EAR metric: 94.5% Random Forest: 91% Paper Approach: 97.5% Average Face & Eye Detection: 100%	PC: 140-170 fps, Jetson TX2: 40-70 fps	Feature- and appearance-based	[52]
Multitask Convolutional Neural Network	99.13%	25 fps	Appearance and feature-based	[53]
SVM, Haar Classifier, Viola-Jones Algorithm	Face Detection: 99.9% Eye Detection: 98.7% SVM: 96.5% Adaboost: 95.4%	--------	Feature-based	[54]
Haar, Multitask Convolutional Neural Network	OpenCV: AP50(68.4%), AP75 (51.4%), MMOD: AP50(83.8%), AP75 (18.1%), MTCNN: AP50(81.4%), AP75 (72.0%)	OpenCV: 400 fps MMOD: 260 fps MTCNN: 4 fps	Feature-and knowledge based	[55]
Artificial Neural Network	63.15%	25 fps	Feature-based	[56]
Convolution Neural Network	96%	21 fps	Feature- and knowledge-based	[57]

3.1.3 Author's opinion

From a literature review on face detection using an embedded camera within ADAS, the entire process significantly aids in observing the activity and status of a driver. There are many algorithms for face detection, including SVM, histogram of oriented gradients (HOG). Haar cascade classifier, the Viola-Jones algorithm, DLib, and CNN. The accuracy, speed, and complexity of each differ and each has its own advantages and disadvantages. For instance, SVM and Haar classifiers are efficient and fast but may not be as precise as CNNs when detecting faces under challenging conditions. CNNs are highly accurate but require more computational power. Studies have demonstrated that CNNs are widely used for face detection in ADAS. Deep CNNs have achieved remarkable results through supervised learning on challenging datasets. In contrast, ReSVM, which utilizes a residual neural network with an SVM classifier, accurately classified different types of driver distractions. Various face detection methods were utilized in this study, including feature-, appearance-, and knowledge-based approaches.

Selecting ADAS face detection algorithms in light of this understanding, will allow a full picture of how a driver behaves, which will also help with gaze and head pose estimation. This integration can increase computational demands; therefore, managing resources effectively is crucial for maintaining real-time responsiveness. Privacy is also a key concern, as ADAS captures sensitive driver data. Selecting algorithms that balance efficiency with privacy protection is vital to ensure effective monitoring and data security in ADAS.

In conclusion, face detection algorithms continue to advance and develop, and the most suitable approach for ADAS depends on the specific requirements and limitations. Therefore, a comprehensive analysis of face detection methods and careful selection of the most appropriate algorithm are crucial for the success of ADAS.

3.2 Head pose detection

3.2.1 Machine learning integrated with head pose estimation

Methods using facial landmarks are popular for estimating head poses. However, these methods unnecessarily increase computation. Facial images can be analyzed using methods that do not rely on facial landmarks, to accurately determine the head pose. Various methods that use CNN algorithms have been proposed to estimate head pose without using facial landmarks. In addition, multitask learning is used when various pieces of information are generated from facial images, such as head-pose estimation, gender determination, and facial landmark detection. The hyperface method uses CNN to perform face detection, recognition, and facial landmark localization, head-pose estimation, and sex determination. Heatmap-CNN regressors are used for key-point and head-pose estimation. Certain approaches utilize depth data to extract three-dimensional (3D) image details. The information provided by these methods is accurate; however, these methods are used less frequently in real-world applications because they require images from special cameras[58].

Figure 4 depicts a categorization of the different techniques employed in head-pose estimation. These methods are classified into two groups: landmark-based and landmark-free methods. Landmark-based methods rely on facial landmarks to determine head pose. Landmark-free methods employ ML algorithms, which can be further subdivided into CNNs, HyperFace, and Heatmap-CNN.

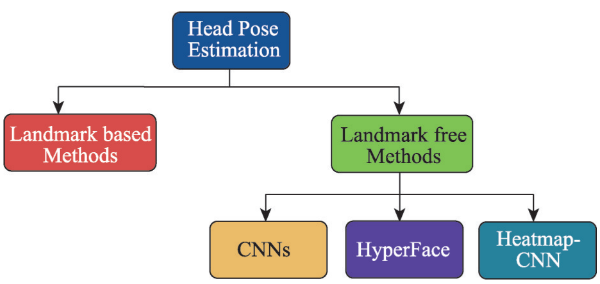

Figure 4 Machine learning for head pose detection.

Head-pose detection is about understanding where a driver is looking or whether they are paying attention. This requires a system that remains accurate even if the driver's head moves around or in the presence of sudden lighting shifts. Techniques vary from simpler feature-based methods to advanced deep learning models. Therefore, we conducted a comparison to determine which approach is consistent in tracking head movements smoothly and accurately in real time.

3.2.2 Case studies

A study by Choi et al. proposed a real-time technique for tracking a driver's head pose and eye-blinking, namely, pose-extended-active shape model (PE-ASM), which outperformed traditional face models in fitting accuracy, especially with extreme poses. The PE-ASM improves facial fitting under challenging conditions by incorporating extreme pose cases. This method can serve as a reliable driver drowsiness detector in commercial cars and can handle diverse visual conditions. It uses two hidden Markov models (HMMs) to estimate head pose, eye blinking, and drowsiness. This study highlights PE-ASM's potential for enhancing driver safety and addresses the limitations faced by existing models in natural driving scenarios[59].

The primary objective of this study by Wang et al. was to overcome the challenges faced by previous methods when analyzing a driver's visual attention based on head pose and gaze. Existing approaches struggle with non-uniform illumination and partial facial occlusion under real-world driving conditions. To address these limitations, researchers have introduced a novel estimation method that utilizes an RGB-D camera, proposing a technique that involves fusing and registering continuous multi-frame point clouds to generate a stable point-cloud representation. Instead of relying heavily on template registration, this method utilizes multiple point clouds within the nearest-neighbor gaze zone as a template, thus reducing the dependence on precise template alignment. The study utilized an image resolution of 720 p. In experimental results, the proposed method outperformed other approaches in head-pose tracking and gaze-zone classification. The average accuracy for gaze zone estimation was 93.97% when the proposed method was combined with the SVM classifier, POSIT, and PointNetLK methods. Furthermore, the accuracy and efficiency of point-cloud registration was improved by incorporating a particle filter and normal distributions transform to track and predict the initial coarse transformation[60].

