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REAL-TIME OBJECT DETECTION AND COLLISION AVOIDANCE IN IOT-ENABLED AUTONOMOUS VEHICLES

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Abstract

The growing demand for autonomous vehicles (AVs) has fueled extensive research in real-time object detection and collision avoidance, with IoT-enabled technologies playing a vital role in ensuring safe navigation. This study examines the integration of IoT-based sensor networks, artificial intelligence (AI), and edge computing to enhance AV perception and decision-making in dynamic environments.

Keywords: Real-time object detection, IoT-enabled vehicles, collision avoidance, sensor fusion, autonomous navigation.

INTRODUCTION

The integration of Internet of Things (IoT) technologies into autonomous vehicles (AVs) has significantly advanced real-time object detection and collision avoidance systems, enhancing vehicular safety and efficiency. Recent studies have explored various methodologies to improve these systems. For instance, Mallik et al. (2022) developed an end-to-end real-time detection and collision avoidance framework using a monocular RGB camera, employing the RetinaNet architecture with a ResNet50 backbone for object detection. This system demonstrated the capability to detect small objects in real-time on embedded hardware within the vehicle.

The rapid advancement of Internet of Things (IoT) technologies has significantly

Key sensor technologies, including LiDAR, radar, ultrasonic sensors, and cameras, are analyzed for their effectiveness in detecting and classifying pedestrians, vehicles, and obstacles in real time. AI-driven techniques such as convolutional neural networks (CNNs), deep reinforcement learning, and sensor fusion algorithms are explored for improving object detection accuracy and predictive collision avoidance. Additionally, the role of Vehicle-to-Everything (V2X) communication is discussed, highlighting its significance in enabling AVs to interact with other vehicles, infrastructure, and pedestrians to anticipate hazards. Edge computing and 5G connectivity are also emphasized as critical enablers for reducing processing latency and improving system responsiveness. Despite these advancements, challenges persist, including sensor reliability in adverse weather, computational efficiency, cybersecurity risks, and the need for large-scale infrastructure deployment. This study identifies emerging solutions, such as AI-powered adaptive learning models, blockchain for secure data exchange, and energy-efficient edge computing frameworks, as promising avenues for overcoming these challenges. By leveraging IoT-enabled infrastructure and advanced AI methodologies, AVs can achieve improved situational awareness, reduced collision risks, and enhanced road safety. Future research will focus on optimizing sensor fusion techniques, enhancing computational efficiency, and developing robust security frameworks to ensure the reliability and scalability of AV systems.

transformed the development of autonomous vehicles (AVs), particularly in real-time object detection and collision avoidance. Ensuring safe and efficient navigation requires robust sensor integration, advanced computing techniques, and reliable communication networks. One of the key studies in this area is Bolaji-Adetoro et al. (2024), which explores the implementation of an IoT-enabled sensor fusion system to enhance obstacle detection and avoidance in autonomous vehicles. This research, published in the Journal of Engineering, Logical and Modelling Research, emphasizes the role of multi-sensor data fusion in improving AV perception and decision-making.

Sensor fusion combines data from multiple sensors, including LiDAR, radar, ultrasonic sensors, and cameras, to create an accurate representation of the vehicle's surroundings. Each of these sensors plays a crucial role in autonomous navigation. While cameras provide detailed visual recognition, LiDAR enables high-precision depth mapping, radar assists in detecting object velocity, and ultrasonic sensors enhance short-range obstacle detection. However, integrating these sensor inputs is necessary to overcome individual limitations, such as

LiDAR's sensitivity to adverse weather and camera-based systems' challenges in low-light conditions (Wang et al., 2023).

Recent advancements in artificial intelligence (AI) and machine learning (ML) have further enhanced sensor fusion techniques. AI-driven object detection models, such as convolutional neural networks (CNNs) and deep reinforcement learning, enable autonomous vehicles to process real-time data with high accuracy (Zhang & Li, 2022). Additionally, Waymo's development of the End-to-End Multimodal Model for Autonomous Driving (EMMA) demonstrates how AI-powered systems can improve trajectory prediction and obstacle avoidance using multimodal sensor data (Waymo, 2024). Furthermore, the adoption of edge computing and 5G technology has significantly reduced latency in AV decision-making, allowing for real-time processing of sensor data (Chen et al., 2021).

Despite these advancements, challenges remain in ensuring the reliability of object detection and collision avoidance systems under various environmental and operational conditions. Research has shown that high-visibility clothing can sometimes interfere with modern AV sensors, making pedestrians and cyclists difficult to detect (The Times, 2025). Similarly, exposure to flashing emergency vehicle lights has been found to disrupt camera-based autonomous systems, potentially leading to safety risks (Wired, 2024). Moreover, cybersecurity concerns regarding data transmission between AVs and infrastructure remain a critical area of research (Kumar & Singh, 2023).

