

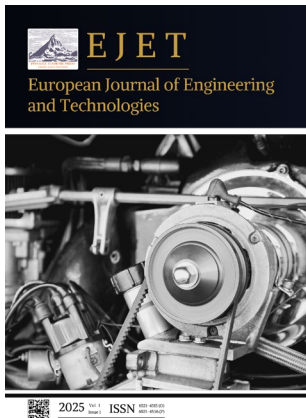
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Research on Application of Deep Learning in Optimizing the Performance of Autonomous Vehicles

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Abstract: With the rapid progress of automatic driving technology, deep learning has received extensive attention in the performance optimization of autonomous vehicles. With its excellent data processing and pattern recognition functions, deep learning has enhanced the perception accuracy, real-time response ability, security and positioning accuracy of the auto drive system. This study explores the practical application of deep learning in autonomous vehicles and provides a detailed analysis of optimization strategies in areas such as image processing, vehicle road collaboration, multi task learning, and global path planning. Aiming at the problems existing in the current auto drive system in terms of insufficient perception accuracy, low real-time performance, and poor positioning accuracy, a series of improvement measures based on deep learning are proposed to improve the overall operation performance of the system and ensure driving safety.

Keywords: deep learning; autonomous driving; performance optimization; image processing; vehicle road collaboration

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1. Introduction

Autonomous vehicles are an important part of the future intelligent transportation system, and in-depth learning has been promoted in many fields such as image recognition, voice recognition, decision-making and planning of autonomous vehicle with excellent data processing capabilities. Although autonomous driving technology has achieved breakthroughs in many fields, it still needs to overcome challenges such as perception accuracy, response speed, safety, and positioning accuracy in specific application processes. The current research focus is on how to use deep learning technology to improve the operational performance of autonomous vehicles, enhance their decision-making level and safety performance in changing environments. This article analyzes the application of deep learning technology in improving the performance of autonomous navigation vehicles and proposes corresponding solutions to assist in the research and development of autonomous driving technology.

2. Overview of Deep Learning

Deep learning is an important branch of machine learning that has its roots in the study of artificial neural networks. By learning from massive datasets and autonomously extracting features, efficient pattern recognition can be achieved. In recent years, deep learning technology has been promoted in multiple industries such as computer vision, language processing, and sound recognition, especially in autonomous driving technology, as shown in Figure 1, where its excellent perception capabilities have made it a core

technological element. The autonomous driving technology system highly relies on deep learning algorithms to complete key tasks such as environmental monitoring, behavior prediction, and decision-making. The advantages of deep learning lie in its ability to handle large-scale unstructured data, such as images, videos, radar signals, etc., and its strong self-adjustment and generalization capabilities, enabling it to achieve efficient driving decisions and route planning in changing environments [1].

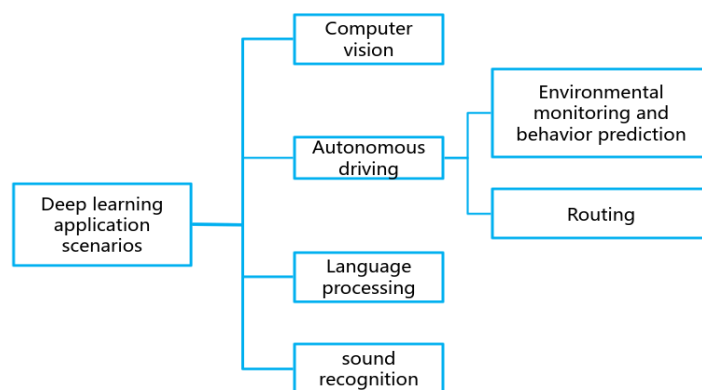


Figure 1. Deep Learning Applications.

3. Current Status of Autonomous Vehicle Performance Optimization

3.1. Insufficient Accuracy of Perception System

Autonomous vehicles rely on various sensors (such as laser radar, radar, camera, etc.) to collect environmental information around them, and then rely on specific algorithms to process the collected data to identify obstacles, traffic signals, pedestrians and other elements and develop driving strategies accordingly. However, in a constantly changing and complex environment, existing perception devices still suffer from insufficient accuracy. The performance of these sensors may be reduced due to external conditions such as light intensity, interference from harsh weather conditions (such as rainfall, fogging, snowfall, etc.), resulting in difficulties in image recognition or data acquisition failure. The perception algorithms currently used may make judgment errors when processing large amounts of data, especially in rapidly changing dynamic scenarios where misidentification and missed recognition are particularly serious. Moreover, deep learning still faces many challenges in applications that require high precision. When dealing with low resolution data, complex background interference, and multi-target recognition tasks, the system is difficult to achieve satisfactory accuracy.

