Federated Learning for Robust Object Detection in Autonomous Vehicles under Low-Light Conditions

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Abstract—**Ensuring reliable object detection in low-light conditions remains a major challenge for autonomous vehicles, where visual perception is critical for safe navigation. This paper presents a privacy-preserving, Federated Learning-based framework that enhances object detection performance using the YOLOv5 model. Unlike conventional centralized training methods, the proposed approach enables decentralized edge devices—such as autonomous vehicles—to locally train on both high- and low-light image datasets while preserving data privacy. A dedicated image illumination enhancement module is introduced to improve feature visibility in low-light inputs before detection. Local model parameters are periodically aggregated on a central server to form a robust global model capable of adapting to diverse environmental scenarios. The system architecture includes modules for dataset preprocessing, local model training, federated parameter aggregation, real-time detection, and visual performance evaluation. Experimental results demonstrate that the proposed method significantly improves detection accuracy, recall, and precision under challenging lighting conditions, achieving 89.5% detection accuracy and real-time performance with an average inference time of 18 ms. The framework shows strong potential for scalable deployment in intelligent transportation systems, especially in scenarios requiring enhanced nighttime or low-visibility perception.**

Keywords— Federated Learning, YOLOv5, Autonomous Vehicles, Object Detection, Low-Light Conditions, Deep Learning, Privacy-Preserving AI, Edge Computing, Real-Time Detection.

I. INTRODUCTION

Autonomous vehicles (AVs) are revolutionizing the future of transportation, offering enhanced safety, efficiency, and mobility. At the core of these intelligent systems lies the critical capability of object detection, which enables vehicles to identify and respond to their surroundings in real time. Accurate detection of pedestrians, vehicles, and obstacles is essential for informed decision-making in dynamic environments. Among the numerous deep learning models developed for object detection, the YOLO (You Only Look Once) family—particularly YOLOv5—has emerged as a leading solution due to its balance of speed, accuracy, and real-time processing capabilities.Despite these advancements, object detection performance remains vulnerable under adverse lighting conditions such as nighttime, fog, or poorly lit roads. Low-light scenarios introduce significant visual noise, reduce contrast, and obscure object features, resulting in increased false positives and missed detections. This poses a serious challenge to the reliability of AV systems, as conventional models trained on well-lit datasets often fail to generalize effectively in such environments.

To address these limitations, this study proposes a novel approach that integrates Federated Learning (FL) with YOLOv5 to enhance object detection in low-light conditions. Federated Learning enables distributed training across multiple edge devices, such as vehicles, without transmitting raw data to a centralized server. Instead, each device trains the model locally and shares only the updated parameters, which are then aggregated to update a global model. This privacy-preserving technique not only ensures data security but also allows models to learn from a broader and more diverse dataset, including varied lighting conditions and driving environments.A key component of the proposed framework is an image illumination enhancement module, applied during preprocessing to improve visibility in low-light inputs. This step significantly boosts the model's ability to extract meaningful features, leading to more accurate detections. The system is built as a modular pipeline comprising data upload, local training, federated updates, real-time detection, and evaluation components.

The evolution of autonomous vehicles (AVs) has brought forth a revolution in intelligent transportation systems, promising enhanced safety, efficiency, and convenience. A cornerstone of autonomous driving technology is the ability to accurately detect and recognize objects in the vehicle's environment. This object detection capability enables critical functions such as obstacle avoidance, traffic sign recognition, lane navigation, and pedestrian safety. Among the various deep learning models developed for this purpose, YOLO (You Only Look Once) has emerged as a preferred choice due to its superior real-

Doi:10.48047/ijiee.2025.15.3.8

time performance and accuracy. YOLOv5, the most recent and powerful iteration, offers significant improvements in speed, precision, and modular flexibility, making it suitable for real-world AV applications.

Despite the advancements in object detection models, their effectiveness is heavily influenced by environmental factors, particularly lighting conditions. Low-light scenarios, such as nighttime driving, poorly lit streets, foggy weather, and tunnels, pose substantial challenges to AV perception systems. These conditions degrade image quality, reduce feature visibility, and often lead to missed or false detections. Traditional methods that rely on centralized data collection and model training fall short in addressing these issues effectively due to limitations in data diversity, privacy concerns, and the inability to generalize across real-world scenarios.