Another study by Ruiz et al. introduced a new approach for determining the orientation of a person's head. This method entails training a multi-loss convolutional neural network using a vast dataset to predict the intrinsic Euler angles directly from image intensities. This method is more reliable than conventional methods, which rely on landmark detection and an external head model. The new method demonstrated excellent results on various real-world pose benchmark datasets with precise pose annotations. The proposed method surpassed the landmark-to-pose methods and proved to be more robust, even in situations of very low resolution. Researchers recommend exploring synthetic data generation for extreme poses and more sophisticated network architectures to improve the performance of this method[61].

A novel approach by Hong et al. used deep and multitask learning was introduced to estimate the pose of human faces, focusing on gaze direction and head posture. This method is crucial for analyzing nonverbal communication and extracting important visual cues. This approach utilizes a DL framework called multitask manifold deep learning (MMDL), which leverages multimodal data. The MMDL approach incorporates enhanced feature extraction based on deep neural networks and multimodal mapping through multitask learning. It also utilizes manifold regularized convolutional layers (MRCL), which improve traditional convolutional layers by learning the relationship between neuron outputs. The effectiveness of the proposed approach was evaluated using three benchmark datasets: DPOSE, human protein interaction database (HPID), and BKHPD. The experimental results demonstrate that this method outperforms previous techniques in face pose estimation. The key contributions of this research include the development of the MMDL framework, utilizing MRCL, and handling of multimodal features using multitask learning[62].

A study by Firintepe et al. was conducted to investigate the accuracy of head pose estimation using infrared (IR) images, to explore how deep learning techniques can improve the results. The study used the AutoPOSE dataset and cropped head images to 64×64 and 128×128 pixels. Two new networks, head orientation network (HON) and ResNetHG, were introduced and compared to existing methods, such as the head pose network (HPN) model from DriveAHead. Researchers have evaluated the performance of these models at various input resolutions and depths and found that higher-resolution images result in more accurate estimations. In addition, researchers discovered that DL methods with fewer layers achieve superior performance in head orientation regression when using infrared (IR) images. Specifically, the HON and ResNetHG18 architectures developed by X outperformed state-of-the-art models on IR images, highlighting a significant reduction in the residual error by up to 74%. To further enhance the accuracy of these models, future research should analyze additional input resolutions and explore different model depths. In addition, benchmarking the models on the DD-Pose dataset, which contains real-world data, would provide valuable insights for comparison and evaluation. By investigating these aspects, researchers can advance the field of head-orientation regression and strive for more accurate and reliable IR image analysis results[63].

Another study by Akhtar et al. discussed the significance of monitoring a driver's facial pose to evaluate the level of attentiveness and decrease the possibility of road accidents. Their suggested solution employs wireless sensing and utilizes channel state information (CSI) from Wi-Fi signals to identify the driver's face nonintrusively. They introduced a novel classification algorithm that leverages a combination of SVM and K-nearest neighbor (KNN) techniques to improve face recognition accuracy. The experimental findings demonstrate that the proposed system achieves high precision in identifying a driver's face with an average recognition rate of 91.8%. This suggests that the algorithm effectively enhances classification accuracy and shows potential in face recognition technology. Researchers have also proposed a hybrid classification scheme known as KSVM, which significantly enhances recognition performance and expands the possibility of various applications, aiming to investigate more complex driving situations and how roadway types may influence these findings[64].

The objective of another study by Zhao et al. was to investigate how the position of the head can be utilized to detect driver distraction. They compared the accuracies of two methods: single regression and a combination of classification and regression methods. Four networks were trained using two datasets. For head-pose estimation, the researchers employed HPE_Resnet50 and applied it to a separate dataset to obtain head-position data. The study findings indicate significant disparities in head position between safe and distracted driving scenarios. Consequently, this information can be leveraged effectively to identify instances of distracted driving. Overall, this study suggests that analyzing head position can serve as a valuable indicator for detecting driver distraction. By comparing different methods and employing head-pose estimation techniques, researchers have elucidated the potential of utilizing head-position data to enhance road safety and address the issue of distracted driving[65].

A study by Murphy-Chutorian et al. focused on the need to determine the state of driver awareness for developing advanced vehicle safety systems. The goal was to establish a system that could track the head pose of the driver accurately irrespective of the identity of the driver and illumination conditions. To achieve this, a video camera was used to detect both visible and near-infrared light. The system employed localized gradient orientation histograms and SVMs for regression to estimate the orientation of the driver's head using two degrees of freedom. By utilizing these techniques, the system aimed to overcome the challenges posed by varying lighting conditions within a moving vehicle. This is crucial for ensuring reliable head-pose estimation, as lighting conditions fluctuate significantly during real-world driving scenarios. The accuracy and stability of the system can be further improved by incorporating a visual tracking system. This research is a crucial step toward developing robust driver activity monitoring systems that can contribute to the development of advanced driver assistance systems[66].

A study by Diaz-Chito et al. introduced a novel technique for measuring the angle of a driver's head turn, which is a critical factor in driving performance and accident prevention. The proposed method focuses on utilizing only three facial landmarks-the center of the eyes and tip of the nose-to compute geometric features and estimate the head pose using two-manifold embedding techniques along with a linear regression model. To evaluate the effectiveness of the method, researchers tested it on the Carnegie Mellon University pose, illumination, and expression (CMU-PIE) and their own driver dataset. The results obtained were comparable to those of other state-of-the-art techniques while maintaining a low computational cost. This indicates that accurate and precise head pose estimation can be achieved using only three facial landmarks. These findings suggest that the proposed technique can be integrated into real-time applications on consumer devices because it provides reliable results without significant computational overhead. By accurately measuring the angle of a driver's head turn, the proposed method can enhance driving performance and reduce the risk of accidents[67].