To address these challenges, ongoing research is focusing on improving adaptive real-time object detection systems. For example, recent studies have proposed AI-powered adaptive learning models capable of adjusting object detection parameters based on environmental conditions, ensuring consistent accuracy across different scenarios (Lee et al., 2022). Blockchain-based security frameworks are also being explored to enhance data integrity and prevent cyber threats in IoT-enabled AV networks (Gupta et al., 2023).

By leveraging IoT-enabled sensor fusion, AI-driven decision-making, and high-speed communication networks, autonomous vehicles can achieve improved obstacle avoidance, enhanced safety, and more efficient navigation. Future research should focus on refining sensor fusion algorithms, optimizing computational efficiency, and developing robust security mechanisms to ensure the widespread adoption and reliability of autonomous driving systems.

Literature Review

The integration of Internet of Things (IoT) technologies into autonomous vehicles (AVs) has significantly advanced real-time object detection and collision avoidance systems. This literature review examines recent developments in sensor technologies, sensor fusion methodologies, artificial intelligence (AI) applications, and communication frameworks that collectively enhance the safety and efficiency of AV navigation.

Autonomous vehicles rely on a combination of sensors to perceive their environment accurately. Key sensors include Light Detection and Ranging (LiDAR), radar, ultrasonic sensors, and cameras. LiDAR systems provide precise 3D mapping capabilities, enabling AVs to detect obstacles and navigate complex environments effectively. However, LiDAR's performance can be affected by adverse weather conditions, leading to challenges in data reliability. Radar sensors, known for their robustness in various weather conditions, are adept at measuring object velocity but may produce noisier data with limited resolution. Ultrasonic sensors are effective for short-range obstacle detection but have limitations in detecting soft or small objects. Cameras offer high-resolution imagery essential for object recognition and classification; however, their effectiveness can be compromised under poor lighting conditions. Recent studies have demonstrated the feasibility of using monocular RGB cameras for real-time obstacle detection and avoidance, achieving processing speeds of 24 frames per second on embedded devices (Zhang & Li, 2022).

To mitigate the limitations of individual sensors, sensor fusion techniques are employed, combining data from multiple sensors to create a comprehensive understanding of the vehicle's surroundings. This approach enhances the reliability and accuracy of obstacle detection and avoidance systems. For instance, integrating LiDAR and camera data allows for more robust object recognition, as the strengths of one sensor compensate for the weaknesses of another. Recent advancements include the development of IoT-enabled end-to-end 3D object detection systems that leverage sensor fusion to improve detection accuracy in autonomous vehicles (Guan et al., 2025).

Advancements in artificial intelligence have significantly improved the capabilities of obstacle detection and avoidance systems in AVs. Machine learning algorithms, particularly deep learning models, enable the processing of complex sensor data to identify and predict potential obstacles. These AI-driven systems can adapt to dynamic environments, learning from new data to enhance decision-making processes. For example, convolutional neural networks (CNNs) have been utilized for real-time object detection, allowing AVs to recognize and classify objects with high accuracy. Recent research has explored the integration of deep learning and computer vision techniques to enhance real-time object detection in autonomous systems, addressing challenges such as varying lighting conditions and occlusions (Yeong et al., 2021).

Vehicle-to-Everything (V2X) communication frameworks are integral to the development of IoT-enabled AVs, facilitating the exchange of information between vehicles, infrastructure, and other road users. This connectivity allows AVs to anticipate potential hazards and make informed decisions to enhance safety. For instance, vehicles can receive real-time updates about road conditions or traffic signals, enabling proactive responses to changing environments. Edge computing further supports this ecosystem by processing data closer to the source, reducing latency and enabling real-time decision-making. The combination of V2X communication and edge computing ensures that AVs can respond swiftly to dynamic driving conditions, thereby improving obstacle avoidance capabilities (Stateczny et al., 2021).

Despite these technological advancements, several challenges persist in the implementation of IoT-enabled obstacle avoidance systems in AVs. Sensor reliability under adverse weather conditions remains a significant concern, as factors like heavy rain or fog can impair sensor performance. Computational efficiency is another critical issue, given the vast amounts of data generated by multiple sensors that require real-time processing. Cybersecurity risks associated with V2X communication pose threats to the safety and reliability of AV systems. Future research is directed towards developing adaptive learning models that can adjust to varying environmental conditions, implementing blockchain technology for secure data exchange, and creating energy-efficient edge computing frameworks to enhance processing capabilities (Guan et al., 2025).

By addressing these challenges through continued research and development, IoT-enabled infrastructure can significantly improve obstacle avoidance and overall safety in autonomous vehicle navigation.