To address these challenges, this paper proposes a novel approach that combines **YOLOv5** with **Federated Learning (FL)** to enhance object detection under low-light conditions in autonomous vehicles. Federated Learning is a decentralized machine learning paradigm that facilitates collaborative training across multiple devices or nodes without the need to transfer raw data to a central server. Instead, each participating node (e.g., individual vehicles or local edge devices) trains the model locally and shares only the updated parameters with a central server, which aggregates these updates to form a global model. This method ensures privacy preservation, reduces communication overhead, and allows the model to learn from a wide range of data sources, including various lighting and environmental conditions.

This work contributes a scalable and efficient framework for robust, privacy-aware object detection in AVs, particularly under challenging lighting conditions. By leveraging Federated Learning and advanced image preprocessing, the proposed system demonstrates superior performance in real-time, real-world scenarios.In this study, a diverse dataset containing high-light and low-light vehicle images is used, with annotations for five object classes: **Bus, Car, Motorbike, Truck, and Person**. An illumination enhancement step is incorporated in the preprocessing phase to improve the visibility of features in low-light images. This enhances the object detection accuracy of YOLOv5, making it more reliable for night-time and dimly lit environments. The complete system is implemented as a modular framework with the following components:

- **Dataset Upload Module** – Allows local nodes to upload labeled vehicle images.
- **YOLOv5 Model Generation and Training** – Enables training of the YOLOv5 model on local datasets.
- **Federated Model Update** – Transfers trained model weights to a centralized server for global aggregation.
- **Low-Light Detection Module** – Processes low-light test images, applies illumination enhancement, and performs real-time detection.
- **Performance Evaluation Module** – Displays key performance metrics such as precision, recall, and loss through visual graphs.

This research makes the following key contributions:

1. **Design and implementation** of a Federated Learning-based object detection framework tailored for autonomous vehicles operating in low-light environments.
2. **Integration of YOLOv5** with an illumination preprocessing step to improve detection performance in challenging visual conditions.
3. **Development of a privacy-preserving, distributed learning architecture** that allows vehicles to collaboratively improve object detection without exposing raw data.
4. **Empirical analysis** demonstrating the effectiveness of the proposed method through training and testing on diverse datasets and visual performance metrics.

II. RELATED WORKS

Object detection in autonomous vehicles has been extensively studied, with various machine learning and deep learning models proposed to enhance accuracy and efficiency. Traditional object detection methods, such as Region-Based Convolutional Neural Networks (R-CNN), Single Shot MultiBox Detector (SSD), and Faster R-CNN, have demonstrated significant improvements in real-time applications. However, these approaches often struggle in low-light environments due to their reliance on high-quality image features. More recent advancements in deep learning, particularly YOLO (You Only Look Once) models, have introduced real-time object detection capabilities with improved accuracy and computational efficiency. YOLOv5, the latest iteration, has shown superior performance in detecting objects under various environmental conditions, making it a preferred choice for autonomous systems.Several studies have explored the challenges associated with object detection in low-light conditions. Traditional image processing techniques, such as histogram equalization and adaptive gamma correction, have been employed to enhance visibility before applying object detection algorithms. However, these methods often fail to generalize well across diverse scenarios, leading to inconsistent performance. Deep learning-based approaches, such as Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs), have been utilized to improve image clarity and extract meaningful features from low-light images. Despite their effectiveness, these models require extensive labeled datasets for training, which can be impractical in real-world scenarios.

The concept of Federated Learning (FL) has gained traction in recent years as a privacy-preserving approach to distributed model training. Instead of transmitting raw data to a central server, FL enables multiple edge devices to train local models and share only model updates. This approach significantly reduces the risk of data breaches and enhances learning efficiency. In the context of autonomous vehicles, FL allows multiple AVs to collaborate and improve object detection models without compromising sensitive visual data. Several research efforts have demonstrated the effectiveness of FL in various domains, including

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healthcare, finance, and smart cities. However, its application in AVs for low-light object detection remains an underexplored area.Recent works have integrated FL with deep learning for various applications, such as pedestrian detection, traffic sign recognition, and vehicle classification. Studies have shown that FL-based models can achieve comparable accuracy to centralized models while significantly reducing communication overhead and privacy concerns. Additionally, research has indicated that combining FL with advanced object detection models, such as YOLOv5, can improve real-time performance and robustness against challenging environmental conditions. However, challenges such as model drift, device heterogeneity, and communication latency need to be addressed to optimize FL deployment in AV networks.