3.2. High Real-Time Requirements

The efficient real-time response of autonomous vehicles is the key to their safe driving under changeable road conditions and emergency driving conditions. Although many auto drive systems rely on deep learning algorithms to process perception information efficiently, in actual operation, such systems still encounter the challenge of lacking real-time performance. Deep learning algorithms rely on abundant computing resources, especially complex network models. These models can easily generate long delays when processing massive sensor information, which presents a significant obstacle for real-time driving decision-making. Especially when driving at high speeds, vehicles must be able to react in a very short amount of time, and any delay in calculations may increase driving risks. Multiple links in the auto drive system (such as perception, decision-making, vehicle control, etc.) often need to operate at the same time. How to optimize the data fusion and calculation allocation between different links to eliminate the system performance

bottleneck has become an important research direction to ensure real-time automatic driving. In addition, delay issues may also occur during the collection, transmission, and processing of sensor information [2].

3.3. Safety and Reliability Issues

In the actual road test, the core of autonomous vehicle is its safety and reliability. The training of deep learning networks is based on numerous labeled data and diverse environmental scenarios, but in practical operations, there will always be some unpredictable extreme situations [3]. For example, in constantly changing and complex traffic conditions, when encountering sudden traffic accidents, roadblocks, or extreme weather conditions, deep learning networks may have difficulty making accurate judgments, thereby posing a threat to driving safety. The "black box" nature of deep learning models makes their decision-making process lack interpretability, making it difficult to effectively analyze the reasons for their failures, which poses challenges to the reliability evaluation of the system. If the decision result of the auto drive system cannot be checked or corrected immediately, it is very likely to increase the probability of system failure. How to ensure the smooth operation of backup systems in special situations encountered by autonomous vehicles, such as hardware errors or algorithm judgment errors, has become a key measure to ensure driving safety.

3.4. Insufficient Positioning Accuracy

Autonomous vehicle must rely on high-precision positioning equipment to identify the specific coordinates where it is located and work out the optimal driving route accordingly [4]. At present, positioning technology has encountered some difficulties, especially in variable or limited spaces, where the accuracy of positioning cannot meet expectations. Generally speaking, the location determination of autonomous vehicle depends on the comprehensive application of global positioning system (GPS) and various ground sensing devices (such as laser radar, inertial navigation system, etc.) to ensure the accuracy of vehicle positioning. However, in cities, GPS signals are often unstable due to the obstruction of high-rise buildings, which affects the accuracy of positioning. In tunnels, underground garages, and harsh weather conditions, the stability of GPS signals sharply decreases. However, even though laser detection radar and optical sensors can provide relatively accurate coordinate data, overcoming the problems of sensor errors and inconsistencies remains a major technical challenge when integrating these data. In the process of integrating information from multiple sensors, the accuracy of localization is influenced by multiple factors such as sensor performance, surrounding environment, and algorithm precision.

4. Application Strategy of Deep Learning in Autonomous Vehicle Performance Optimization

4.1. Using Deep Learning Models to Process Image Data

In the process of improving the performance of autonomous vehicles, deep learning algorithms play a very important role in efficient image information processing. The auto drive system uses cameras, laser radars and other devices to collect the visual data of the surrounding environment. A convolutional neural network, as a deep learning technology, has been widely used in the real-time analysis and evaluation of images. Convolutional neural networks can extract image features through their multi-layer structure, identify key information such as roads, traffic signals, pedestrians, etc., and ensure high-precision perception of the environment by the system. This network captures local details by performing convolution operations on the input image, reduces feature dimensions through pooling layers, and achieves the final decision output through fully connected layers. Setting the image data as I , the output of the convolution operation can be represented by the following equation:

$$Y=f(W*I+b) \quad (1)$$

In formula (1), Y is the output feature map, W is the convolution kernel, b is the bias term, f is the activation function (such as ReLU), and $*$ represents the convolution operation. This process utilizes multiple layers of convolution and pooling operations to extract gradually enriched image features. Fine tuning deep neural networks typically involves optimizing model parameters, enhancing data processing, and innovating training methods. In the field of autonomous driving technology, deep learning technology is widely used in image analysis, which enhances the ability of vehicles to cope with changing road conditions. For example, in low light or harsh weather conditions, deep learning networks can rely on their adaptive algorithms to optimize the understanding of image features, improve obstacle recognition and path selection accuracy. When dealing with pedestrian detection tasks in dim light, an auto drive system improved the recognition accuracy by 15% through deep learning optimization, reducing the risk of traffic accidents [5].