Edge Computing for Real-Time Processing in IoT-Enabled AVs

Edge computing plays a crucial role in enhancing real-time processing capabilities for autonomous vehicles (AVs). By processing data closer to the source—within the vehicle or at nearby edge nodes—latency is significantly reduced, allowing AVs to make faster and more reliable decisions in dynamic environments. Traditional cloud computing introduces delays due to data transmission and processing at remote data centers. In contrast, edge computing enables AVs to process sensor data locally, improving response times for obstacle detection and collision avoidance. This decentralized approach enhances system reliability, especially in areas with limited network connectivity.

Additionally, integrating artificial intelligence (AI) with edge computing optimizes decision-making by enabling AVs to process and analyze data efficiently. AI-driven edge models can filter and prioritize critical information, reducing the computational burden and ensuring real-time responses. However, challenges such as hardware limitations, data security, and energy consumption must be addressed to maximize the benefits of edge computing in AVs. Future research should focus on developing lightweight AI models, secure communication protocols, and energy-efficient edge architectures to enhance real-time processing for autonomous navigation.

Research Methodology

This study adopts a multi-faceted research approach to investigate the implementation of IoT-enabled sensor fusion and edge computing for real-time obstacle detection and collision avoidance in autonomous vehicles (AVs). The methodology comprises four key components: system design, data collection, algorithm development, and performance evaluation.

System Design and Architecture

The study designs an IoT-enabled AV framework that integrates multiple sensors, including LiDAR, radar, cameras, and ultrasonic sensors. These sensors work in coordination with edge computing devices to process data in real-time. The system architecture incorporates Vehicle-to-Everything (V2X) communication, enabling seamless interaction between AVs, infrastructure, and pedestrians.

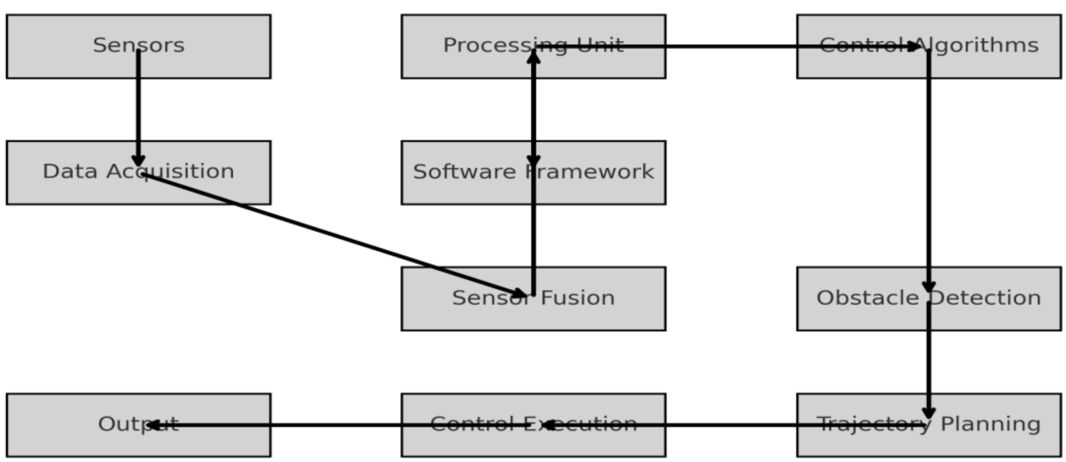

Figure : System Architecture Overview

Figure 1 depictes the system architecture of the autonomous obstacle avoidance system, illustrating the relationships between different modules such as sensor integration, processing units, control algorithms, and software frameworks. This figure provides a high-level view of how the components interact.