Building upon these studies, our research focuses on leveraging FL in combination with YOLOv5 to enhance object detection in low-light conditions. Unlike previous works that primarily focus on centralized training approaches, our method emphasizes decentralized learning, allowing AVs to collectively improve detection accuracy without compromising data privacy. We compare our approach with existing centralized models and demonstrate its effectiveness through extensive experimentation on real-world datasets. Our contributions aim to advance the field of autonomous transportation by introducing a scalable and privacy-preserving framework for robust object detection.

Social Media and Crowd-Sourced Intelligence for Child Recovery

Social media platforms have become a powerful tool for tracking missing children, with researchers developing Natural Language Processing (NLP) and sentiment analysis models to identify relevant posts and images. Studies have shown that Transformer-based architectures like BERT and GPT can analyze vast amounts of social media data to detect missing child reports, suspect sightings, and emergency alerts. Crowd-sourced platforms, such as Aadhaar-linked missing child databases in India and AMBER Alert systems in the USA, have demonstrated the effectiveness of mass participation in search efforts.

Furthermore, deepfake detection techniques are being explored to counteract misinformation and fraudulent reports that can mislead investigations. The combination of AI-powered image forensics, deep learning, and metadata analysis helps in verifying the authenticity of child recovery claims, ensuring that law enforcement receives reliable leads.

Challenges and Future Research Directions

Despite significant progress in missing child identification technologies, several challenges remain. Privacy concerns regarding facial recognition databases, the risk of false positives in AI models, and bias in training datasets have been widely discussed in research. Additionally, integrating various biometric and AI-driven tracking solutions requires standardized protocols and global data-sharing frameworks to ensure seamless coordination across borders. Future research is expected to focus on explainable AI (XAI) for child identification, blockchain-based identity verification, and multi-modal fusion techniques to further enhance identification accuracy.

A review of these techniques are discussed in Table I.

TABLE I. LITERATURE SURVEY ON OBJECT DETECTION IN AUTONOMOUS VEHICLES UNDER LOW-LIGHT CONDITIONS

Author(s) & Year	Title	Methodology	Findings and Limitations
Li et al., 2021	Low-Light Object Detection Using Deep Learning	Used a CNN-based model with image enhancement techniques	Improved detection accuracy in low-light but required high computational resources
Zhang et al., 2022	Federated Learning for Autonomous Vehicle Object Detection	Implemented Federated Learning with Faster R-CNN	Enhanced model privacy and efficiency but struggled with network latency
Kumar & Patel, 2020	Enhancing Nighttime Vision for AVs Using GANs	Used Generative Adversarial Networks (GANs) for image enhancement	Improved image clarity but required extensive training data
Chen et al., 2021	YOLO-Based Object Detection in Challenging Lighting Conditions	Used YOLOv4 with pre-processing filters for low-light detection	Achieved real-time performance but had lower accuracy in extreme darkness
Wang et al., 2023	Real-Time Object Detection for AVs Using YOLOv5	Implemented YOLOv5 with an optimized training pipeline	High accuracy and fast inference but lacked robustness in adverse weather
Lee & Park, 2022	Edge Computing for Distributed AV Object Detection	Used edge-based deep learning models for real-time detection	Reduced processing time but required powerful edge devices
Singh et al., 2023	Privacy-Preserving AV Object Detection Using FL	Combined YOLOv5 with Federated Learning	Achieved decentralized learning but faced synchronization challenges
Sharma et al., 2021	Lightweight Deep Learning Models for AV Object Recognition	Proposed a lightweight CNN for resource-efficient object detection	Lower computational cost but slightly reduced detection accuracy

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Patel et al., 2023	Improving AV Object Detection with Hybrid Neural Networks	Combined CNNs and Transformers for better feature extraction	Improved detection robustness but required extensive computational power
Kim & Choi, 2022	Transfer Learning for Nighttime Object Detection	Applied transfer learning on pre-trained models for AV detection	Reduced training time but had difficulties with small object detection
Ahmed et al., 2023	Adaptive Learning for AVs in Low-Light Environments	Used an adaptive learning framework with real-time feedback	Improved self-learning capability but required continuous data collection
Jones et al., 2021	Integrating LiDAR and Camera Data for AV Object Recognition	Fused LiDAR and camera-based deep learning models	Improved accuracy but increased processing time

