iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** III **Month of publication:** March 2025

DOI: https://doi.org/10.22214/ijraset.2025.67524

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue III Mar 2025- Available at www.ijraset.com

Adaptive Object Detection in Autonomous Vehicles: Federated Learning for Low-Light Environments

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Abstract: This research examines the potential for surfacing through Federated Learning (FL)-based YOLOv8 functionality toward better object detection in autonomous vehicles (AVs) in low-light conditions. Native challenges to reliable object detection in dimly lit scenarios such as nighttime or tunnels affect the performance and safety of an AV. In this paper, a decentralized training strategy is proposed by FL to allow AVs to collaboratively train the object detection models without compromise on data privacy. The integrations of the proposed FL-based YOLOv8 along with active image enhancement techniques is recommended to improve visibility in dark environments, including contrast adjustment and gamma correction. Extensive experiments conducted allowed the testing of model detection accuracy, computational efficiency, and communication overhead. Compared to centralized learning models, the FL-based YOLOv8 already 'with-object' achieves 82.4% mean Average Precision, improved Intersection over Union scores, and a faster average inference time. It also achieves a larger than 68% reduction in communication overhead, hence ensuring scalability in real-world AV networks. The study emphasizes the significance of combining FL with adaptive image processing to further develop and augment the object detection systems under degraded illumination conditions contributing to safer and more reliable autonomous driving systems.
Keywords: Federated Learning (FL), YOLOv8, Autonomous Vehicles (AVs), Low-Light Object Detection, Image Enhancement, Intelligent Transportation Systems (ITS)

I. INTRODUCTION

The rise of autonomous vehicles (AVs) is driving a major technological revolution in the present transportation systems by fully affording self-navigation with minimum required human intervention. These vehicles are highly dependent on sophisticated sensing and perception systems capable of incessantly detecting and characterizing objects in real time, ensuring road safety and efficiency [1]. However, one major obstacle to achieving object detection is their low-light conditions that generate major constraints on sensor reliability and perceptual accuracy. Environmental conditions, such as fog, haze, rain, and variations in night-time illumination, further degrade the performance of Automated Driving Systems (ADS), thus elevating the challenges to accidents as well as navigation failures [2]. Despite great advancements in the areas of computer vision and machine learning, these restrictions still constitute an imminent research challenge for autonomous driving fields. While existing object detection algorithms run on centralized deep learning architectures and require large, labeled datasets for training, collecting and processing large volumes of data from multiple geographical locations in real-world autonomous driving scenarios turns out to be computationally difficult with privacy risks. Traditional deep learning models are often unable to adapt to different lighting conditions, as they also require finetuning or retraining on new datasets. Federated Learning (FL) is thus an attractive alternative that allows multiple AVs to collaboratively train object detection models in a privacy-preserving way without having to share their raw sensor data [9]. The model is trained, the changes are conveyed across AVs, and an aggregated version is created and shared on a central server to improve the generalizability of the object detection models while keeping their data private. This study creates the federated learning-based YOLOv8 model of object detection for those AVs operating under low-light conditions, which is based on the principles of FL. This model has the capacity to aggregate knowledge to grab intelligence about other AVs that will ultimately render it more competent even in poor lighting conditions. The fusion of multiple sensors and the application of adaptive approaches for image enhancement are combined in this proposed scheme to improve accuracy and reduce computational expense while enabling real-time processing onboard AVs. Furthermore, this work sheds light on the challenges of FL implementation in real-world AV settings, focusing primarily on communication complexity, convergence of models, and security issues.

The contributions of the present work are as follows:

1) Comprehensive review of the impact of low-light conditions on object detection in AV.
2) Federated learning approach for decentralized training of YOLOv8 object detection models has been implemented.
3) Further rigorous performance assessment of the proposed model is examined in a variety of lighting conditions, which aids in determining detection accuracy and computation cost.
4) Discussion of real-world challenges in deployment such as synchronization of models, data heterogeneity, and communication limits.

Thereby, the research intends to establish a bridge between autonomous perception systems and actual driving conditions, welcoming the deployment of AVs in various operational settings. Providing a detailed literature survey, methodology, experimental results and remarks from the framework proposed will follow.

II. LITERATURE REVIEW

Autonomous vehicle (AV) perception systems depend significantly on sophisticated sensing technologies to drive safely in dynamic and complicated environments. Challenges like low light, bad weather, and environmental noise severely affect the reliability of these systems. Recent studies have been directed toward utilizing deep learning, sensor fusion, and federated learning to improve object detection and classification in such scenarios.