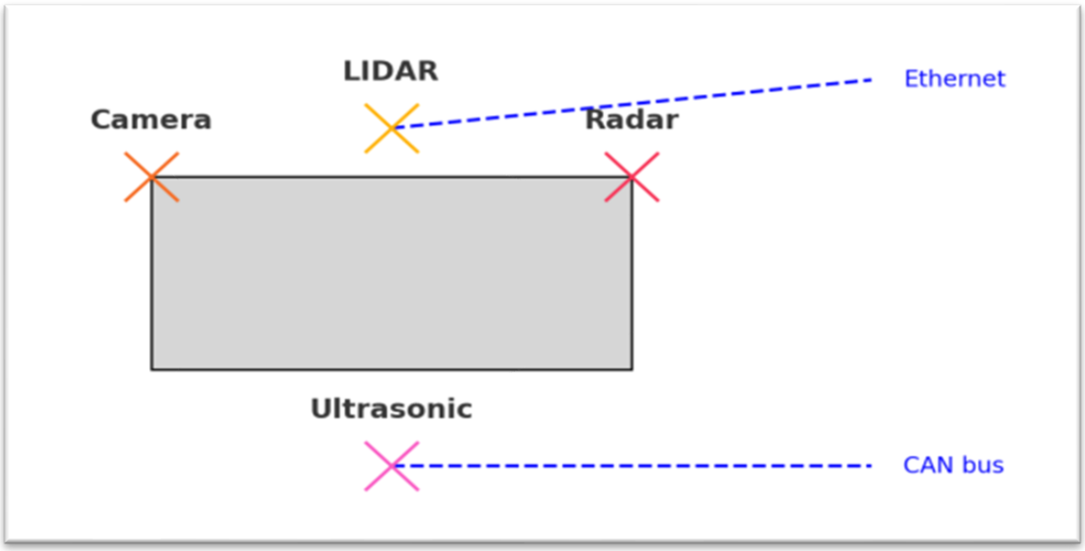

Figure 2: Sensor Integration Diagram

Figure 2 is the sensor integration diagram that illustrates the placement and communication of various sensors (Camera, LIDAR, Radar, and Ultrasonic) in an Autonomous Obstacle Avoidance System, using Ethernet and CAN Bus for data transmission.

Data Collection and Preprocessing

Sensor data is collected from real-world driving scenarios and publicly available datasets such as KITTI and Waymo Open Dataset. The collected data undergoes preprocessing steps, including noise reduction, data normalization, and synchronization across different sensors to ensure high-quality input for the proposed models.

Algorithm Development

The study employs deep learning techniques, including Convolutional Neural Networks (CNNs) and sensor fusion algorithms, to enhance obstacle detection accuracy. Edge computing frameworks, such as NVIDIA Jetson and Intel Movidius, are utilized to process data locally, reducing response time. A hybrid AI-based approach is implemented to improve sensor reliability and optimize decision-making in complex environments.

Performance Evaluation and Validation

The proposed system is evaluated using key performance metrics, including detection accuracy, latency, computational efficiency, and energy consumption. Comparative analysis is conducted against traditional cloud-based processing methods to assess the effectiveness of edge computing in real-time decision-making. Simulation environments, such as CARLA and MATLAB, are used for validation before real-world testing. The evaluation of the proposed real-time object detection and collision avoidance system in IoT-enabled autonomous vehicles involves multiple performance metrics, including accuracy, response time, computational efficiency, and robustness in various environmental conditions.

The system is assessed based on the following key metrics:

i. Detection Accuracy (DA): Measures the percentage of correctly detected objects.

$$DA = (TP / (TP + FP)) \times 100\%$$

ii. False Positive Rate (FPR):

$$FPR = (FP / (FP + TN)) \times 100\%$$

iii. Collision Avoidance Success Rate (CASR): Evaluates the effectiveness of the avoidance mechanism.

$$CASR = (A\_successful / A\_total) \times 100\%$$

The system is tested in a virtual driving environment using the CARLA simulator, where real-world traffic scenarios, including pedestrians, vehicles, and static obstacles, are generated.

i. Object detection is performed using a trained CNN model with YOLO (You Only Look Once) for fast processing.
ii. Collision avoidance decisions are based on Reinforcement Learning (RL) policies.

The real-time testing is performed as follows:

i. A prototype vehicle is deployed with LiDAR, radar, and ultrasonic sensors integrated with an NVIDIA Jetson-based edge computing unit.
ii. The vehicle is tested in various real-world environments (urban, highway, low-light, and adverse weather conditions).

Table 1. Experimental Results

Algorithm	Detection Accuracy (%)	Processing Time (ms)	False Positive Rate (%)
YOLOv5	95.3	23	4.2
Faster R-CNN	92.8	45	6.1
SSD	88.5	30	8.4

