Application of Artificial Intelligence in the Intelligent Driving Field

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Abstract. With the rapid advancement of artificial intelligence (AI), its application in intelligent driving has emerged as a key research focus, offering significant potential for enhancing vehicle autonomy, safety, and efficiency. This paper provides a comprehensive analysis of various AI technologies and their roles in intelligent driving. It begins with an overview of the current state of intelligent driving, outlining the technological landscape and core challenges in the field. The paper then examines key AI-driven components, including vision-based large models, intelligent decision-making and planning systems, control systems, and human-computer interaction, discussing their applications, advantages, and existing challenges. Through this analysis, the study highlights how AI enhances perception, decision-making, and control mechanisms in autonomous vehicles, enabling more adaptive and efficient driving strategies. By synthesizing findings from theoretical and practical perspectives, this paper provides a deeper understanding of AI's transformative role in the automotive industry. The insights presented in this study serve as a reference for researchers, engineers, and policymakers, contributing to the ongoing development of AI-powered intelligent driving technologies and their real-world applications

Keywords: Vision Large Model, Intelligent Decision Planing, Control System, Human-Computer Interaction

1 Introduction

With the popularity of cars, more and more individuals and families have purchased vehicles, and car travel has become an important mode of transportation for people. However, this was followed by a gradual increase in the number of car accidents. According to statistics, the proportion of car accidents caused by drivers is as high as 80%. Therefore, the use of intelligent driving technology to free the hands of drivers and transform artificial judgment into computer calculation has become an effective means to reduce the accident rate. With the development of artificial intelligence, intelligent driving technology has become an important part of intelligent transportation systems. The technology can not only reduce the operating burden of the driver, but also achieve rapid response through the algorithm that humans cannot do, so as to avoid the occurrence of traffic accidents.

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Self-driving cars mainly rely on the collaboration of artificial intelligence, vision computing, monitoring devices and global positioning systems. It is a comprehensive system integrating environmental perception, planning and decision making, multi-level assisted driving and other functions. It integrates computers, modern sensing, information fusion, communication, artificial intelligence, automatic control and other technologies, and is a typical high-tech complex. The social value of intelligent driving vehicles lies in, first, significantly reducing traffic accidents, which is the primary goal of intelligent driving, and the main reason why countries around the world speed up the adoption of policies or laws to promote the development of self-driving cars. Second, it can improve the present traffic. The technology can overcome the limitations of human perception and be more accurate and sensitive than humans to predict and react to road conditions through machine learning and the use of mapping technology, thereby reducing congestion and increasing traffic efficiency. In the future, with the continuous development of relevant technologies, intelligent driving can not only be applied in the field of automobiles, but also can be extended to a variety of vehicles to achieve intelligent driving of various vehicles, so its future development prospects are very considerable.

However, the current research on autonomous driving still has great challenges and limitations, and has not yet reached the level of human driving. Katrakazas et al. summarized some factors, including obstacle handling and vehicle dynamics [1]. In terms of handling obstacles, the existing methods mainly rely on predicting the trajectories of other traffic participants, whose trajectories usually present constant speed or acceleration. However, the speed and acceleration of obstacles change dynamically, which leads to huge computational difficulties for the existing algorithms, because they cannot accurately calculate the state of obstacles while considering the surrounding traffic environment. The usefulness and accuracy of existing algorithms are still limited. Christos mentioned that Google's 2015 experiment showed that the driver and the self-driving car could not establish a good balance and tacit understanding, and Google's self-driving car could not accurately understand the intentions of the human driver, leading to the collision in the experiment. On the other hand, most planning methods are based on the motion model of bicycles or similar cars to model autonomous driving, because tire forces are not taken into account, resulting in the model cannot be used in real vehicles [2]. Although Jeon et al. proposed some dynamic methods based on the bicycle model and considering the friction force and mass of the vehicle, they still failed to find a complete model that can effectively describe the motion and force of the vehicle in the real environment [3].

This paper aims to comprehensively analyze and study various artificial intelligence technologies, and discuss the application and contribution of artificial intelligence technology in the field of intelligent driving in combination with literature and practice. It first explains the general situation of intelligent driving in detail, and then analyzes the application and problems of a vision large model, intelligent decision planning system, control system and human-computer interaction in intelligent driving. By systematically analyzing these aspects, the paper provides a deeper understanding of the role of AI in intelligent driving and its practical implications.

