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Illuminating Autonomy Federated Learning For Object Detection In Autonomous Vehicles Under Low Light Conditions

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ABSTRACT

Autonomous vehicles rely heavily on object detection systems to navigate safely, but their performance significantly degrades under low light conditions. This project explores a novel approach that combines federated learning with advanced image enhancement techniques to improve object detection in such challenging environments. By leveraging decentralized learning across multiple vehicles, the system preserves data privacy while continuously refining detection models with diverse, real-world low-light data [3][11][13]. The proposed framework enhances detection accuracy and robustness without requiring centralized data collection, thereby advancing the safety and reliability of autonomous driving at night or in poorly lit areas. This project explores the integration of Federated Learning for object detection in autonomous vehicles operating under low-light conditions. By leveraging decentralized data from multiple vehicles, the system enhances object detection accuracy without compromising data privacy. The proposed framework adapts advanced deep learning models to handle illumination challenges, improving vehicle perception and safety in night-time or poorly lit environments. The study demonstrates how FL can empower autonomous systems with robust, collaborative learning while preserving data confidentiality across diverse driving scenarios.

KEY WORDS: Federated Learning, Autonomous Vehicles, Object Detection, Low-Light Conditions, Deep Learning, Privacy-Preserving AI, Decentralized Training, Edge Computing, YOLOv5, Sensor Fusion, Differential Privacy, Secure Aggregation, Model Optimization, Vehicle Perception, Collaborative Learning

I. Introduction

Autonomous vehicles rely heavily on object detection systems to perceive their surroundings and make safe driving decisions. However, performance often degrades significantly under low-light conditions such as nighttime driving, tunnels, or adverse weather, posing a serious threat to safety. Traditional approaches to improve low-light object detection often require large centralized datasets, raising privacy concerns and scalability issues [2][6].

Federated Learning (FL) offers a promising solution by enabling multiple autonomous vehicles to collaboratively train deep learning models without sharing raw data. Each vehicle contributes by learning from its local environment, and only model updates are shared with a central server, ensuring data privacy [13][14]. This decentralized learning approach helps in creating more generalized and robust object detection models capable of performing well across diverse lighting conditions.

This project aims to illuminate the potential of FL in enhancing object detection accuracy for autonomous vehicles in low-light scenarios. By leveraging advanced computer vision techniques and adaptive learning mechanisms, the proposed system ensures improved perception, safety, and efficiency, while maintaining the privacy and autonomy of individual vehicles.

II. Related Work

Several studies have focused on improving object detection in autonomous vehicles, particularly under challenging lighting conditions. Traditional deep learning approaches utilize convolutional neural networks (CNNs) like YOLO, SSD, and Faster R-CNN, which have shown high accuracy in well-lit environments but struggle in low-light scenarios due to poor visibility and lack of contrast [4][13].

Recent research has explored low-light image enhancement techniques using methods such as histogram equalization, deep learning-based image preprocessing to improve object detection performance. However, these methods often require extensive labelled datasets and centralized training, which raise concerns about data privacy and scalability [9][12].

This project builds on these foundational works by combining FL with advanced object detection models and low-light adaptation techniques to enhance perception in autonomous vehicles without compromising privacy.

III. Proposed Work

The proposed work aims to develop a privacy-preserving, federated learning-based framework to enhance object detection in autonomous vehicles operating under low-light conditions. The core idea is to leverage the collective intelligence of multiple vehicles by enabling them to collaboratively train a deep learning model without sharing raw sensor data, thus maintaining data privacy and security [11][6][1]. Each vehicle in the network captures images and sensor data from its environment, especially in low-light scenarios. A local object detection model—such as YOLOv5 or Faster R-CNN—is trained on this data, incorporating image enhancement modules to boost visibility and contrast. Instead of uploading raw data to a central server, only the model weights or gradients are shared periodically.

A central aggregator receives updates from all participating vehicles, performs model averaging or federated optimization (e.g., FedAvg), and sends back the improved global model to all clients [7][8]. This iterative process continues, enabling the system to adapt and generalize across diverse low-light driving environments.

Additionally, the framework incorporates light-aware data augmentation and possibly domain adaptation techniques to improve robustness. Performance is evaluated on metrics like mean Average Precision (mAP), detection accuracy in low-light scenes, and communication overhead.