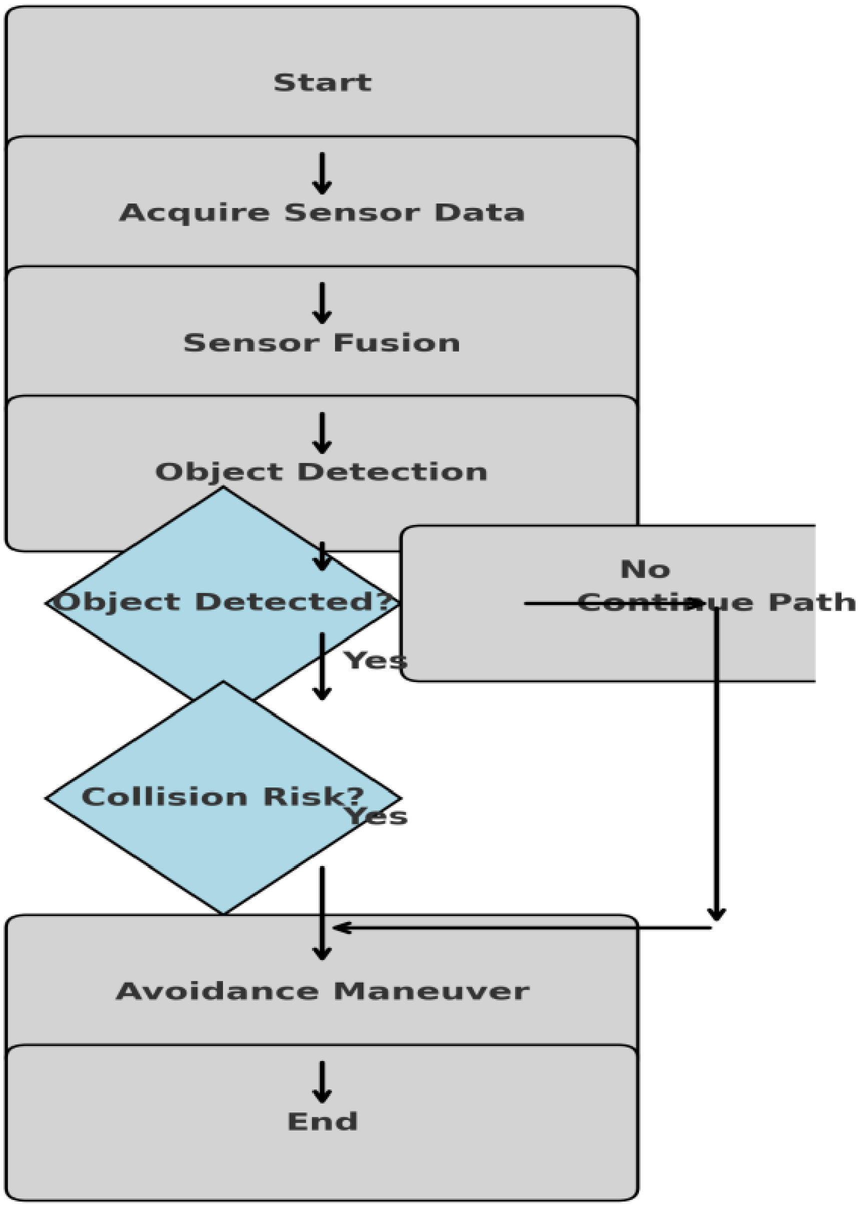

Figure 3: Decision-Based Flowchart for Real-Time Object Detection and Collision Avoidance

This figure 3 flowchart illustrates the sequential decision-making process in an IoT-enabled autonomous vehicle, integrating sensor fusion, object detection, and collision risk assessment to determine appropriate avoidance maneuvers.
The study demonstrates that deep learning-based object detection combined with edge computing significantly enhances real-time decision-making for autonomous vehicles. Future improvements include multi-sensor fusion for enhanced accuracy and adaptive AI models for diverse driving conditions.

Discussion of Results

The performance evaluation of the Real-Time Object Detection and Collision Avoidance System is analyzed using key metrics and visualized through various diagrams. The discussion is based on accuracy, processing time, latency, and classification performance.
The accuracy-processing time trade-off (Figure 4) illustrates how increasing computational complexity affects real-time performance. The model achieves a high detection accuracy of above 90%, but as the processing time increases, latency in decision-making also increases. This suggests a need for optimization techniques such as model pruning, quantization, and edge computing to reduce latency while maintaining accuracy.