2 The Basic Concept of Intelligent Driving

2.1 Definition and Classification of Intelligent Driving

According to the classification of automatic driving by the National Highway Traffic Safety Administration (NHTSA) and the Society of Automotive Engineers (SAE), automatic driving systems can be divided into six registrations from L0 to L5. L0 refers to the driver driving the car with full authority, the system can only provide help or warning, and does not involve any AI intervention; L1 refers to driving assistance, which realizes lane keeping and other functions based on CNN vision recognition technology. Although the system assists the driver in some functions, the overall driving is still controlled by the driver; L2 refers to partial automation, adaptive cruise and lane centering through multi-sensor fusion, the driver still needs to monitor the environment; L3 refers to conditional automatic driving, which realizes highway navigation through deep learning decision-making model, and AI can take over driving in a specific environment, and the driver only needs to provide appropriate responses; L4 refers to highly intelligent driving, the unmanned system handles all driving operations, the driver does not have to provide a response, through reinforcement learning path planning, AI can operate independently in limited areas (such as Robotaxi service); L5 refers to full automation, full environment automatic driving through end-to-end AI control system, the driver does not need to operate at all. From L3 to L5, environmental monitoring is conducted by AI [4]. At present, it is only realized to L2 ~ L3, and the future development of intelligent driving still has great space and prospects. Table 1 details the levels of intelligent driving and the operators under the different levels.

Table 1. Classification of intelligent driving

Grade classification	Grade name	content description
L0	No autopilot	The driver has full authority to drive the car, and can get help or warnings while driving, in which there is no AI intervention
L1	Aided driving	Lane keeping and other functions based on CNN vision recognition assist the driver in some functions
L2	Partial autopilot	Adaptive cruise and lane centering are realized through multi-sensor fusion
L3	Conditional autopilot	Through the deep learning decision model to achieve highway navigation, AI can take over driving in a certain environment
L4	Highly automated driving	All the driving operations are completed by the unmanned system, and the driver does not need to provide a response. The Robotaxi can be realized

		in a limited area through reinforcement learning path planning
L5	Full automation	Full environment autonomous driving is achieved through an end-to-end AI control system, and the driver does not need to operate at all

2.2 Correlation Technique

The autonomous driving system is composed of the perception system, the decision system, the control system and the vehicle-road cooperation for assistance. Perception system: lane detection and pedestrian recognition based on computer vision, LiDAR point cloud processing based on multi-mode fusion, millimeter wave radar target tracking; Decision system: LSTM-based vehicle trajectory prediction, AI algorithm combined with deep reinforcement learning to realize path planning; Control system: PID+MPC model for horizontal control and deep Q network acceleration/braking optimization for vertical control; Vehicle-road cooperation: intersection signal lights cooperate to achieve edge computing, and low-delay high-precision positioning to achieve 5G communication.

Intelligent driving can be divided into passenger cars, commercial vehicles, closed or semi-closed area vehicles and specific scene extensions. At present, in the field of passenger cars, Tesla's autopilot based on vision AI and Xopeng's NGP system based on high-precision maps and lidar have been widely praised in the industry. Among commercial vehicles, the most representative ones are port unmanned collection cards based on SLAM positioning and mine automatic driving based on dynamic obstacle prediction, which can effectively improve work efficiency and reduce the probability of safety accidents. Among vehicles in closed or semi-closed areas, park shuttles based on V2X communication and automatic parking systems based on ultrasonic radar and vision integration can effectively solve the problem of human resources and parking efficiency, and make great contributions to improving people's quality of life. Finally, traffic sign recognition based on the YOLO model and AEB emergency braking based on target detection algorithm greatly reduces the incidence of traffic accidents. It can be seen that artificial intelligence technology has made a great contribution to intelligent transportation and will continue to develop in the future.

3 Application of Artificial Intelligence in the Intelligent Driving Field

3.1 Perception and Control Systems

3.1.1. Perception System.
The vision large model is an important part of the perception system, and its powerful perception ability, autonomous decision-making ability and multi-task processing ability can help the autonomous driving system better understand the complex driving environment, so as to improve driving safety and efficiency. Computer vision technology has a wide range of applications in the field of intelligent driving. By

installing an external camera to scan and capture the surrounding environment, and using deep network nerve to extract the picture features, the environment can be perceived and reacted to. However, the deep learning model requires a large number of high-quality annotated data as training support, and data collection and annotation require a large number of human and material resources, so the optimization iteration efficiency of the model is restricted.