Table 2 Summary of papers on head pose estimation

Algorithm	Accuracy	Model	Dataset	Reference
Deep learning	VoD: 95.40% DVD: 95.90%	Deep convolutional neural network model	CAS: PEAL dataset	[68]
Iterative closest point and Farneback algorithms	> 92%	Face from Depth 3D model	Biwi Kinect Head Pose, ICT: 3DHP, Pandora	[69]
Deep convolutional neural network	Pitch: 96.50% Yaw: 89.20%	Deep convolutional neural network model	Pointing'04, AFLW, Boston University, ICT: 3DHP	[70]
Viola Jones, Zernike moments Algorithm	85%	Geometric and CNN-based model	MPIIGaze dataset	[71]
CNN: based head pose estimation and Grad: CAM: based attention mapping	90.20%	A denseness-based facial landmark detection module	HPE: AFLW2000, BIWI, GE: MPIIGaze, d UT: Multiview	[72]
Emotion recognition via facial expressions (ERFE)	Head Pose Changes: 83.95% Emotion Changes: 76.58%	Candide3 model	Head Pose Estimation dataset	[73]
MTCNN, Levenberg–Marquardt (LM) algorithm	Eye State: 98.962% Mouth State: 98.561%	RCAN (Residual Channel Attention Network) based model	BIWI dataset, AFLW2000 dataset.	[74]
Active shape model (ASM) and boosted regression with Markov networks (BoRMaN).	< 96.63%	Cascade: CNN: based models, R: CNN: based models	DrivFace dataset, Boston University (BU) dataset, FT: UMT dataset, Pointing'04 dataset	[75]
Fisher's linear discriminant (FLD) and principal component analysis (PCA), Neural Networks	98.81%	Support vector regressors, Sparse Bayesian regression	CMU: PIE dataset, Personal dataset	[67]
HOG, Haar, SVM	Pitch: 97.5% Yaw: 98.2%	SIFT, SURF, ORB	Pointing'04, Kinetic Sensor	[76]

3.2.3 Author's opinion

Advanced driver assistance systems or ADAS are regarded as the backbone of modern vehicles because they provide real-time support to improve road safety. Head-pose estimation is considered an important module of ADAS which helps monitor the head position and orientation of the driver. This allows the system to detect and alert drivers who may be distracted or not be fully attentive to the road. Head-pose estimation uses techniques, such as computer vision, machine learning, and deep learning, to provide valuable real-time data on driver alertness. Various datasets and algorithms have been applied to achieve real-time head pose estimation with high accuracy.

When considering head pose estimation in ADAS, it is important to address the interdependencies with other algorithms, such as gaze detection and face recognition, which together provide a comprehensive view of driver attention. Integrating these can increase computational demand, requiring careful resource management to ensure that the system runs in real time without lag. Privacy is also crucial, as ADAS systems process sensitive driver data; therefore, selecting algorithms that balance computational efficiency with robust privacy safeguards is essential.

In summary, head pose estimation shows strong potential for enhancing driver safety in ADAS. Providing timely data on driver focus and awareness can prevent accidents and save lives on the road.

3.3 Gaze estimation

3.3.1 Machine learning integrated with gaze estimation

Gaze estimation is used in vehicles to determine the degree of driver alertness. It can be used to determine whether the driver thinks of changing lanes or is alert about an upcoming obstacle. These fatal accidents can be prevented by informing drivers of upcoming dangers. Gaze cues that depict a driver's attentiveness include blink rate, temporal gaze variation, speed of eyelid movements, and degree of eye openness. SVM, linear polynomials, and Gaussian kernels are used for eye verification before gaze estimation. Several classifiers can be used for gaze estimation in the final stage of the face detection algorithm. SVM-based classifiers are commonly used for real-time gaze estimation in the automotive industry. Another application of gaze estimation is that it can be used along with other visual and facial parameters to infer the driver's state of mind and predict the next decision[77].

Figure 5 shows the classification used in automobiles for gaze estimation. All the steps of gaze estimation are the same as those of face detection, except for the last step when using various classifiers. For real-time gaze estimation, automobiles use ML and thus require SVM-based classifiers. These SVM-based classifiers are further divided into various categories depending on their accuracy in different environments of low lighting and eyeglass use. SVM-based classifiers can be multiclass, use linear polynomials, Gaussian kernels, or random forest regression.

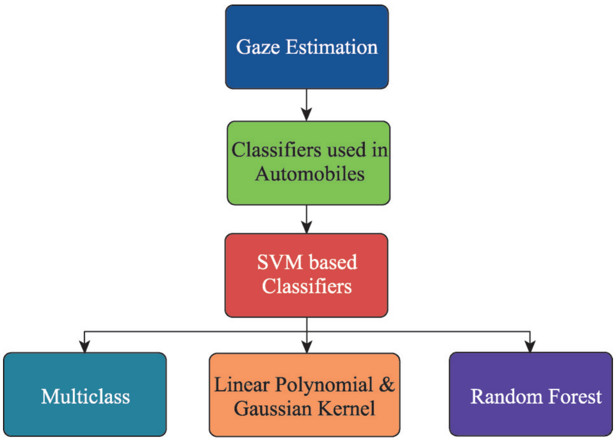

Figure 5 Machine learning with gaze estimation.

For gaze estimation, the system has to determine the focus of the driver's eyes to help detect distractions. This is slightly more challenging because it requires precision even if the driver's head moves or lighting changes. We compared approaches such as appearance-based methods and deep learning models that concentrate on the eye region, focusing on options that offer both continuous tracking and a quick response.

3.3.2 Case studies

A method of estimating the constant gaze area of a driver in ADAS by Wang et al. is to adopt an application-focused approach that introduces a multi-zone iterative closest point (ICP)-based point-cloud alignment technique to accurately determine the head pose and a two-stage neighbor selection process to estimate the eye gaze system based on appearance. To enhance the speed at which the ICP iterations converge, they employed multizone templates and particle filter-tracking techniques to initialize and update the optimal modification of the source face template. By calculating head orientation and angle, they established a gaze zone based on the gaze angle while correcting the head pose. The proposed approach surpasses existing methods in estimating gaze and provides reliable head posture monitoring for analyzing driver behavior in real-world driving scenarios[78].

A critical study of deep-learning approaches by Cheng et al. for gaze estimation based on external features covers four vantage points: deep feature extraction, designing a deep neural network architecture, self-calibration, and device and platform considerations. Regarding cross-subject gaze estimates, the performance is enhanced by using an approach based on deep learning rather than based on the subject's outward appearance. In addition, some techniques use CNN models in conjunction with gaze information. The study compiled summaries of available public datasets and constructed benchmarks for gaze estimates based on postprocessing techniques for the collected data. Unconstrained 2D gaze-point estimation algorithms are often evaluated using gaze-capture datasets. Examples include RT-Gene, Gaze360, ETH-XGaze, and E.E.E. datasets. This study provides a systematic review of gaze estimation techniques and uses webcam images of the eyes to predict the gaze subject. The study introduces four novel aspects: deep feature extraction, design of the DL network architecture, individual calibration, and hardware/software platform[79].

Another study by Ishikawa et al. presented an active appearance model (AAM) used by an algorithm for driver gaze estimation to track the eye corners, extract the eye region, estimate the face size, and estimate the head position. Standard methods were used to find the iris in the eye area, and a standard geometric model was used to determine the direction of gaze based on this information. The system owes its reliability and accuracy to AAM tracking of the entire head instead of using a technique based on local features[41].