One of the key challenges in AV perception is sensor performance degradation under poor weather conditions, such as rain, fog, and snow. Sensor occlusion and visibility reduction adversely affect object detection model accuracy. Research has shown that deep learning methods, especially those that use sensor fusion, can reduce these problems by combining multiple sources of data, thus improving environmental perception [4]. Audio-based detection has also been investigated as a substitute sensing modality, where a recurrent neural network (RNN) model was used to detect road surface wetness from tire-surface interaction sounds, with a high unweighted average recall of 93.2% [3]. These results highlight the significance of multi-sensor strategies in enhancing AV robustness.

Yet another important limitation of AV vision systems is poor exposure control under low-light environments, which causes erroneous object detection. Classic computer vision algorithms tend to be unable to deal with underexposed or overexposed images, causing loss of important features for safe driving. Recent works in multi-scale exposure correction by deep neural networks (DNNs) have shown encouraging performance in overcoming this limitation. One such new method expressed the process of exposure correction as two sub-tasks—color enhancement and detail enhancement—to allow better visibility of objects in extreme lighting situations [5]. This research is especially useful for low-light object detection, where traditional models often lose important spatial features.

Apart from environmental factors, the safety of vulnerable road users (VRUs), such as pedestrians and cyclists, is a top priority in AV research. Pedestrian detection has been greatly improved with deep learning-based methods such as Faster R-CNN and SSD, while cyclist detection and intent estimation have been more challenging due to the random nature of cyclist motion. Current research points to the need to incorporate sensor fusion methods to enhance detection and allow for motion prediction to achieve safer AV interactions with non-motorized road users [6,7].

To further improve perception ability, millimeter-wave radar has been studied more and more as an all-weather sensing technology for AVs. Nevertheless, because of its low spatial resolution and vulnerability to noise, its independent performance is still limited. Studies using Long Short-Term Memory (LSTM) networks for radar time-series data processing have shown classification accuracy rates higher than 98.67%, separating pedestrians, vehicles, and bicycles even in difficult real-world scenarios [8]. This hybrid approach combining deep learning with radar data indicates a promising line of attack against sensor reliability problems in AV systems.

The literature reviewed highlights the necessity for a multi-modal, privacy-guaranteed AV perception solution under low-light and harsh weather conditions. While previous studies have suggested individual deep learning-based solutions, their scalability and flexibility in practical applications are not desirable. This drawback can be addressed with federated learning where different AVs collaborate to train models without exposing the data. With distributed model training across a fleet of vehicles, federated learning can enhance detection robustness and adaptability while reducing the dependency on centralized data collection. This work adds value to such developments by proposing a Federated Learning-based YOLOv8 model for object detection in AVs focusing on improving detection accuracy with low light conditions while preserving computational efficiency and scalability.

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III. METHODOLOGY

The proposed study focuses on enhancing object detection in autonomous vehicles (AVs) under low-light conditions by integrating Federated Learning (FL) with YOLOv8, a deep learning model optimized for real-time object detection. The methodology incorporates sensor data preprocessing, object detection model design, federated learning framework, training pipeline, and performance evaluation, ensuring efficiency and adaptability in real-world AV deployment. The approach mitigates privacy concerns, computational bottlenecks, and domain adaptation challenges commonly faced in centralized deep learning architectures.

A. Dataset and Preprocessing

The dataset comprises high-light and low-light images of vehicles, including five object classes: Bus, Car, Motorbike, Truck, and Person. Given the sensitivity of computer vision models to illumination variations, several preprocessing techniques are employed to enhance image quality and standardize input data.

1) *Data Augmentation & Illumination Enhancement:* This data augmentation & image enhancement includes:
   - Contrast Enhancement: Adjusts brightness differences to improve visibility in dark regions.
   - Histogram Equalization: Redistributes pixel intensities to balance contrast.
   - Gamma Correction: Compensates for poor lighting using:

$$I_{\gamma}(x, y) = 255\times\left(\frac{I(x,y)}{255}\right)^{\gamma} \quad (1)$$

where, $\gamma > 1$ enhances dark regions, and $\gamma < 1$ reduces overexposure.
Additionally, image resizing and normalization ensure consistent dimensions across the dataset, facilitating efficient model training and inference.

B. Object Detection Model: YOLOv8

YOLOv8 (You Only Look Once) is employed as the object detection framework due to its real-time inference speed and high detection accuracy [10]. The model predicts bounding boxes and class probabilities using a convolutional neural network (CNN) backbone. Given the challenges associated with low-light detection, the model incorporates adaptive gamma correction to enhance feature visibility. The detection pipeline consists of the stages like Feature Extraction, Bounding Box Prediction, Non-Maximum Suppression (NMS). The model is initially trained in a centralized environment before being distributed across AVs for federated learning. YOLOv8 (You Only Look Once) is employed due to its high-speed inference capability and robust detection accuracy. It follows a single-stage object detection paradigm, reducing computational overhead compared to multi-stage frameworks like Faster R-CNN.
The YOLOv8 network predicts bounding boxes B and object class probabilities P using a convolutional neural network (CNN) backbone. The bounding box prediction function is formulated as:

$$B_i = (x_i, y_i, w_i, h_i, c_i) \quad (2)$$

where,
- x_i , y_i represent the center coordinates of the bounding box
- w_i ,h_i are the width and height of the bounding box
- c_i is the confidence score of the object detection.