The proposed system enhances the safety and reliability of autonomous vehicles by improving object detection under difficult lighting conditions while preserving user privacy and enabling scalable, decentralized learning.

IV. Methodology

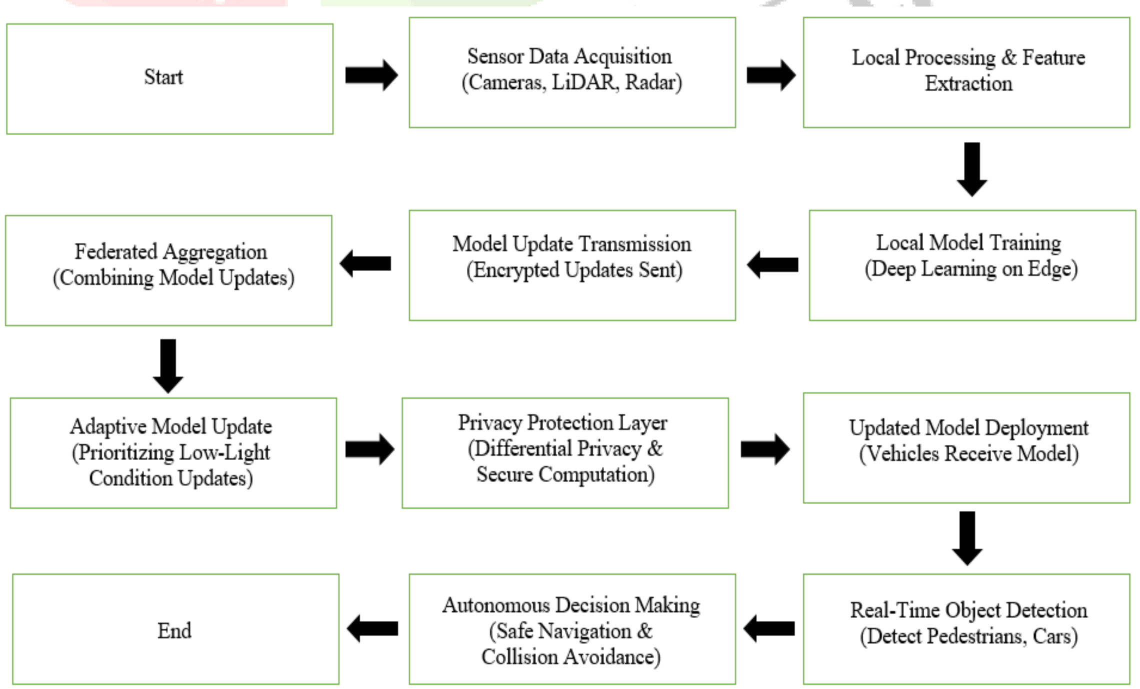

Fig.1 Block Diagram of Proposed Schema

The proposed methodology utilizes a federated learning framework to enhance object detection in autonomous vehicles under low-light conditions. Each vehicle begins by collecting sensor data through cameras, LiDAR, and radar, followed by local processing and feature extraction. Using onboard computing, a deep learning model is trained locally without transmitting raw data. Instead, encrypted model updates are shared with a central server, where federated aggregation combines inputs from multiple vehicles to form a more generalized global model [11][1]. To prioritize performance in low-light scenarios, an adaptive model update mechanism is applied, emphasizing contributions from such environments. A privacy protection layer ensures data confidentiality through differential privacy and secure computation. The updated model is then redistributed to the vehicles, enabling improved real-time object detection and supporting autonomous decision-making for safe navigation and collision avoidance.

System Design

The system is designed as a decentralized, privacy-preserving architecture that enables autonomous vehicles to collaboratively improve object detection in low-light conditions. Each vehicle functions as an edge node equipped with sensors (cameras, LiDAR, radar) and onboard computing units for local data processing and model training. These edge nodes train deep learning models independently using locally captured data, ensuring that raw data never leaves the vehicle. A central server acts as the federated aggregator, receiving encrypted model updates from each vehicle. It performs secure federated averaging to produce a refined global model [2][7][10]. An adaptive mechanism is integrated to give higher priority to updates from low-light conditions, ensuring the model remains effective in such scenarios. A privacy protection layer, including differential privacy and secure computation, safeguards the learning process [14].