A study by Rangesh et al. was conducted to enhance the reliability and applicability of gaze estimation utilizing real-world data captured under challenging conditions, including scenarios involving eyeglasses, bright lighting, night-time driving, and various head positions. An infrared camera with appropriate equalization and normalization techniques was employed to address these challenges. In addition, a gaze-preserving cycle GAN (GPCycleGAN) that trains a generator capable of removing eyeglasses while preserving the original gaze image was proposed. The combined model outperformed the vanilla CycleGAN+SqueezeNet model by 1.5% and exhibited a higher accuracy than the baseline method by 10.5% in terms of micro-average accuracy and 8.9% in terms of macro-average accuracy. Future work will focus on improving different components of the model, such as the generator, discriminator, and gaze classifier, to further enhance performance[80].

A new methodfor estimating driver’s gaze using CNN in a vehicle environment was proposed by Yoon et al. This method differs from traditional approaches in that it uses images from both the front and side cameras simultaneously to estimate the driver’s gaze. The input image for the deep ResNet network combines the three-channel images obtained from both cameras. Unlike commercial systems such as faceLAB and Tobii, which require initial calibration by having the driver gaze at certain positions, this method does not require any calibration. This is because predetermined positions in the front window of a car are difficult to define, and the driver may not cooperate for calibration. With this method, only one CNN model is used, which increases reliability and reduces the computational cost. The authors suggest further accuracy improvements by reconstructing the eye region of interest using super-resolution and decreasing the number of layers and filters to accelerate processing[81].

A study by Pathirana et al. was conducted to determine the effects of climate change on crop production in a particular geographical setting. In recent decades, researchers have analyzed crop and weather data for the regions available as a public dataset. They employed a machine learning methodology, specifically a random forest model, to analyze data and predict future crop yields under different climate scenarios. A significantly negative response of crop yields was obtained to climate change, depending on the specific climate change scenario. The implication here is that the outcomes derived from the results can suggest which crops are more affected by climate change and which regions are most impacted. The study focused on possible adaptive measures that may alleviate the adverse effects of climate change on crop production. This calls for action regarding the urgency of the impact of climate change on agriculture. This study provides valuable insights for policymakers and farmers to develop effective adaptation strategies[82].

A study by Kasahara et al. developed a methodology to estimate the driver's focus of attention while driving, which is crucial for ensuring road safety. To accomplish this, the researchers introduced a novel dataset named "Look Both Ways" that contains video recordings capturing the driver's face, the road scene ahead, and accurately annotated gaze data. Unsupervised and self-supervised learning techniques were employed to train two models: one to estimate the driver's gaze direction and the other to estimate scene saliency. The findings demonstrated the superior effectiveness of the proposed approach compared with existing supervised methods in accurately estimating gaze direction and scene saliency. The authors discuss how this method can be useful for developing more accurate and reliable driver assistance systems and improve road safety. They concluded that the proposed method effectively studies driver behavior and attention, which has important implications for road safety[83].

A study by Nikan and Upadhyay explored how well different appearance-based approaches estimate gaze work by directly applying DNN models to an image of an eye, slowly decreasing the gaze angle. Gaze estimation is an efficient technique for determining what people think and how much attention they pay to what they see. The original dataset was used to train the models. However, because the dataset was small and required more variation in the appearance of objects, the performance of the models trained with synthetic data dropped significantly. To improve how well in-cabin gaze estimation works in driver status monitoring (DSM), error metrics should be easy to understand and fit the applications in terms of distance and scene settings. In the future, in-car images can be used to conduct experiments in this regard[84].

Dua et al. discussed estimating a driver's gaze on the road, which is important for improving road safety, thereby proposing a technique that utilizes inexpensive camera equipment and machine learning techniques to estimate a driver's gaze. To accomplish this goal, the authors introduced a new dataset named "DGAZE" , consisting of synchronized video recordings capturing the driver's face, the road scene, and precise gaze data obtained from an eye tracker. The methodology employs a CNN to establish a common feature space for the driver's face and road scene, followed by a regression model to estimate the gaze point on the road. The results indicated that the proposed approach achieved high accuracy in estimating the gaze point on the road, with an average error of less than 1° in visual angle. These findings contribute to the development of a cost-effective and precise method for estimating driver gaze on the road. The discussion centers on the potential applications of the proposed technique in enhancing driver assistance systems, in studies of driver behavior and attention. The study concluded that the proposed method is effective and has practical utility in real-world scenarios for improving road safety[85].

3.3.3 Author's opinion

Gaze estimation methods play a crucial role in driver-monitoring systems by pinpointing the driver's gaze. If a driver frequently gazes away from the road, it indicates a lack of focus, which can lead to dangerous situations and potentially fatal accidents. This technology can alert both the driver and passengers when the driver's attention drifts, which is vital because many serious accidents are caused by distracted driving. Moreover, gaze estimation can help predict the driver's next moves, such as lane changes, by analyzing cues such as blink rate and eye openness. However, gaze estimation faces several challenges. Many algorithms assume the driver is at a certain distance and require high-quality images for accuracy, which are difficult to achieve under low-light conditions. In addition, real-time processing is essential to ensure its effectiveness. Further studies are required to overcome these limitations.

Considering how gaze estimation interacts with other algorithms such as head-pose estimation and face

Table 3 Summary of papers on gaze estimation

Model	Accuracy	Dataset	Sensor Type	Reference
2D and 3D CNN Model	2D CNN Model: 74.96% 3D CNN Model: 87.02%	Custom benchmark dataset	Infrared Cameras	[86]
CNN Model (YOLO-V4 Darknet-53 and YOLO-V4 Inception-v3)	92.71%	Personal dataset	Multiple Cameras and Smart Eye Pro Tracking (Smart Glasses)	[87]
CNN Model (VGG-16 & AlexNet)	VGG-16 Model: 93.36% AlexNet model: 88.91%	GazeCapture, TabletGaze	Infrared Cameras	[88]
CNN Model (VGG-16 & AlexNet)	VGG-16 Model: 92% MPIIGaze: 82%	MPIIGaze, Columbia, EYEDIAP	Infrared Cameras	[89]
Personalized Gaze Estimation Model and 3D Model	Dataset 1: 93.72% Dataset 2: 84%	Personal datasets	Set of Cameras	[90]
Global and User Level 3D- based Models	91.40%	bug 300-W dataset	Set of Cameras	[91]

detection is also important. Although this interconnectedness can enhance the overall understanding of driver attention, it may also increase the computational demands of the system. Effective resource management is necessary to ensure smooth operation. Privacy is another key concern because these systems handle sensitive driver data. Selecting algorithms that ensure privacy, while maintaining accuracy and efficiency, is vital for the dependable use of gaze estimation in ADAS.