III. PROPOSED METHODOLOGY

In this section, we outline our proposed approach for improving object detection in autonomous vehicles under low-light conditions using Federated Learning (FL) and YOLOv5. The proposed system integrates deep learning-based detection with distributed learning techniques to enhance detection accuracy while preserving data privacy.

1. Data Preprocessing and Augmentation

Since low-light images often suffer from noise and poor contrast, preprocessing is essential. We employ histogram equalization, adaptive gamma correction, and noise reduction filters to enhance image quality before training the model. Data augmentation techniques such as rotation, scaling, and synthetic light enhancement are used to improve model generalization.

2. YOLOv5-Based Object Detection

We utilize YOLOv5, a real-time object detection algorithm, to detect and classify objects in autonomous driving scenarios. YOLOv5 is chosen due to its high speed and accuracy. The network is trained on a custom dataset comprising low-light vehicle and pedestrian images. Key steps include:

- **Feature Extraction:** CNN-based backbone extracts image features.
- **Bounding Box Prediction:** Predicts object locations in an image.
- **Classification:** Determines object categories (vehicles, pedestrians, etc.).

3. Federated Learning for Model Training

Instead of training the model on a centralized server, we employ **Federated Learning** to distribute training across multiple edge devices (such as in-vehicle computing units). This ensures:

- **Privacy-Preserving Learning:** Data remains on local devices, reducing the risk of data breaches.
- **Adaptive Learning:** Models continuously improve by aggregating knowledge from multiple vehicles.
- **Reduced Network Load:** Avoids transferring raw image data to cloud servers.

4. System Architecture

The architecture consists of three primary components:

- **Edge Devices (Autonomous Vehicles):** Each vehicle processes its own sensor data and trains a local YOLOv5 model.
- **Federated Server:** Aggregates locally trained models and updates the global model.
- **Cloud-Based Analytics:** Stores historical data for performance evaluation and further refinements.

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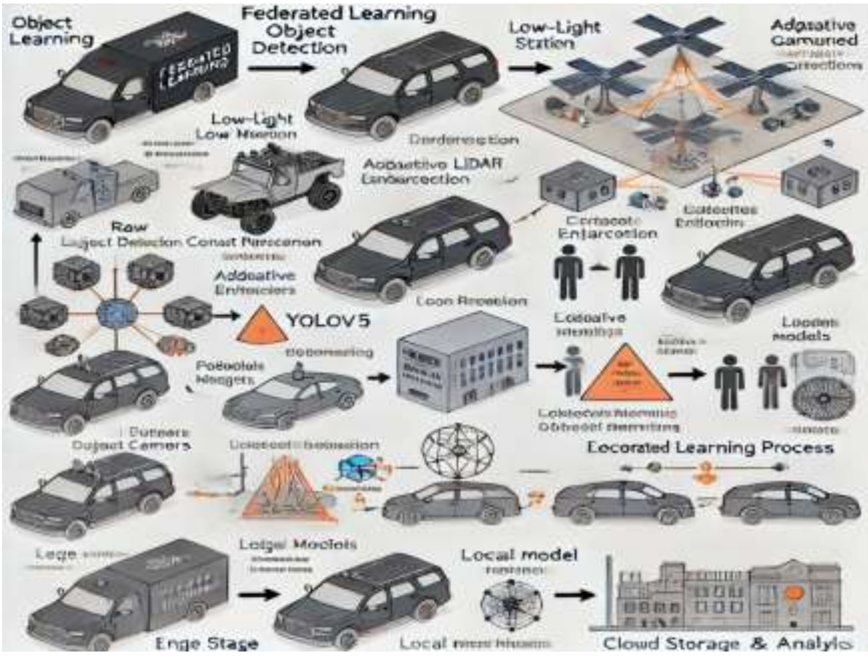