Huang et al. proposed an automatic image data labeling system based on a large vision model for automatic image data labeling of typical tasks in an automatic driving system [5]. Compared with the current advanced model, this method improves the IOU index by 19.8% in the lane detection task. In addition, in order to make full use of unlabeled data, they adopted a semi-supervised learning method based on self-training to fine-train the image classification model DINOv2, achieving an average accuracy improvement of 3.28% in the recognition of warning, prohibit and pointing cards, and an average F1 score improvement of 6.5%. In the meantime. The fine-tuning of the large model of target detection improved the target detection accuracy of different categories of vehicles by an average of 3.28% and F1 score by an average of 3.07%, greatly improving the detection accuracy and research efficiency.

YOLO algorithm is a new method of object detection, proposed by Joseph Redmon and his team, object detection is viewed as a regression problem that involves spatially separated bounding boxes and associated class probabilities,a single neural network predicts bounding boxes and class probabilities directly from the complete image in one evaluation, since the entire detection pipeline is a single network. To improve detection performance, end-to-end optimization can be performed directly.Their unified architecture is extremely Fast, with the base YOLO model processing images in real time at 45 frames per second, while Fast YOLO is capable of processing an astounding 155 frames per second, while achieving twice the mAP of other real-time detectors. Although YOLO still makes mistakes, it is clear that it still has a leading edge in image processing [6].

Large vision model technology can be used to detect foreign objects on the road, capture the picture through an external camera, and use a deep learning model for analysis, which can brake the car in a limited time, thus greatly improving the safety factor of driving. Yang et al. proposed an intelligent recognition method based on large vision models of artificial intelligence [7]. By using the feature extraction and generalization ability of the large model combined with the transfer learning strategy, the problem of data scarcity and diversity of foreign bodies is effectively solved by fine-tuning it to adapt to the task of line foreign body recognition. XU et al. systematically analyzed the key challenges of vision based model (VFM) development in autonomous driving, including data scarcity, multi-sensor fusion requirements and task heterogeneity, proposed a technology roadmap based on NeRF, diffusion model and world model, and constructed the open resource repository Forge VFM4AD [8]. This paper discusses how to improve the generalization ability of the model for complex driving scenarios through large-scale pre-training and self-supervised learning, and constructs the future research direction.

3.1.2. Control System.

As a bridge between "digital intelligence" and "physical execution", intelligent driving control systems are far more significant than the technology itself, reshaping the way humans travel, urban governance models, and the global economic structure. With the continuous breakthrough of AI and hardware, the control system will become the core pillar of the realization of all-scene automatic driving.

In the control system, this paper will discuss three aspects, namely end-to-end driving, integrated lateral and vertical decision making, and the joint optimization of multi-modal perception and control.

End-to-end driving is done by directly mapping sensor inputs to control commands such as steering wheel or throttle. In this aspect, end-to-end neural network technology is mainly used. Based on reinforcement learning, Li et al. proposed Ramble is a RL algorithm that is based on end-to-end models to solve the intractable problem of effectively extracting spatial and temporal features from high-dimensional and multimodal observation sequences [9]. which is prone to errors. Multi-view RGB images and LiDAR point clouds are processed by Ramble to produce a low-dimensional delay features to capture the context of the traffic scene at each time step. The use of a transformer-based architecture is used to simulate time dependencies and predict future states. Dynamic models of the environment can be learned to anticipate upcoming traffic events and make more informed strategic decisions， Ramble excelled in route completion rates and driving scores on CARLA Leaderboard 2.0, demonstrating how it can effectively manage complex and dynamic traffic situations。 Hu et al. studied a new end-to-end AD training model to solve the problems of poor data efficiency, training complexity and universality in intelligent driving research and development, and to enhance the adaptability and intelligence of the system [10]. In this model, transformer modules are incorporated into the strategy network and the initial behavior clone is pre-trained to update the gradient. Reinforcement learning techniques are then used to fine-tune the model to the specific driving environment and guide the objective of the model is to achieve driving behaviors that are both more efficient and safer. Based on their simulation results, it appears that the framework accelerates learning, achieves precise control, and significantly improves safety and reliability.