Overall, gaze estimation has significant potential for boosting driver safety; however, ongoing research and attention to technical and ethical challenges are essential to fully leverage its benefits.

3.4 Blink detection

3.4.1 Machine learning integrated with blink detection

There are two approaches to blink detection: video- and non-video-based. ML has been utilized in many non-video-based approaches. These methods include a training model from which the algorithm learns the types of movements that contribute to blink detection. After training, the machine learning algorithm can predict outcomes using the training dataset. These methods are more accurate than video-based methods, and require less computational power after training. Machine learning techniques include deep and shallow learning. Deep learning includes neural networks containing more than one inner layer. Shallow and deep learning are mutually exclusive. Many techniques are available that can be classified into deep and shallow learning, such as SVMs, CNNs, and long short-term memory (LSTM)[92].

Figure 6 depicts the various approaches used for blink detection, dividing them into video- and non-video-based approaches. Video-based approaches were used earlier and can be classified into appearance- and motion-based approaches. Non-video-based approaches use ML and can be classified into shallow or deep learning-based. SVMs use shallow learning, whereas CNNs and LSTMs use deep-learning-based approaches for blink detection.

Blink detection helps monitor signs of drowsiness, necessitating that the system catches even subtle eye movements. The goal is to find an approach that is sufficiently sensitive to detect blinks reliably, even in dim lighting or in the presence of reflections. By comparing traditional methods with modern deep learning techniques, we can select a method that is both accurate and adaptable to changing conditions.

3.4.2 Case studies

A system by Chang et al. was designed to detect drowsiness in drivers by monitoring their eye movements and facial physiological signals. The study developed a reliable and precise system that could be integrated with in-car monitoring systems to improve driving safety. The researchers used computer vision techniques

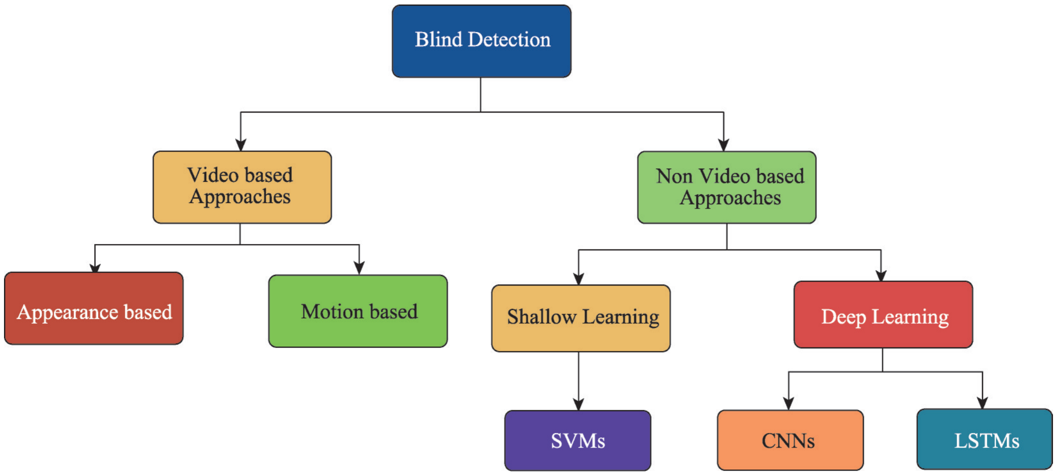

Figure 6 Machine learning with blink detection.

and ML algorithms to create this system. They tested its accuracy by evaluating the publicly available "Drowsy Driver Detection" dataset, which contains videos of drivers experiencing varying levels of drowsiness. The study further suggested integrating photoplethysmography imaging (PPGI) and heart rate variability (HRV) analysis to detect the LF/HF ratio, further monitoring the percentage of eyelid closure over the pupil over time (PERCLOS), which resulted in a system accuracy of 92.5%. This research emphasizes the promising prospects of employing computer vision and machine learning methods to develop reliable drowsiness detection systems. These systems can alert drivers when their drowsiness levels exceed a predefined threshold, thereby enhancing driving safety[93].

A study by Gawande and Badotra aimed to enhance the precision and resilience of an eyeblink detection system by employing a deep learning approach and hybrid optimization concepts, using a dataset containing eye images with corresponding labels of blinking and non-blinking eye images. This methodology used a deep CNN architecture and hybrid optimization techniques, such as adaptive moment estimation (Adam), root mean squared propagation (RMSProp), and AdaDelta. The improved active shape model (I-ASM) and local binary patterns (LBP) were extracted to train the optimized CNN architecture. The proposed kernel median filtering (KMF) method enhanced the image quality in the frames. The results demonstrate that the proposed system outperformed existing methods in terms of accuracy and robustness, and the hybrid optimization approach successfully optimized the deep CNN architecture with high accuracy and low computational cost. This study discusses the possible applications of the system in the fields of human-computer interaction, biometric identification, and healthcare, concluding that the proposed approach has the potential for efficient eyeblink detection and can further be improved using more extensive datasets and additional optimization techniques. Overall, this study emphasizes the usefulness of deep learning and hybrid optimization concepts in developing precise and efficient eyeblink detection systems[94].

Another study by Schmidt et al. explored the performance of blink detection algorithms in conditionally automated driving and manual scenarios. This study compares a blink detection process that uses electrooculography and cameras, along with various signal-processing algorithms and two different data sampling frequencies. Additionally, the study assessed the performance of 24 reference groups in detecting blinks. Although the correct detection rates for manual and alert driving were high (maximum 94%), they decreased significantly during the drowsy and conditionally automated driving phases. This study suggests that the measurement frequency, driver state, level of automation, and algorithmic techniques all influence blink detection. It also emphasizes the importance of detecting drowsiness while driving and developing reliable systems to detect, warn, and prevent drowsiness by monitoring blinking and eyelid movements[95].