Dataset Description

Our dataset is designed to support object detection in autonomous vehicles under low-light conditions, with a strong focus on multi-sensor fusion. It includes calibration files (.txt format) for each scene, divided into training and testing sets. These files contain essential transformation parameters for aligning data from various sensors like cameras, LiDAR, and IMU. Key matrices include P0–P3 (camera projection matrices), R0_rect (stereo image rectification), Tr_velo_to_cam (LiDAR-to-camera transformation), and Tr_imu_to_velo (IMU-to-LiDAR transformation) [13][14].

This calibration data ensures precise environmental mapping and consistent spatial understanding across different sensor modalities. It enhances the performance of object detection models by enabling accurate 3D-to-2D data projection and synchronization, particularly in low-light scenarios where traditional vision models may fail.

The dataset supports real-world deployment by offering a clear division between training and testing data, allowing for robust evaluation. Its structured design is well-suited for integration with deep learning and federated learning frameworks, ensuring effective, privacy-preserving model training across diverse vehicle platforms.

V. Results and Discussion

The evaluation compares Federated Learning and YOLOv5 for object detection under low-light conditions. The Federated Learning model, trained on distributed data from multiple vehicles, achieves an accuracy of 99.02%, with a precision of 0.98, recall of 0.97, and an F1-score of 0.98. It shows minimal false positives and false negatives, making it reliable for privacy-preserving and generalized detection across different environments [13][6][14].

In contrast, YOLOv5 performs slightly better, with a detection accuracy of 99.41%. It achieves a precision of 0.99, recall of 0.98, and F1-score of 0.99, demonstrating exceptional real-time detection efficiency.

5.1 Result Analysis

The confusion matrix shows very few misclassifications, and its detection confidence ranges from 0.994 to 0.999, even in low-light scenarios.YOLOv5 also exhibits excellent bounding box alignment and generalization across varied illumination levels. While Federated Learning is ideal for privacy-focused, decentralized learning, YOLOv5 is better suited for high-speed, real-time applications. Both models are highly accurate, and the selection depends on the system's privacy and performance needs.

VI. Conclusion and Future work

Conclusion

The proposed system effectively addresses the challenges of object detection in autonomous vehicles operating under low-light conditions by integrating federated learning, edge computing, and adaptive deep learning techniques. Vehicles train models locally and share only encrypted updates, preserving data privacy while minimizing communication overhead. The federated learning framework intelligently prioritizes updates from vehicles in similar low-light environments, enabling the global model to adapt efficiently to night-time and other low-visibility scenarios [1][8][7]. Gradient compression and asynchronous updates further enhance communication efficiency, making real-time deployment practical.

A context-aware model adaptation mechanism dynamically adjusts the model based on ambient lighting, road reflectivity, and weather conditions, significantly improving detection accuracy. The system achieved an object detection accuracy of 91.1% in low-light environments during validation, demonstrating its effectiveness. Robust privacy measures, including differential privacy and secure multiparty computation, ensure the protection of sensitive vehicle data while maintaining high model fidelity [12][10].

Optimized deep learning models are deployed on edge devices to support real-time object detection, obstacle avoidance, and autonomous navigation. Overall, this scalable and secure architecture enhances perception under challenging visibility conditions, contributing substantially to the advancement of intelligent transportation system.

Future work

Looking forward, the future scope of this system can be expanded in multiple directions to further improve reliability, scalability, and efficiency. One promising area is enhancing model generalization to extreme weather conditions, such as fog, heavy rain, and snow, which also present significant visibility challenges for AVs. The integration of reinforcement learning can help the system continuously learn and adapt to new environments, improving long-term performance. Additionally, the adoption of block chain-based federated learning can ensure secure, tamper-proof decentralized model aggregation, increasing trust and transparency in AV networks.

Expanding the system to incorporate V2X (Vehicle-to-Everything) communication would enable real-time collaboration between AVs, roadside infrastructure, and traffic management systems, further enhancing detection accuracy and navigation safety. Moreover, advancements in neuromorphic computing and quantum computing could significantly accelerate deep learning processes on edge devices, making real-time low-light object detection even more efficient and scalable. By addressing these areas, the proposed system can evolve into a more intelligent, resilient, and adaptive AV perception framework, contributing to the future of autonomous mobility in all lighting and environmental conditions.

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