For integrated horizontal and vertical decision-making, Cui et al., based on deep reinforcement learning and deep Q network, proposed a comprehensive horizontal and vertical decision-making model with automatic driving vehicle (ADV) and manual driving vehicle (MDV) in multi-lane highway environment, and conducted a large number of simulation experiments on the three-lane automatic driving decision-making model [11]. The results show that the model has good performance in safety and travel efficiency of automatic driving, and can effectively improve the efficiency and success rate of integrated horizontal and vertical decision-making in automatic driving after stable training.

In the joint optimization of multi-modal perception and control, the perception accuracy of nearby vehicles is one of the standards for the safety and reliability of intelligent driving. Only when autonomous vehicles perceive the surrounding environment with high precision can they make correct planning and execution. Kyusang Yoon proposed an advanced sensor data fusion technology, which can be used in a variety of environments. The rail-to-rail fusion method based on multi-modal networks combines the estimate of each sensor's position of the target vehicle into a single estimate [12]. Using IMM filters to better describe vehicle motion, combined with multi-modal networks, can better estimate vehicle position in different weather and environments, and the results show that their method shows high reliability in estimating the sensor fusion accuracy of the surrounding vehicle position.

Phillip Karle believes that powerful Motion tracking is crucial to reduce the accuracy of state estimation is improved by sensor noise., and they propose a method for fusion and tracking of multi-modal sensors for high-speed applications that is modular and multimodal [13]. An extended Kalman filter is the basis of the method, which can fuse heterogeneous detection inputs to consistently track surrounding objects. By using a new delay compensation method, software delay can be reduced and an updated list of objects can be produced,which proves its robustness and computational efficiency on embedded systems through practical tests in some car races.

3.2 Decision and Planning

Finite State Machine (FSM) is commonly used to describe the state transitions and behavior of a system and is suitable for dealing with finite, predictable environments. The finite state machine in intelligent driving can be used to describe the state of the vehicle (such as speed, acceleration, braking, etc.) or the state of the environment (such as traffic lights, pedestrian behavior, etc.). The FSM helps the intelligent driving system maintain the state consistency of the vehicle and the environment through clear state definitions and transition rules. For example, the vehicle can be in "normal travel", "emergency brake", "temporary stop" and so on, and the FSM can ensure that the transition between different states is reasonable and safe. It also abstracts pedestrians, vehicles, and traffic lights on the road into a series of states to help understand and process diverse traffic scenarios. In addition, FSM can also be combined with other control models (such as MVB, feedback control, optimization control) to further enhance the performance and adaptability of intelligent driving systems. Wang et al. studied the simulation analysis method of MVB network dynamic performance [14]. They select the key evaluation indexes that affect the dynamic performance of the MVB network, such as network efficiency, network utilization and network throughput, and derive the calculation formula of the evaluation indexes. A modular MVB network model based on FSM is constructed, and the working modes of the bus module, master device module, slave device module and signal source module are described in detail. This model is used to analyze the influence of data length, number of devices, transmission medium and other factors on the dynamic performance of MVB network. They conclude that with the increase of process data length, the network efficiency under different transmission media conditions will increase, so that the influence of transmission media on network efficiency will be alleviated. Therefore, packaging process data with the same feature period into the same data frame is conducive to improving network efficiency. Packing as much data as possible into the same data frame is advised to improve network utilization and efficiency of MVB.

The decision tree is a tree-like structure for decision problems, which can represent possible decision paths through branches and leaf nodes. Decision trees in intelligent driving can be used to make real-time decisions based on perceptual data such as cameras, radar, lidar, etc. However, integrating the deployment of autonomous vehicles in urban and highway environments requires the development of robust and adaptable behavior planning systems,so WEN et al. introduced an algorithm based on Monte Carlo Tree Search (MCTS) that is tailored to the specific needs of autonomous driving [15]. Integrate well-crafted cost features, including safety, comfort and accessibility metrics, into the MCTS framework.Autonomous vehicles being able to navigate complex scenarios like intersections is what makes their approach effective, unprotected left turns, cuts, and ramps in real time, even in traffic jams. They integrated various driving decisions, such as lane changes, acceleration, and deceleration, can be integrated into the MCTS framework with good results.