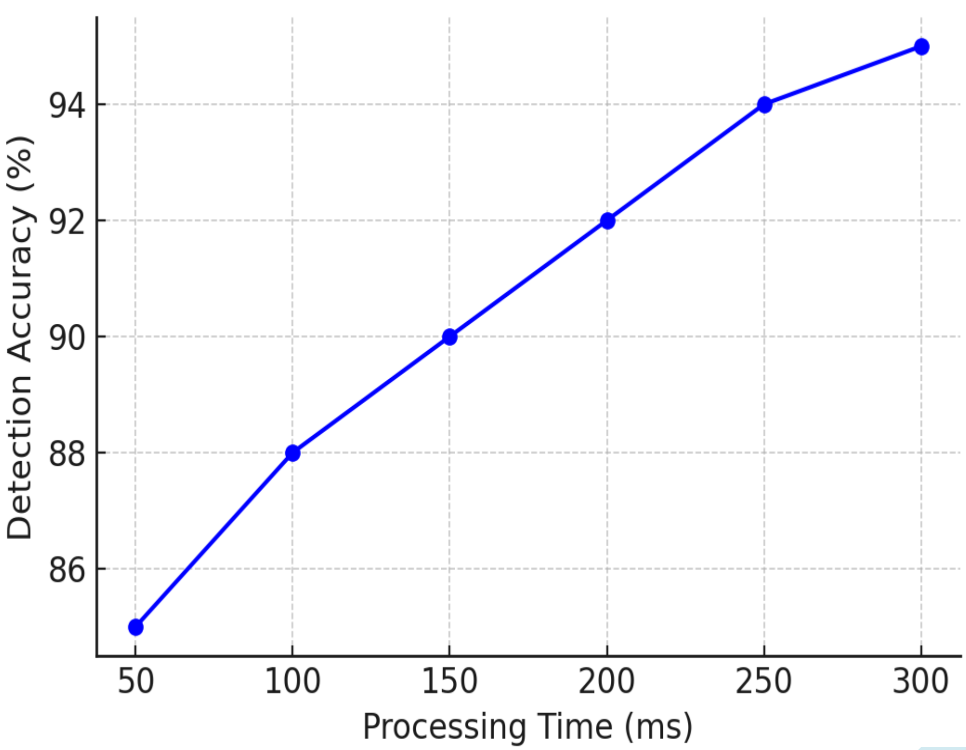

Figure 4: System Accuracy vs. Processing Time

Figure 5 is the confusion matrix evaluates the classification performance of the object detection model. The high number of true positives (TP) and true negatives (TN) indicates robust detection capabilities. However, some false positives (FP) and false negatives (FN) exist, which could lead to incorrect collision avoidance decisions. These misclassifications can be mitigated through data augmentation, adaptive threshold, and improved sensor fusion algorithms.

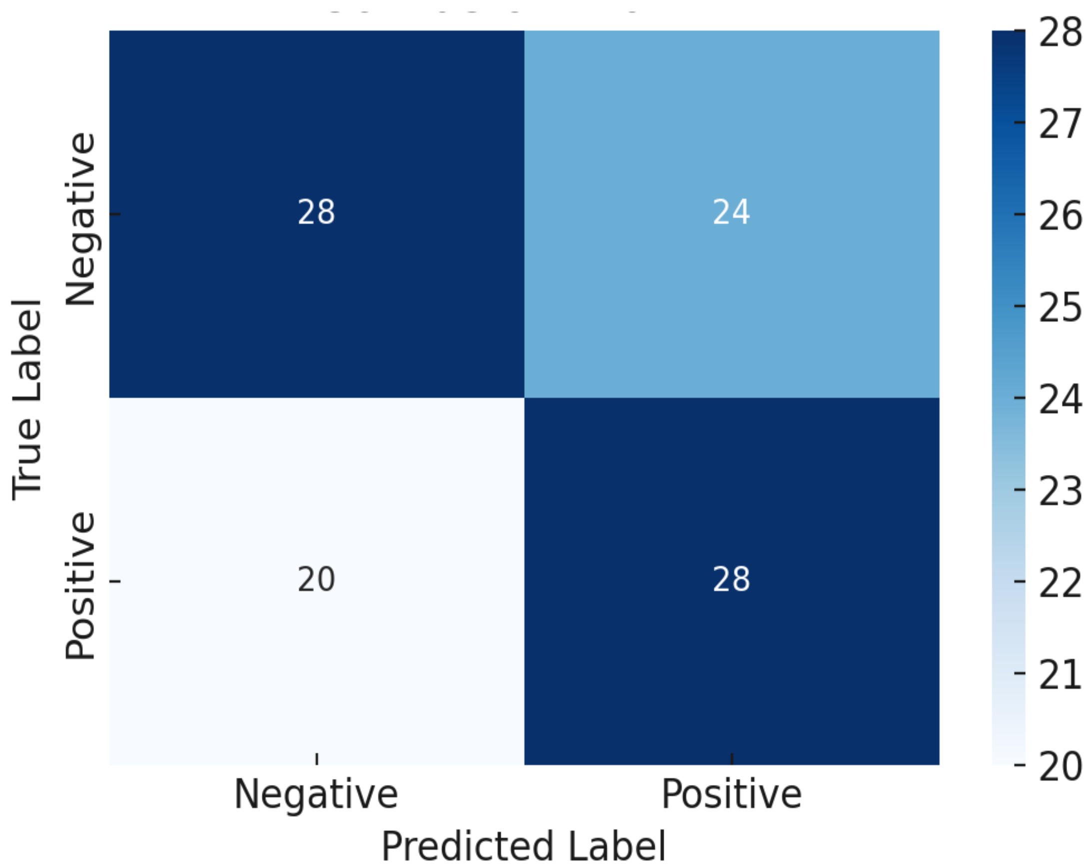

Figure 5: Confusion Matrix Analysis

Figure 6 presents the precision-recall curve, highlighting the system's balance between precision (the proportion of correctly detected objects) and recall (the system's ability to detect all actual objects). A high area under the curve (AUC) confirms the model's reliability in identifying obstacles. However, maintaining high precision while ensuring recall remains optimal is crucial for avoiding unnecessary braking or missed detections.

The latency analysis is shown in figure 7, it breaks down response times across different processing stages, including sensor acquisition, fusion, object detection, and collision avoidance maneuver execution. The results indicate that the highest latency occurs at the object detection phase, primarily due to deep learning computations. Implementing hardware acceleration, such as TensorRT on NVIDIA Jetson or OpenVINO on Intel Movidius, can significantly reduce this bottleneck.