Gaffary & Lécuyer also developed a real-time mobile-phone-based system using the Android platform for eyeblink detection and gaze tracking. Using a Haar classifier and the normalized summation of square of difference template matching method, the system achieved an impressive 98% accuracy rate for blink detection from both eyes at the 0° angle. The blinks were categorized into short, medium, and long durations based on blink duration and closure degree. The system underwent extensive testing, including variations in lighting, subjects, sex, angles, processing speed, random access memory (RAM) capacity, and distance, performing well in real-time scenarios for both single- and dual-eye detection. The practical applications of this system are significant, particularly for detecting driver drowsiness and enabling eye-operated mouse control for individuals with disabilities. Overall, the study highlights the potential of the mobile phone-based system for accurately detecting eye blinks and tracking gaze, opening possibilities for improving driver safety and assistive technologies[96].

A study by Salehian and Far proposed an algorithm for detecting eye blinking based on two approaches: shape analysis and histogram analysis. Using computer vision techniques and efficient images, the blinking patterns of the driver were analyzed in almost real time. The initial results demonstrate that the proposed method can be useful for monitoring blink detection to determine whether someone is tired. In the future, the system can be improved for obtaining images, add more preprocessing methods, and use adaptive methods in the edge detection and global thresholding steps. Using the same methods to recognize other visual cues, such as facial expressions and yawning, may make it easier to determine when a driver is tired[97].

One study by Ryan et al. explored the use of a fully convolutional neural network and a lightweight method for detecting blinks to locate and track faces and eyes in event cameras. They manually collected test datasets and evaluated the performances of both methods using qualitative and quantitative measures. The findings indicate that event cameras are promising for driver-monitoring systems (DMS). Event cameras offer several advantages over regular cameras, including a higher temporal resolution and the ability to adjust frame rates based on the task. Leveraging these features enables the development of more advanced DMS solutions that surpass the capabilities of current fixed frame rate approaches. The study highlights the potential of event cameras in revolutionizing DMS technology, unlocking new possibilities for enhanced driver safety and monitoring[98].

Another study by Dewi et al. proposed a method that introduces the modified eye aspect ratio (Modified EAR) as a new threshold parameter to automatically classify blink types. The experiment demonstrated that utilizing the Modified EAR improved blink detection accuracy. In future work, the researchers aim to focus on datasets that include additional facial actions, such as smiling and yawning, to enhance the versatility of blink detection algorithms. They also suggest that ML methods can be employed for more effective blink detection in future studies. By combining the Modified EAR and ML techniques, researchers anticipate the development of advanced blink detection systems capable of accurately identifying blinks in various contexts. This research paves the way for improved blink detection algorithms that can be applied to diverse applications, such as driver monitoring, facial expression analysis, and human-computer interaction[99].

A combination-based method by Bhavana and Sivakumar determined whether a driver is too tired to drive, starting with a strong indicator of a landmark and then using a simple eyeblink detection technique to identify the person based on SVM. This strategy is independent of the topic, and there is no good reason for constructing this framework. The experimental results show that the algorithm works well, with a best-case accuracy of 96% for the EAR SVM classifier. Future work can be incorporated into the framework of universally utilized applications such as Uber and Ola[100].

Another study by Hu et al. implemented a low-cost, contactless, and user-friendly sleep-driving detection system that protects the privacy of drivers while maintaining satisfactory monitoring accuracy. Through theoretical and experimental research, they statistically modeled the relationship between signal changes and tiny eye-induced movements such as blinks. Comprehensive experimental findings demonstrated the efficiency of the system, with a median detection accuracy of 95%[101].

Table 4 Summary of papers on Blink Detection

Detectors/Classifiers	Datasets	Accuracy	Speed	Reference
Histogram of oriented gradients (HOG)	Talking Face and EyeBlink8	Talking Face: 97.10% EyeBlink8: 97%	30 fps	[102]
Linear SVM classifier with HOG features and the LeNet-5 CNN model	CEW and ZJU Eye-blink datasets	95%	> 10 fps	[103]
Canny edge detector and SVM	Caltech and Eye-blink databases.	CCD Camera: 95.3% CMOS Camera: 96.3%	15 fps	[104]
Viola Jones face detector and neural network-based eye detector.	JZU eyeblink database	94%	110 fps	[105]
Adaboost-based face detector, Haar Classifier, and Viola Jones algorithm	Personal dataset	> 90%	0.5 fps-2.5 fps	[106]

3.4.3 Author's opinion

Advanced driver assistance systems are primarily used to monitor the alertness of a driver, to reduce the risk of accidents. This technique computes the driver's blink rate by determining the face from images. A noticeable drop in blink frequency indicates that the driver is getting sleepy and losing focus on the road. This alerts the driver and passengers to avert an accident. There are two basic approaches: video- and nonvideo-based techniques. Non-video-based methods often use ML techniques that tend to be more accurate and require less time after the initial training. These algorithms can effectively locate the eyes, which enhances the performance of other driver-monitoring systems.

Although blink detection is valuable on its own, it works best when integrated with other systems, such as gaze and head pose estimation. This interdependence can improve the overall assessment of driver attention but may also increase the system's computational demands. Balancing these demands is crucial for achieving real-time performance. Privacy concerns are also significant because technology captures sensitive driver information, making it essential to select algorithms that prioritize both privacy and efficiency of blink detection.

Blink detection is fundamental for understanding driver attention and serves as a stepping stone for other monitoring technologies. By addressing the technical and ethical challenges, we can harness its potential for enhancing road safety.

4 Control system perspectives of ADAS & machine learning

The accuracy of ADAS is currently poorer than that of human drivers as the technological advancements required to implement it are lacking. Therefore, ADAS and human drivers must be used to support the driving systems. In this system, human drivers are the primary decision-makers and ADAS assists them only in decision-making. In addition, in this system, ADAS controls the vehicle in certain situations, but keeps human drivers in the loop. According to various researchers, maintaining human drivers in the loop is necessary because AI decisions cannot be trusted. Therefore, a control structure is necessary to determine when an automatic control system should assist the driver and when to take control of the vehicle. Various studies have been conducted on control structures to compare their performances[107].

Under certain conditions, automatic control systems are not capable of making decisions, requiring that the vehicle control be handed over to the human driver. Here, a problem arises with hand-over duration. Occasionally, the driver takes time to seize control of the vehicle, which can be dangerous in certain situations. A visual-auditory handover request was observed to be more effective than a pure visual request. Six types of control transitions were defined, considering human factors. The longitudinal and lateral behaviors of the vehicle during handover was observed to depend on various factors, such as handover duration, traffic situation, vehicle speed, and the driver's secondary task. Therefore, a controller that assists human drivers at this critical time should be designed[108].