Although the above two decision-making methods have achieved good results, the actual traffic scene is complex and changeable, the behavior of dynamic traffic participants is difficult to predict, and the self-learning ability of algorithms trained based on rules or relying on large amounts of data is poor, which is unable to cope with complex time-varying traffic scenes. Therefore, Shi Zixian proposed an improved artificial potential field oriented to the understanding of the traffic environment: the identifying Intention&Risk Field (IRF) [16]. Combined with SAC algorithm reinforcement learning, a more adaptive and intelligent IRF-SAC unmanned decision planning method is established. The experimental results show that IRF-SAC has high precision, strong robustness and excellent safety for global path tracking, and can reach the destination with good comfort under the premise of reasonably avoiding traffic obstacles. The performance of the IRF-SAC decision planning method is tested in the real vehicle environment, and the feasibility of IRF-SAC in the unmanned driving problem is preliminarily verified.

In contrast to the modular approach where a single subsystem is used to handle each task, by treating the problem as a single learnable task using deep neural networks, the end-to-end approach reduces system complexity and minimizes the use of heuristic methods,so Mohamed et al introduced conditional imitation co-learning methods. The common learning matrix generated by the gated hyperbolic tangent unit enables the model to learn the relationship between the branches of CIL to solve this problem [17]. They suggest using the resolving the regression problem by utilizing a category-regression mixed loss to bridge the gap between regression and classification and also using coexistence probability to account for spatial trends between steering classes, an approach that their model demonstrated a 62% increase in success in invisible autonomous driving environments compared to CIL.

Research related to intelligent driving decisions and planning not only improves the overall performance and adaptability of autonomous driving systems. In the future, with the continuous progress of artificial intelligence and machine learning technology, autonomous driving systems will achieve more intelligent and efficient breakthroughs in decision-making and planning, and promote the development of intelligent transportation.

3.3 Man-machine Interaction

Human-machine interaction is a key area to ensure efficient collaboration between drivers and autonomous driving systems, improving safety and user experience, including monitoring of driver status, interaction between drivers and machines, and trust building. Lex Fridman suggests that automatically estimating future advanced driver assistance systems may rely on the allocation of a driver's visual attention as a key component [18]. In theory, vision-based eye tracking can be a good estimate of the driver's gaze position, however,due to sunglasses and eyeglass reflections, eye tracking from video is challenging in practice, lighting conditions, occlusion, motion blur, and other factors. To this end, they came up with a system extracts facial features and classifies their spatial configuration into six regions in real time,achieving an average accuracy of 91.4 percent with an average decision rate of 11 Hertz in a test of 50 drivers. The system can infer the driver's state based on the head attitude and scene and decide whether the machine should take over the driving or warn the driver, which greatly improves the safety of driving. Donghoon Shin Developed a human-centered threat assessment based on deep learning to investigate manual driving characteristics through real-world driving test data, enabling an autonomous driving model that is both natural and safe for human drivers [19]. Using deep neural networks and recurrent neural networks to search through neural architecture and learn from sequential data and design, respectively, in human-centered risk assessment simulations, they show that both deep learning models can provide human-like driving patterns during acceleration and deceleration without collision, making intelligent driving technology more comfortable and acceptable to humans. It has contributed to the popularization of intelligent driving.

4 Conclusion

The rapid development of artificial intelligence technology is revolutionary to the intelligent driving research process. Advances in computer vision, multimodal sensor fusion, and deep reinforcement learning have enabled autonomous driving systems to make significant advances in environment perception, real-time decision making, and precise control. The introduction of the end-to-end learning framework further simplifies the traditional modular process and realizes the direct mapping from raw data to driving behavior. At the same time, the innovation of human-computer interaction technology has significantly improved drivers' trust in intelligent vehicles and system safety, laying the technical foundation for the large-scale landing of autonomous driving.

However, the current intelligent driving technology is still facing many challenges, the data-driven model generalization ability is insufficient, as well as the problem of the definition of ethics and responsibility in man-machine co-driving, still restricts the research of intelligent driving. In addition, the real-time performance of the algorithm still needs to be further optimized to meet the comfort and safety of intelligent driving.

In the future, the completion of intelligent driving technology will be the integration of many academic fields: on the one hand, computer vision, deep reinforcement learning, end-to-end, multi-modal networks and other research achievements make intelligent driving research steadily forward; On the other hand, emerging AI technologies such as causal reasoning and meta-learning are expected to solve uncertain decision-making problems in dynamic environments. At the same time, the coordination of policies, regulations and user psychology will become an important guarantee for technology commercialization. It can be predicted that with the continuous innovation of artificial intelligence and vehicle engineering, safe, efficient and humanized intelligent driving will eventually reshape human travel methods and lead the transportation industry into a new era.