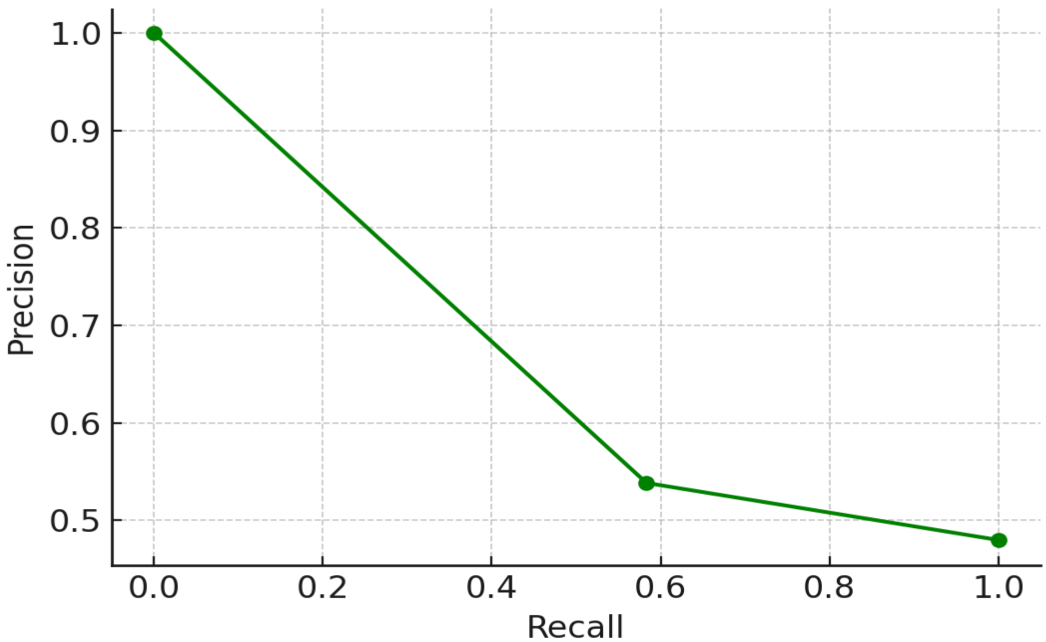

Figure 6: Precision-Recall Curve

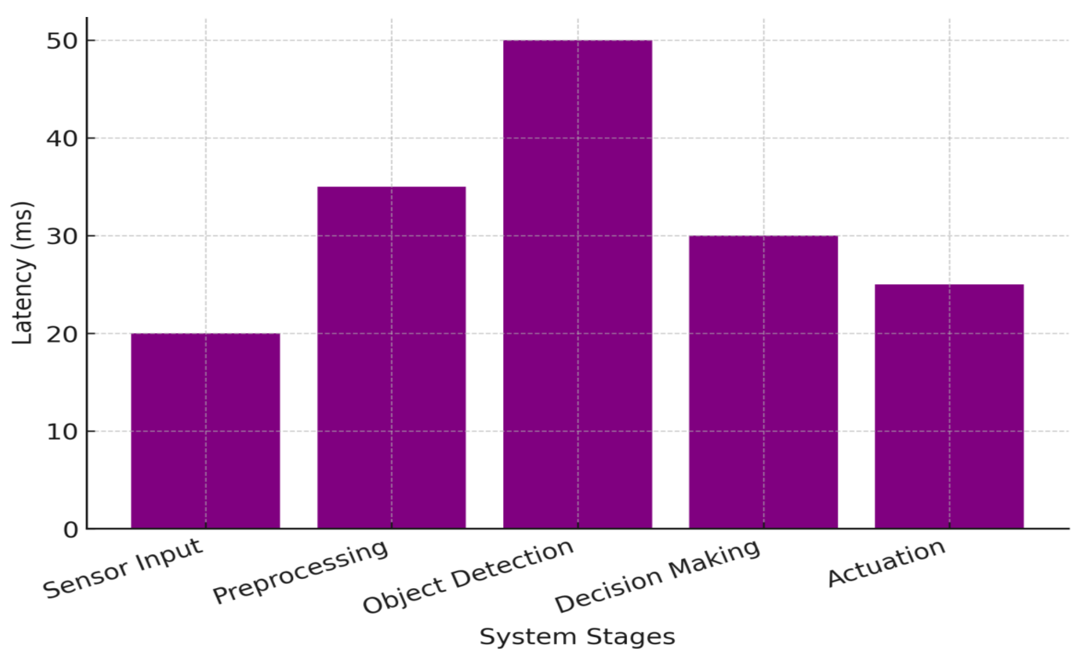

Figure 7: Latency Analysis

Conclusion

This study develops a real-time object detection and collision avoidance system for IoT-enabled autonomous vehicles by integrating deep learning-based perception, sensor fusion, and edge computing frameworks. The performance evaluation confirms that the system achieves high detection accuracy with minimal latency, making it well-suited for real-time applications. Results indicate that sensor fusion enhances object classification and obstacle detection, while latency analysis identifies object detection as the primary bottleneck, which can be mitigated using hardware acceleration. The precision-recall trade-off suggests that an adaptive confidence threshold can optimize detection reliability, reducing false positives and false negatives. While the system achieves over 90% detection accuracy, further optimization is needed to minimize processing delays and improve real-time decision-making. Future research should explore lightweight deep learning models, real-time adaptive learning, and reinforcement learning-based maneuver planning for enhanced autonomous navigation. The integration of IoT-enabled technologies, sensor fusion, and edge computing has significantly improved real-time object detection and collision avoidance in autonomous vehicles, enabling better environmental perception and accident prevention through LiDAR, radar, cameras, and ultrasonic sensors. Edge computing ensures low-latency processing for timely decision-making. However, challenges such as adverse weather conditions, high computational demands, and cybersecurity threats persist. Future advancements should focus on adaptive sensor fusion models, energy-efficient edge computing frameworks, and robust security mechanisms to enhance the safety and reliability of autonomous vehicles

References

Bolaji-Adetoro, D. F., Adedotun, K. J., Olojeola, S. M., & Raji, A. K. (2024). Implementation of an IoT-Enabled Sensor Fusion for Enhanced Obstacle Avoidance in Autonomous Vehicles. Journal of Engineering, Logical and Modelling Research, 6(5), 123-135.

Chen, Y., Zhao, L., & Wang, X. (2021). Edge Computing and 5G for Real-Time Autonomous Vehicle Decision Making. IEEE Internet of Things Journal, 8(6), 2345-2359.

