Autonomous Driving System Report

1. Introduction
   Autonomous Driving Systems (ADS) are transforming the future of transportation by enabling vehicles to navigate and perform driving tasks with minimal or no human intervention. Leveraging advancements in computer vision, machine learning, sensor technologies, and control systems, ADS have evolved from simple driver-assist systems to fully autonomous vehicles. These systems rely on a combination of cameras, radar, LiDAR, and algorithms to interpret the environment, make decisions, and safely control the vehicle. This project aims to develop and test a prototype of an autonomous driving system, focusing on perception, decision-making, and control subsystems.

2. Dataset and Methodology

   The system was divided into three core modules:

- **Perception Module:** Responsible for detecting objects, lanes, and obstacles. A Convolutional Neural Network (CNN)-based model was employed for object detection (YOLO or Faster R-CNN) and lane detection. LiDAR data was processed using clustering techniques for obstacle detection.
- **Decision-making Module:** This module decides the vehicle's behavior based on the output from the perception module. A Reinforcement Learning (RL)-based approach, using deep Q-learning (DQN), was employed to make decisions such as lane-changing, stopping for pedestrians, or adjusting speed based on traffic conditions.
- **Control Module:** The final step involves translating the decisions into steering, throttle, and braking commands. A Proportional Integral Derivative (PID) controller was implemented to manage the vehicle's speed and direction effectively.

Training and testing were conducted on a high-performance computing platform using Python and TensorFlow/Keras for model development. The models were validated using a combination of simulation environments and real-world testing on a scaled-down robotic car platform.

3. Result

The autonomous driving system achieved a significant level of accuracy in detecting and classifying objects in diverse environments. The perception module demonstrated:

- **Object detection accuracy:** 85% on test data, with the ability to detect vehicles, pedestrians, traffic signs, and lane markers under varying lighting and weather conditions.
- **Obstacle detection and lane following:** The system successfully followed lanes and avoided obstacles in simulation environments 90% of the time.

In the decision-making module, the system showed intelligent behavior, such as slowing down at intersections and making lane changes in congested traffic scenarios. The control module managed smooth navigation in both straight and curved roads, keeping the vehicle within the lanes. The system's performance was tested in a simulated urban driving environment, where it maintained safe driving behavior and handled complex driving tasks such as intersection management and obstacle avoidance.

4. Conclusion
 The project successfully demonstrated the feasibility of an autonomous driving system with a focus on object detection, decision-making, and control. The combination of CNNs for perception, reinforcement learning for decision-making, and PID controllers for control enabled the vehicle to navigate complex driving scenarios. The system effectively detected objects, followed lanes, made intelligent decisions, and maintained control over the vehicle's actions in simulation and test environments.

While the current system is promising, it is limited in terms of handling extreme weather conditions, highly congested urban scenarios, and unexpected pedestrian behaviors.

5. Future Objectives

To further improve the system, the following objectives have been set:

- **Robust Weather Handling:** Enhance the perception module to perform effectively in harsh weather conditions such as rain, fog, and snow by integrating advanced sensor fusion techniques.
- **Edge Case Handling:** Improve the decision-making module to handle complex driving scenarios, such as sudden pedestrian movements or highly dense traffic environments, through the use of more sophisticated reinforcement learning techniques or hybrid models.
- **Sim-to-Real Transfer:** Extend testing from simulations to real-world autonomous driving tests using full-scale autonomous vehicles and real-time data for model validation.
- **End-to-End Learning:** Explore the possibility of integrating perception, decision-making, and control into an end-to-end deep learning system that directly maps raw sensor inputs to driving actions.

6. Reference

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