Another method for solving the problem of low accuracy in ADAS systems is to use a cooperative approach. This approach shares the vehicle control between the human driver and automatic control system, whereby the automatic control system assists the human driver in making various decisions without restricting the driver from making critical decisions that are not detected by the system. This method ensures proper authority over the automatic control system by including the human driver in the decision-making loop such that the human driver can disagree with the decision made by the control system and take control of the vehicle if required. In a vehicle's lane-keeping assistance system (LKAS), the human driver and control system can share the vehicle's steering. The driver knows every decision of the control system through the steering movements. If the driver finds something wrong, he can immediately restrict the steering movement and change the decision. This system decreases the driving burden and is safe because the driver can take control at any time[109].

5 Challenges

ADAS technology holds immense potential to transform our driving experience, but its true power lies in its ability to protect lives on the road. The development of ADAS has presented numerous challenges. These systems aim to enhance vehicle safety and assist drivers. However, this has been marred by challenges such as achieving proper object detection, dealing with adverse weather conditions, implementing advanced sensor technologies, eliminating cybersecurity concerns, and smooth human driver interactions. All these have to be overcome for ADAS to be implemented successfully and for autonomous driving technologies to be promoted. In the past century, ADAS has witnessed tremendous progress, which can change how humans interact with vehicles. However, behind the cutting-edge technology challenge, ADAS faces a multitude of hurdles in ensuring reliable and accurate performance. One such challenge lies in face detection, which is a critical component that enables the system to identify drivers' faces and track their movements. Another obstacle is head-pose estimation, which accurately determines a driver's head position and orientation. An important aspect of blink detection is to check the level of the driver fatigue or distraction. Finally, gaze estimation allows ADAS to know the driver's focus and what the driver is likely to do next. In the following sections, we detail these four methods and explore their significance in enhancing road safety.

Hybrid models have demonstrated improved performance compared with individual supervised ML or DL approaches, primarily by combining the strengths of both techniques. The success of these models depends on factors such as the quality and volume of labeled datasets, task complexity, and effective integration of ML and DL methods. However, the research on supervised ML and DL for computer vision still faces significant challenges. Key issues include the limited generalizability of models to diverse datasets, need for better interpretability, and concerns about data efficiency. DL models are often regarded as "black boxes" and lack transparency, which complicates their application in high-stakes fields where explanations are critical. Moreover, the requirement for large, labeled datasets presents a major hurdle because data collection and annotation can be resource-intensive, impacting the scalability and practicality of these models in broader applications[110].

Face detection in ADAS is challenging. Despite the development of various face recognition methods, only a few match the human ability to recognize faces under different conditions. Systems become more complex as their applications expand, making face detection a significant challenge. A major challenge is the variation in lighting conditions, which affects the efficiency of the system in accurately detecting and recognizing faces. Different lighting levels make it difficult to effectively perform face detection. Additionally, variations in poses, such as changes in viewing angles or head rotations, can create problems for the system. Another challenge is the variation in facial expressions. Different emotions can cause variations in facial appearance, making it challenging to identify faces correctly. Aging is also a factor impacting face recognition accuracy, as the face changes over time. Occlusions where objects partially cover the face further complicate the detection process. Furthermore, similar faces, especially identical twins, can lead to higher false recognition rates. Varying the image resolution and complex background in facial images also affects the efficiency of face detection. Addressing these challenges requires the development of robust algorithms that are capable of handling variations in lighting, pose, expression, aging, occlusion, similar faces, and image resolution. Innovations in face recognition aim to improve the accuracy and reliability of face detection systems for ADAS applications[111].

Head pose estimation is vital for analyzing driver behavior and attention in ADAS. However, existing algorithms for head-pose estimation must perform well under real driving conditions, which poses a few key challenges. First, the varying illumination in the driving environment poses a problem. Lighting conditions, including shadows or bright sunlight, can change rapidly, making it difficult for algorithms to accurately detect and track facial features. Second, occlusion poses a significant challenge. Occlusions include cases in which parts of the face, such as the eyes or mouth, are partially or fully blocked. This is very common with glasses, especially when the frames are thick, which blocks the view of the facial features. Hence, algorithms that estimate head pose find it difficult to obtain the correct head position and orientation. Third, drivers in real-world scenarios may exhibit extreme head rotations that exceed the typical range. To provide reliable results, the estimation algorithms must handle these rotations. Extreme yaw and pitch angles can create difficulties and lead to inaccurate or unreliable head pose estimations. Finally, current algorithms for controlled environments perform poorly under driving conditions because of the challenges mentioned above. Developing improved head-pose estimation algorithms that can effectively handle varying illumination is crucial for overcoming these limitations. Addressing these challenges is essential for accurately analyzing driver behavior, monitoring attention levels, and developing effective in-vehicle systems for ADAS[112].

Blink detection involves the detection of eye blinks; however, it also presents challenges. One of the main difficulties is that the appearance of the eyes can change with factors such as lighting, head movement, and blockage. This makes it difficult to detect blinks accurately. To overcome this, researchers have used facial landmark detection to identify the eye and eye aspect ratio, to detect blinks and improve accuracy. Another challenge is the quick and accurate detection of blinks in real time. This requires fast algorithms and hardware to handle large amounts of data. Researchers have used USB cameras and dynamic template matching to achieve real-time processing of eye images. The accurate detection of blinks in different situations, such as varying lighting conditions and eye movements, poses another challenge. To address this, the team used adaptive algorithms that can adjust to different situations and enhance blink detection accuracy. Blink detection is complex because it requires efficient algorithms, hardware, and adaptive techniques for accurate real-time detection in varying contexts[113].

Gaze estimation involves monitoring eye movements and focus. In ADAS applications, several challenges are associated with the placement of camera sensors in relation to the driver's seat. Camera sensors must be placed correctly such that they do not obstruct the view of the road when tracking the driver's gaze. Another challenge is dealing with low-light conditions, which make locating the driver's pupils in the image difficult. Techniques such as infrared illumination and improved image quality may be necessary to address this issue. In addition, the system for detecting the pupils may require enhancements to accurately track the driver's gaze under different lighting conditions. Adjustments may be required in the proposed gaze-tracking approach. This may involve changing the camera sensor or exploring other gaze-tracking systems. Advancements in differential gaze estimation, robust 3D eye-gaze tracking, and neuro-inspired eye tracking can improve the accuracy and dependability of gaze trackers with ADAS. Gaze tracking in ADAS incorporates several challenges that must be overcome to enable high-precision and dependable tracking. However, research and development are ongoing to improve gaze tracking before warnings about potential hazards along the road reach the driver[114].