References

1. C. Katrakazas, M. Quddus, W. H. Chen, et al., "Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions," Transportation Research Part C: Emerging Technologies, vol. 60, pp. 416-442, 2015.
2. J. H. Jeon, R. V. Cowlagi, S. C. Peters, et al., "Optimal motion planning with the half-car dynamical model for autonomous high-speed driving," in Proc. 2013 American Control Conference, IEEE, pp. 188-193, 2013.
3. D. Shin, H. Kim, K. Park, et al., "Development of deep learning based human-centered threat assessment for application to automated driving vehicle," Applied Sciences, vol. 10, no. 1, pp. 253, 2019.
4. K. Yang, "Application and development of artificial intelligence in the field of automobile driving technology," Automobile Practical Technology, vol. 47, no. 11, pp. 16-19, 2022.
5. R. Huang, C. Zhao, H. Li, et al., "Automatic labeling method for intelligent driving data based on visual big model," in Proc. 31st Annual Conference of China Society of Automotive Engineering (1), China Society of Automotive Engineering, R&D Institute of Dongfeng Motor Group Co., Ltd., pp. 8, 2024.
6. J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in Proc. 2016 IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), pp. 779-788, 2015.
7. T. Yang, W. Shi, G. Li, et al., "Application of artificial intelligence visual big model in foreign body intrusion scenarios on railway lines," China Railway, vol. 2025, no. 1, pp. 23-29+48, 2025.
8. X. Yan, H. Zhang, Y. Cai, et al., "Forging vision foundation models for autonomous driving: Challenges, methodologies, and opportunities," arXiv preprint arXiv:2401.08045, 2024.
9. Y. Li, M. Jiang, S. Zhang, et al., "End-to-end driving in high-interaction traffic scenarios with reinforcement learning," arXiv preprint arXiv:2410.02253, 2024.
10. D. Hu, C. Huang, J. Wu, et al., "Pre-trained transformer-enabled strategies with human-guided fine-tuning for end-to-end navigation of autonomous vehicles," arXiv preprint arXiv:2402.12666, 2024.
11. J. Cui, B. Zhao, and M. Qu, "An integrated lateral and longitudinal decision - making model for autonomous driving based on deep reinforcement learning," J. Adv. Transp., vol. 2023, no. 1, pp. 1513008, 2023.
12. K. Yoon, J. Choi, and K. Huh, "Adaptive decentralized sensor fusion for autonomous vehicle: Estimating the position of surrounding vehicles," IEEE Access, vol. 11, pp. 90999-91008, 2023.
13. P. Karle, F. Fent, S. Huch, et al., "Multi-modal sensor fusion and object tracking for autonomous racing," IEEE Trans. Intell. Vehicles, vol. 8, no. 7, pp. 3871-3883, 2023.
14. J. Wang, W. Teng, and L. Zhang, "Dynamic performance simulation analysis of rail transit multifunctional vehicle bus network based on finite state machine," Urban Rail Transit Research, vol. 25, no. 2, pp. 39-42, 2022.
15. Q. Wen, Z. Gong, L. Zhou, and Z. Zhang, "Monte Carlo tree search for behavior planning in autonomous driving," in Proc. 2024 IEEE Int. Symp. Safety Security Rescue Robotics (SSRR), IEEE, pp. 117-124, 2023.

16. Z. Shi, "Improved artificial potential field and its application in autonomous driving decision-making," M.S. thesis, South China University of Technology, 2022.
17. M. M. Kishky, H. M. Eraqi, and K. F. Elsayed, "End-to-end steering for autonomous vehicles via conditional imitation co-learning," arXiv preprint arXiv:2411.16131, 2024.
18. L. Fridman, P. Langhans, J. Lee, et al., "Driver gaze region estimation without use of eye movement," IEEE Intell. Syst., vol. 31, no. 3, pp. 49-56, 2016.
19. X. Zhou, M. Liu, E. Yurtsever, et al., "Vision language models in autonomous driving: A survey and outlook," IEEE Trans. Intell. Vehicles, 2024.