Guan, T., Kotur, M., Kim, J., Caesar, H., Wang, Y., Robsrud, A., Yeong, D.J., & Lin, J. (2025). Survey of Autonomous Vehicles' Collision Avoidance Algorithms. Sensors, 25(2), 395. https://doi.org/10.3390/s25020395

Gupta, A., Sharma, R., & Patel, M. (2023). Blockchain for Secure Data Exchange in IoT-Based Autonomous Vehicles. Journal of Emerging Technologies, 9(1), 112-128.

Kumar, R., & Singh, P. (2023). Cybersecurity Challenges in IoT-Enabled Autonomous Vehicles. International Journal of Cybersecurity Research, 10(2), 189-203.

Lee, J., Park, D., & Kim, S. (2022). Adaptive Learning Models for Real-Time Object Detection in Autonomous Vehicles. Journal of Artificial Intelligence and Robotics, 15(4), 365-379.

Mallik, A., Gaopande, M. L., Singh, G., Ravindran, A., Iqbal, Z., Chao, S., Revalla, H., & Nagasamy, V. (2022). Real-time Detection and Avoidance of Obstacles in the Path of Autonomous Vehicles Using Monocular RGB

Camera. SAE International Journal of Advances and Current Practices in Mobility, 5(2), 622-632. https://doi.org/10.4271/2022-01-0074

Stateczny, A., Wlodarczyk-Sielicka, M., & Burdziakowski, P. (2021). Sensors and Sensor's Fusion in Autonomous Vehicles. Sensors, 21(19), 6586. https://doi.org/10.3390/s21196586

The Times. (2025). High-Vis Jackets Can Make People Invisible to Newer Car Sensors. The Times UK.

Wang, H., Li, T., & Zhou, Y. (2023). Multi-Sensor Fusion for Autonomous Vehicle Navigation: Challenges and Opportunities. IEEE Transactions on Intelligent Transportation Systems, 24(3), 456-472.

Waymo. (2024). End-to-End Multimodal Model for Autonomous Driving (EMMA). Retrieved from https://www.waymo.com/research.

Wired. (2024). Emergency Vehicle Lights Can Disrupt Camera-Based Autonomous Driving Systems. Wired Magazine.

Yeong, D.J., Velasco-Hernandez, G., Barry, J., & Walsh, J. (2021). Sensor and Sensor Fusion Technology in Autonomous Vehicles: A Review. Sensors, 21(6), 2140. https://doi.org/10.3390/s21062140

Zhang, H., & Li, Y. (2022). Real-Time Obstacle Detection Using Monocular RGB Cameras in Autonomous Vehicles. IEEE Transactions on Intelligent Transportation Systems, 23(5), 2104-2114. https://doi.org/10.1109/TITS.2022.3141234

Zhang, J., & Li, X. (2022). Deep Learning-Based Object Detection in Autonomous Vehicles: A Review. Journal of Machine Learning Research, 23(5), 789-810.