4.2. Integration of Deep Learning and Vehicle Road Collaboration System

The strategy of integrating deep learning technology with the vehicle-road collaboration system plays an important role in improving the performance of autonomous vehicles. This system continuously collects information on road conditions, traffic flow, and road surface conditions, and transmits this intelligence in real time to autonomous vehicles to optimize their driving strategies. Deep neural networks utilize these inputs to accurately predict traffic dynamics, obstacle avoidance, and changes in road conditions, and perform intelligent decision-making and dynamic route adjustments. The vehicle-road collaboration system utilizes wireless communication technology (such as V2X communication) to transmit real-time data captured by roadside sensors (including traffic lights, cameras, radar, etc.) to vehicles. After processing these data, deep learning algorithms can predict short-term traffic flow and signal changes, optimize vehicle speed and travel paths based on this, ensure smooth traffic, and maximize driving safety and efficiency. In the context of the comprehensive application of deep learning and vehicle road collaboration system, the decision logic of the system can be explained by constructing an optimization problem model for vehicle driving. Assuming the current position of the vehicle is $p(t)$, the speed is $v(t)$, and the expected target position is P_{target} , with the support of road condition information, the deep learning model generates an optimized speed planning function $v(t)$ to enable the vehicle to reach the target position in the shortest possible time and avoid potential traffic obstacles. The objective function of the optimization process can be represented by the following mathematical formula:

$$\min_{v(t)} \int_0^T [\|p(t) - P_{target}\|^2 + \lambda \cdot \|v(t) - V_{desired}\|^2] dt \quad (2)$$

In formula (2), T is the planned time period, λ is the weighting coefficient, and $V_{desired}$ is the expected speed of the vehicle. Through the training of deep learning models, it is possible to adjust $v(t)$ in real-time, enabling vehicles to obtain optimal driving strategies under different road conditions. A specific test was conducted to evaluate the performance of integrating deep learning technology with connected car systems. This test involves two different scenarios: scenario one relies on conventional autonomous driving programs for navigation without integrating deep learning and vehicle networking technologies; scenario two adopts a strategy of combining deep learning algorithms with vehicle networking systems to optimize driving. The experimental results are shown in Table 1 below:

Table 1. Test Results Table.

Scene	Travel time (seconds)	Number of collisions	Traffic flow	Average speed (km/h)
1	180	2	200	45

2	160	0	200	50
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Observing Table 1, it can be seen that in the application scenario of deep integration of deep learning and vehicle-road collaboration technology, the time required for vehicle travel is shortened, and collision accidents are avoided during actual driving. This phenomenon indicates that integrating deep learning technology into vehicle road collaboration systems can help enhance the performance of autonomous vehicles. When facing complex and changing traffic conditions, the system can more accurately predict and adapt to road conditions [6].

4.3. Multi Task Learning Enhances System Security

One of the core technologies of autonomous driving is Multitask Learning (MTL), which plays a crucial role in enhancing system safety. By implementing synchronous training of multiple related tasks in a unified neural network, information exchange and sharing have been achieved, enhancing the collaborative effect between tasks and further optimizing the overall performance and security level of the system. The many safety elements involved in the field of autonomous driving, such as obstacle avoidance, vehicle status monitoring, and prediction of driving actions, are closely related. Multitask learning enables models to support each other in various tasks, enhancing the system's ability to adapt to changing environments. The core concept is that a neural network model can perform multiple tasks simultaneously and achieve multi-dimensional understanding and prediction of vehicle behavior by jointly using the parameters of the hidden layer. In the auto drive system, a multi task learning model can be built, including obstacle detection, lane maintenance, driving speed prediction and driving behavior identification tasks. The input is x , including the sensor data of the vehicle (such as camera images, laser radar point clouds, GPS positions, etc.). The model output is the prediction values of multiple tasks, such as obstacle detection results $y_{obstacle}$, lane line detection results y_{lane} , driving speed prediction values y_{speed} , and driving behavior prediction $y_{behavior}$. When training the model, it is desired to minimize the loss function of multiple tasks, and the overall loss function L can be expressed as:

$$L = \alpha_1 L_{obstacle} + \alpha_2 L_{lane} + \alpha_3 L_{speed} + \alpha_4 L_{behavior} \quad (3)$$

In formula (3), $L_{obstacle}$, L_{lane} , L_{speed} , and $L_{behavior}$ are the loss functions for each task, while α_1 , α_2 , α_3 , and α_4 are the task weight parameters. By adjusting these parameters, the model can achieve balance in different tasks [7]. In the practice of multitask learning, the main pursuit is to enhance the comprehensive security performance of the system. Taking autonomous driving as an example, in complex traffic situations, if the recognition of obstacles is not accurate enough, collisions may occur. If the lane keeping function deviates, it may lead to vehicle loss of control and cause traffic accidents. In order to evaluate the improvement effect of the safety of the auto drive system, detailed tests were carried out in a series of standardized test environments by comparing the performance of the system before and after the improvement. The following Table 2 is the comparison data of the system performance before and after the optimization (unit: accuracy%):

Table 2. Comparison before and after Optimization.