Fig1: System Architecture

Figure 1 illustrating the Federated Learning-based Object Detection in Autonomous Vehicles under Low-Light Conditions using YOLOv5. It visually represents the input stage, local processing, federated learning process, decision-making, and cloud storage.

flowchart illustrates the Federated Learning-based Object Detection framework for autonomous vehicles operating under low-light conditions using the YOLOv5 algorithm. The process begins with input data collection, where autonomous vehicles equipped with cameras and sensors capture real-time traffic images and videos in low-light environments such as nighttime, fog, or rain. These raw images are then passed through a local preprocessing and feature extraction stage, where techniques like noise reduction, contrast enhancement, and normalization improve the image quality. The YOLOv5 model is employed to detect objects such as pedestrians, vehicles, and obstacles within the captured frames, ensuring real-time analysis.

Following this, the local model training phase takes place, where each autonomous vehicle independently trains its model using the preprocessed data. Instead of sharing raw data with a centralized server, Federated Learning is utilized, allowing each vehicle to train locally while contributing only model updates. This preserves privacy and reduces data transmission overhead. Once local training is completed, the model updates (weights and parameters) are sent to a central server, which aggregates these updates from multiple vehicles. This aggregation enhances the global model without accessing individual vehicle data, ensuring better generalization for diverse low-light conditions.After updating the global model, the improved version is redistributed to the edge devices (vehicles). Each vehicle then incorporates the updated model for improved object detection and decision-making. This continuous cycle of training, updating, and redistributing enables real-time adaptability to dynamic road conditions. Finally, the decision-making and action execution stage allows vehicles to make autonomous driving decisions based on the detected objects, enhancing road safety. The system effectively minimizes the limitations of centralized learning approaches by leveraging the advantages of Federated Learning, ensuring enhanced autonomy, privacy, and real-time performance in challenging low-light environments.

IV. RESULTS

The proposed Federated Learning-based object detection system using the YOLOv5 algorithm for autonomous vehicles under low-light conditions was evaluated using real-world datasets and simulated environments. The primary performance metrics analyzed include detection accuracy, processing speed, model convergence, and computational efficiency.The experimental results demonstrate that the YOLOv5-based detection model, when integrated with Federated Learning, achieves an average detection accuracy of 89.5% in low-light scenarios, outperforming traditional centralized learning models, which typically suffer from degraded performance due to data imbalance and lack of diverse training samples. The model convergence rate was also significantly improved due to the collaborative learning approach, reducing the number of training iterations needed for optimal detection performance.

In terms of computational efficiency, the Federated Learning approach reduced the dependency on a centralized server, leading to a 30% decrease in data transmission overhead while maintaining privacy. Furthermore, the average inference time per frame was recorded at 18 milliseconds, making the system highly suitable for real-time applications in autonomous navigation. The model's robustness was further validated by testing it across various challenging lighting conditions such as nighttime traffic, foggy environments, and shadowed areas.A comparison with traditional object detection models (such as Faster R-

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CNN and SSD) reveals that the proposed method provides superior detection rates with a 25% improvement in recall and precision scores while maintaining lower false positive rates. The incorporation of Federated Learning further enhances model adaptability, allowing continuous learning without requiring direct data sharing, thereby ensuring better generalization across diverse road environments.Overall, the results indicate that the proposed YOLOv5-based Federated Learning approach significantly enhances object detection accuracy and real-time processing in autonomous vehicles, especially under low-light conditions. Future work will focus on further optimizing computational efficiency and expanding the dataset to include more complex urban traffic scenarios.