In conclusion, the challenges in ADAS include complexity, dependence on other vehicle systems, misjudgment and misdetection of surrounding vehicles, lack of consumer awareness, high costs, and the need for adaptable and flexible modeling platforms to verify performance.

6 Future scope

The future scope of ADAS is almost limitless because it opens up a new generation of intelligent transport. Advanced driver assistance system technology is the future of the automotive business. It has various applications in technology. ADAS will be useful when incorporated into automobiles, leading to better vehicle performance and saving humans from the various perils associated with accidents. It is a breakthrough technology that is highly beneficial to human life. There are various ways to improving the effectiveness of ADAS technology. One such approach involves the development of more advanced and accurate sensors. Object detection can be made possible by incorporating AI and ML algorithms. Therefore, cybersecurity measures should be enhanced to prevent hacking. The main consideration for all ADAS manufacturers is to make the cost of ADAS accessible to all users. ADAS should be integrated into smart city projects because it can help reduce traffic congestion, controlling traffic signals efficiently and sustainably.

Face detection technology has made significant progress in recent years and holds immense potential for the future. Its development is particularly important in the fields of security and surveillance as it has become a crucial tool for law enforcement agencies and security personnel to use for real-time identification of people through face detection, in the prevention and detection of criminal activities in public places, such as airports, train stations, and shopping malls. Healthcare is another area witnessing remarkable development. This is particularly beneficial in critical care units where continuous monitoring is vital. In marketing and advertising, face-detection technology offers the ability to analyze customers' facial expressions and emotions. This valuable insight into preferences and behaviors helps businesses tailor their products and services to cater to their customers' needs. Furthermore, face detection technology can enhance accessibility for individuals with disabilities. For instance, it can facilitate the control of devices, such as wheelchairs or prosthetic limbs, thereby granting greater independence to people with limited mobility. In summary, the prospects for face detection technology are extant and diverse, with applications spanning across various domains. With the ongoing advancements, we anticipate the development of innovative and exciting applications in the coming years[115].

Head-pose estimation can be performed using deep neural networks to predict an individual's attention span, which is a fundamental factor in various areas, including education and driving, and the ability to forecast it is immensely useful. The challenges for developing the model include the requirement for massive training data and precise estimation of the head pose. This work can be extended to encompass eye-gaze prediction, which can be very helpful in applications such as examinations, interviews, and ADAS. Hence, by using additional DL algorithms and techniques, sustainable and safe solutions can be provided for drivers[116].

The utilization of driver gaze estimation is crucial in various applications such as in the detection of driver attentiveness and visual distraction, gaze behavior understanding, and building driver assistance systems. This study aims to offer a comprehensive summary of driver-eye activity principles, approaches for assessing them, and their applications to real-world driving conditions. Future research can facilitate the evolution of this domain and contribute to the development of safer transportation systems. Studies on the development of ADAS should incorporate the basics of driver gaze estimation, current benchmark driver gaze datasets, algorithms for driver gaze estimation, and real-time applications. The prospects of driver gaze estimation and gaze-based applications can be addressed using deep learning algorithms, such as CNN, which would make the automobile industry safer[117].

Blink detection algorithm can also serve as a visual cue for driver fatigue. The primary obstacle to using this algorithm in a real-world setting is the need for a shorter processing time to allow adequate response time for drivers. To address this issue, optimization techniques should be implemented to meet latency requirements. Additionally, the algorithm should be validated through visual inspection of video sequences to assess precision and accuracy. The image acquisition system is expected to remain unchanged, and no enhancements or modifications are planned for future work in this field. Using similar techniques to identify other visual cues such as facial expressions and yawning may also enhance the accuracy of driver fatigue detection. The blink detection algorithm presented in this paper demonstrated a precision rate of 84% and an accuracy rate of 69% through 12 video sequences of varying durations and lighting conditions and a small sample of participants. This emphasizes the possibility of employing noninvasive real-time image processing and computer vision techniques to monitor weariness in the future[97].

In summary, ADAS is expected to become increasingly popular in the coming years, as people demand safety and efficiency in vehicles. The priority should be to integrate deep learning techniques with existing ADAS systems. However, challenges such as high costs and consumer awareness need to be addressed, and further research is required to improve performance and develop adaptable and flexible modeling platforms.

7 Conclusion

To conclude, this introduction provided an overview of ADAS objectives, its evolution and applications in machine learning. The main aim of ADAS is to mitigate fatal accidents by assisting drivers in making better decisions, as most accidents are attributable to human error. The discussion focused on four crucial algorithms employed in ADAS.

The face detection algorithm is utilized to identify faces under various environmental conditions. ML techniques have been employed to enhance the accuracy of this algorithm, particularly in challenging situations with low lighting or partial face visibility.

The head-pose estimation algorithm estimates the head pose of a driver in an image to assess the attention level. By analyzing head pose the driver can be warned to prevent distraction and enhance alertness. ML is employed in this algorithm to improve attention estimation accuracy.

The blink detection algorithm detects signs of drowsiness and sleepiness in drivers. The blinking rate is constantly monitored, with a decreasing rate indicating drowsiness and total stoppage implying that the driver has dozed off.

The gaze estimation algorithm is employed to determine the visual focus of the driver. If the driver’s gaze is consistently directed away from the road, this is a warning sign of potential distraction. In the gaze estimation algorithm, ML is used to accurately recognize the driver's face, and subsequent deviations are tracked based on the initial facial recognition patterns.

Machine learning has proven to be highly effective in refining the algorithms that are essential for real-time driver monitoring and alerting, thereby enhancing ADAS. Despite notable advancements, future research can enhance the reliability and responsiveness of ADAS across diverse driving environments and driver demographics. Research directions can include exploring robust ML models for improved accuracy under extreme conditions, such as varying light levels or obstructions, and developing cross-functional integrations between ADAS components for a comprehensive assessment of driver behavior.

Overall, these algorithms focus on predicting the driver's mental state and issue warnings when driving conditions become risky, thereby reducing human error on the road. The implementation of these methods has the potential to significantly affect the automotive industry.

Declaration of competing interest

We declare that there are no competing interests.

CRediT authorship contributions statement

Harsh Shah: Conceptualization, Writing−original draft. **Karan Shah:** Writing−review & editing. **Kushagra Darji:** Data curation, Methodology. **Adit Shah:** Validation. **Manan Shah:** Conceptualization, Supervision.

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