Task type	Before optimization	After optimization
Obstacle detection	85.2	91.7
lane keeping	78.6	84.3
Prediction of driving speed	80.3	85.1
Driving behavior recognition	77.4	83.0

After multitask training, the overall accuracy of the model has been improved by about 5%–6%, and the performance under changing scenes is more reliable, which further confirms the role of this strategy in enhancing the safety of the auto drive system.

4.4. Global Path Planning Based on Deep Learning

When the auto drive system executes the global path planning, the key is to determine the optimal travel path from the start to the end. Traditional path planning methods, such as A* or Dijkstra's algorithm, are mostly based on static maps and preset rules. The application of deep learning technology can optimize the path planning process through autonomous learning of diverse patterns in a changing environment. The global path planning strategy constructed using deep learning can flexibly respond to real-time changes in the environment, including road conditions, traffic signals, roadblocks, and other factors, to develop safer and more efficient driving paths. In the practice of global path planning, deep learning techniques play a key role, especially algorithms based on convolutional neural networks and recurrent neural networks. These algorithms have mastered the optimal path selection strategy from the starting point to the endpoint by analyzing a large amount of road information and driving behavior data. At the practical level, the data input to the neural network covers the real-time status of the road network, such as road conditions, traffic flow, obstacle distribution, and other elements, while the network outputs the specific path planning scheme. To better describe the optimization process of deep learning models in global path planning, the optimization objective of the path can be expressed through the following mathematical formula:

$$\min_P \sum_{i=1}^n (w_1 \cdot d_i + w_2 \cdot t_i + w_3 \cdot r_i) \quad (4)$$

In formula (4), $P = (p_1, p_2, \dots, p_n)$ represents each path point in the path, d_i is the distance between path point p_i and the previous path point, t_i is the travel time of path point p_i , r_i is the traffic condition score of path point p_i , w_1 , w_2 , w_3 are the corresponding weight coefficients, reflecting the importance of distance, time, and road conditions to path planning. Through the training of deep learning models, the network can automatically adjust weight coefficients and optimize path selection in real-time. In this series of adjustments, the neural network structure can absorb static road information, and can also flexibly change according to the current traffic environment to enhance the comprehensive efficiency of the auto drive system.

5. Conclusion

With the continuous evolution of deep learning technology, the performance improvement of autonomous vehicles has entered a new stage. Deep learning has improved the accuracy of recognition systems and optimized them comprehensively through multi task training, vehicle road interaction, and other means. Although there are still many problems with autonomous driving technology, it is expected that these issues will gradually be overcome with the continuous improvement and enhancement of deep learning algorithms. This research discusses the application of deep learning in the field of autonomous driving and proposes various improvement strategies based on deep learning to provide innovative ideas for the future development of auto drive systems. With the continuous innovation of technology, the influence of deep learning in autonomous driving will continue to increase, helping autonomous driving technology develop towards intelligence and safety.

References

1. L. Berek, "Autonomous vehicles from another perspective—a literature analysis," *Interdiscip. Des. Complex Syst. INDECS*, vol. 21, no. 2, pp. 180–187, 2023, doi: 10.7906/indexs.21.2.7.
2. N. Defauw, M. Malfante, O. Antoni, T. Rakotavao, and S. Lesecq, "Vehicle detection on occupancy grid maps: comparison of five detectors regarding real-time performance," *Sensors*, vol. 23, no. 3, p. 1613, 2023, doi: 10.3390/s23031613.
3. K. Khnissi, C. B. Jabeur, and H. Seddik, "Implementation of a compact traffic signs recognition system using a new squeezed YOLO," *Int. J. Intell. Transp. Syst. Res.*, vol. 20, no. 2, pp. 466–482, 2022, doi: 10.1007/s13177-022-00304-6.
4. J. C. Chen, Y. Qin, H. Y. Wang, and C. Xu, "Simulation might change your results: a comparison of context-aware system input validation in simulated and physical environments," *J. Comput. Sci. Technol.*, vol. 37, no. 1, pp. 83–105, 2022, doi: 10.1007/s11390-021-1669-1.

5. S. Mehtab and W. Q. Yan, "Flexible neural network for fast and accurate road scene perception," *Multimedia Tools Appl.*, vol. 81, no. 5, pp. 7169–7181, 2022, doi: 10.1007/s11042-022-11933-0.
6. A. Hosney Radwan and A. A. Ghaney Morsi, "Autonomous vehicles and changing the future of cities: Technical and urban perspectives," *J. Urban Regener. Renew.*, vol. 16, no. 1, pp. 85–108, 2022.
7. M. K. A. Chy, A. K. M. Masum, K. A. M. Sayeed, M. Z. Uddin, et al., "Delicar: a smart deep learning based self driving product delivery car in perspective of Bangladesh," *Sensors*, vol. 22, no. 1, p. 126, 2021, doi: 10.3390/s22010126.

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