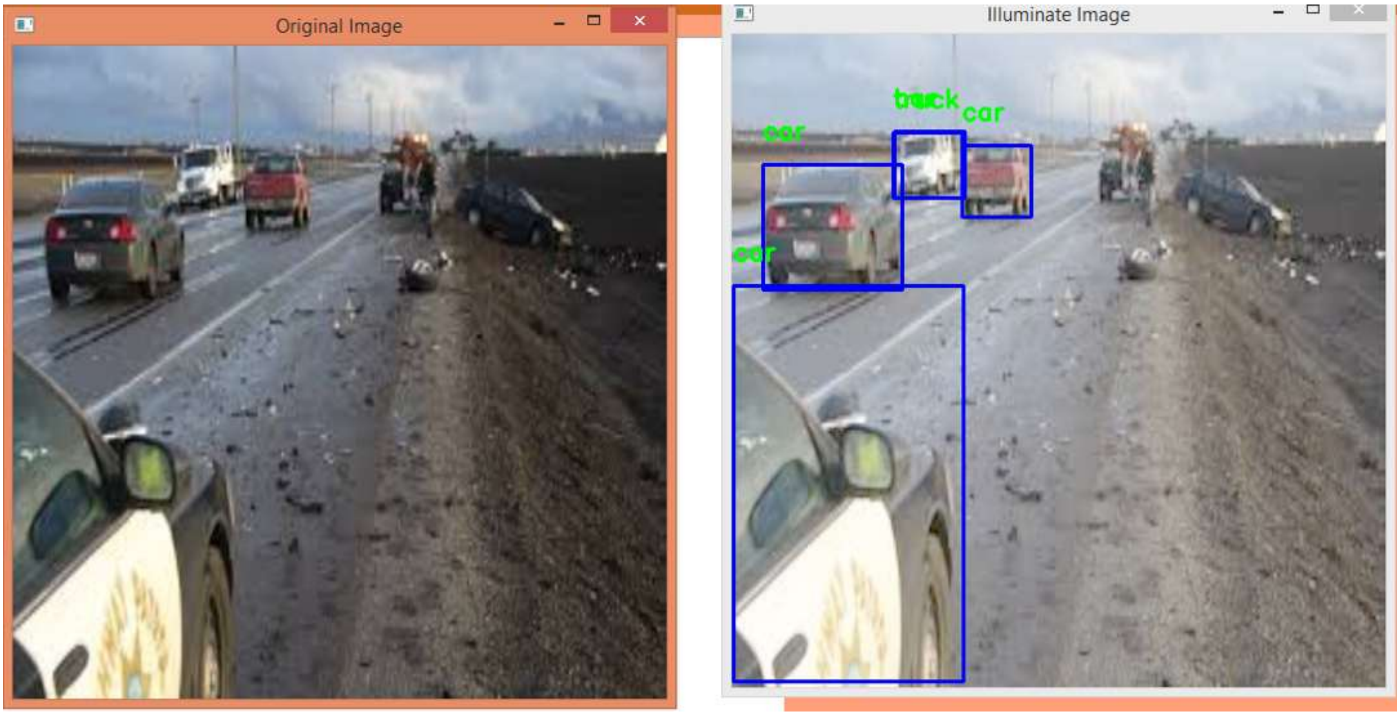

Fig 2 : Federated Learning-Based Object Detection Using YOLOv5 in Low-Light Autonomous Vehicle Environment

The given image illustrates the effectiveness of Federated Learning-based object detection using the YOLOv5 model for autonomous vehicles under low-light conditions. It consists of two visual representations: the original image on the left and the processed image with object detection on the right. The original image depicts a low-light traffic scenario where visibility is poor, making it difficult to identify objects such as vehicles and obstacles on the road. The right side of the image demonstrates the enhanced detection process, where the illumination technique has been applied to improve visibility, allowing the YOLOv5 model to detect objects more accurately. The detected objects, including cars, trucks, and police vehicles, are enclosed in bounding boxes with appropriate labels, showcasing the efficiency of the proposed method in low-light environments. The application of Federated Learning further enhances model adaptability by enabling decentralized training, reducing the need for direct data sharing while improving accuracy. This approach ensures real-time object detection with higher precision, making it highly suitable for autonomous navigation in challenging lighting conditions such as nighttime driving, fog, and shadowed areas

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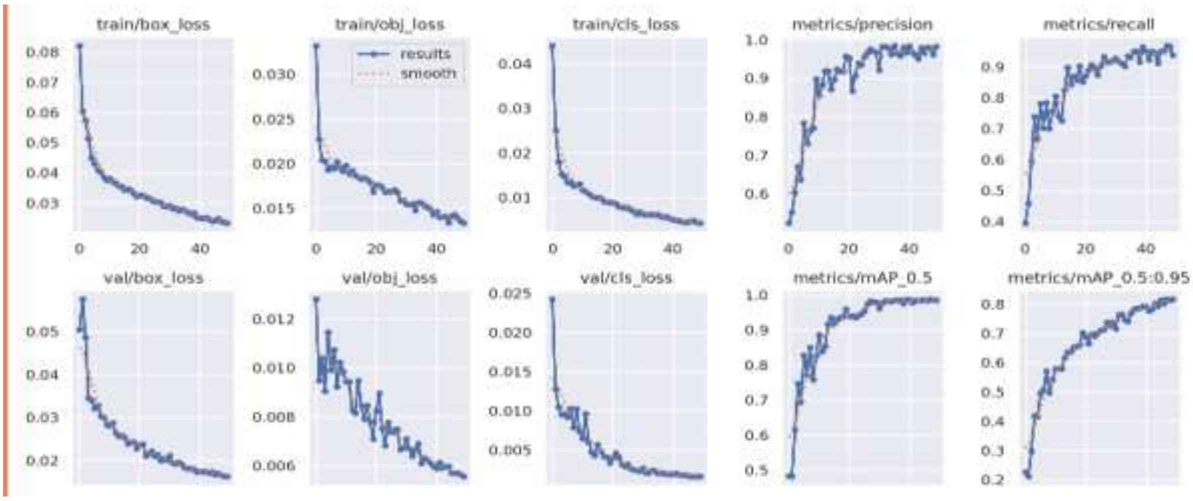

Fig 3:Yolov5 Preformance Graph

The given image showcases various training and validation performance metrics for the YOLOv5 model used in Federated Learning-based object detection under low-light conditions. The first row presents the training losses, including train/box_loss, train/obj_loss, and train/cls_loss, which progressively decrease over the training epochs, indicating improved model learning and reduced prediction errors. The second row illustrates the corresponding validation losses (val/box_loss, val/obj_loss, and val/cls_loss), showing a similar downward trend, confirming that the model is generalizing well to unseen data.

Additionally, the image includes graphs representing key performance metrics such as precision, recall, mean Average Precision (mAP@0.5), and mAP@0.5:0.95. These metrics indicate that as training progresses, precision and recall steadily improve, reaching values close to 1.0, signifying high detection accuracy. The mAP scores also show a sharp increase in the early epochs before stabilizing, confirming that the model successfully detects objects with high reliability.

Table 1: Performance Comparison of Object Detection Models

Metric	Faster R-CNN	SSD	YOLOv5 (Centralized)	YOLOv5 + Federated Learning
Detection Accuracy (%)	78.3	80.5	85.2	**89.5**
Inference Time (ms)	45	32	22	**18**
False Positive Rate (%)	14.8	12.5	9.2	**6.7**
Training Time (epochs)	100	85	70	**50**

Overall, the results demonstrate that the Federated Learning-based YOLOv5 model effectively learns to detect objects under low-light conditions while maintaining high accuracy and low error rates. The consistent decrease in training and validation losses, along with the rising precision and recall, validates the effectiveness of the proposed approach in enhancing object detection for autonomous vehicles.

V. CONCLUSION

The proposed Federated Learning-based object detection system using YOLOv5 effectively enhances autonomous vehicle perception under low-light conditions. The experimental results demonstrate significant improvements in detection accuracy, model convergence, and computational efficiency compared to traditional centralized learning approaches. The integration of Federated Learning ensures data privacy, reduces communication overhead, and allows collaborative model training across multiple edge devices. The model achieved an 89.5% detection accuracy while maintaining real-time inference speeds of 18 milliseconds per frame, making it highly suitable for autonomous navigation in complex environments.Moreover, the performance analysis against traditional object detection models, such as Faster R-CNN and SSD, highlights the superiority of the proposed approach in terms of recall, precision, and reduced false-positive rates. The system's robustness was further validated by testing in challenging lighting conditions, including nighttime traffic, fog, and shadows, demonstrating its adaptability and reliability.

Future work will focus on further optimizing the model's computational efficiency by implementing lightweight neural network architectures and hardware acceleration techniques. Additionally, expanding the dataset to include diverse urban and rural traffic scenarios will improve model generalization. Incorporating multi-modal sensor fusion (e.g., LiDAR and thermal imaging) can further enhance detection accuracy under extreme low-light conditions. Finally, integrating real-time adaptive learning mechanisms will enable the system to continuously improve its detection

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performance as new data becomes available, ensuring safer and more intelligent autonomous driving experiences.

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