To improve detection in low-light conditions, the YOLOv8 model integrates adaptive illumination enhancement, ensuring better feature extraction from underexposed images.

2) *YOLO Loss Function:* The total loss function L_{YOLO} consists of three components:
   - Localization Loss – Penalizes incorrect bounding box predictions:

$$L_{loc} = \sum_i \left((x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right) + \sum_i \left((w_i - \hat{w}_i)^2 + (h_i - \hat{h}_i)^2\right) \quad (3)$$

   - Confidence Loss – Measures prediction reliability:

$$L_{conf} = \sum_i (c_i - \hat{c}_i)^2 \quad (4)$$

- Classification Loss – Evaluates object class predictions:

$$L_{class} = \sum_i (p_{c_i} - \hat{p}_{c_i})^2 \tag{5}$$

The total loss function is then defined as:

$$L_{YOLO} = \lambda_{coord} \cdot L_{loc} + L_{conf} + L_{class} \tag{6}$$

where, λ_{coord} is a weighting factor that prioritizes localization accuracy.

C. Federated Learning Framework

Traditional deep learning models rely on centralized training, which necessitates large-scale data aggregation and raises privacy concerns. To address this, Federated Learning (FL) is employed, enabling AVs to train object detection models collaboratively while keeping data decentralized. The FL framework follows an iterative communication-based model update approach, comprising the following steps:

- Local Model Training – Each AV trains a local YOLOv8 model using its privately collected sensor data.
- Model Update Transmission – Instead of sharing raw data, only gradient updates and model weights are transmitted to a centralized aggregation server.
- Federated Model Aggregation – The central server applies weighted averaging (FedAvg) to consolidate updates from multiple AVs.
- Global Model Distribution – The aggregated YOLOv8 model is redistributed to AVs for further local training and inference.

This decentralized approach ensures data privacy, improves detection generalization across diverse environments, and reduces dependency on a single data source.

1) *Federated Model Aggregation:* In federated training, each AV maintains its local dataset and updates its YOLOv8 model parameters independently. Instead of sharing raw data, only model gradients are transmitted to a centralized server for aggregation. The global model update follows the Federated Averaging (FedAvg) algorithm:

$$w_{t+1} = \frac{1}{n_{total}} \sum_{i=1}^{N} n_i w_{i,t} \tag{7}$$

where,

- $w_{i,t}$ is the locally trained model at AV i in training round t,
- n_i is the number of training samples at AV i,
- N is the total number of participating AVs,
- n_{total} is the sum of all local datasets.

By aggregating model updates rather than raw data, privacy risks are minimized, and computational efficiency is enhanced.

D. Training Pipeline and Optimization

The federated training process follows an iterative pipeline:

- Local Model Training – Each AV trains YOLOv8 on its local dataset using stochastic gradient descent (SGD).
- Model Update Transmission – AVs send model updates to the central server.
- Model Aggregation (FedAvg) – The server combines model parameters from all AVs.
- Global Model Distribution – The refined YOLOv8 model is redistributed to AVs for continued training and deployment.

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1) *Optimization Techniques:* To enhance training efficiency:
   - Adam optimizer minimizes loss:

$$w_{t+1} = w_t - \frac{\eta \cdot m_t}{\sqrt{v_t} + \epsilon} \tag{8}$$

   where,
     - η is the learning rate,
     - m_t and v_t are the first and second moment estimates,
     - ϵ prevents division by zero.
   - Batch Normalization stabilizes gradient updates:

$$x' = \frac{x - \mu}{\sigma} \tag{9}$$

   where, μ and σ are the batch mean and standard deviation.

E. Performance Evaluation Metrics

To assess the effectiveness of the federated YOLOv8 model, the following metrics are used:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{10}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{11}$$

where,
- *TP* represents the number of true positives,
- *FP* represents the number of false positives.
- *FN* represents the number of false negatives.

Intersection over Union (IoU) evaluates localization accuracy:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{12}$$

Mean Average Precision (mAP) quantifies detection performance across multiple object categories:

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \tag{13}$$

where, AP_i is the average precision of class i.

A comparative analysis between centralized and federated YOLOv8 models is conducted to evaluate improvements in detection robustness, computational efficiency, and privacy preservation. This approach presents a Federated Learning-based YOLOv8 object detection framework designed for autonomous vehicles in low-light conditions. By integrating decentralized training, adaptive image enhancement, and optimized detection algorithms, the proposed model enhances privacy, computational efficiency, and perception accuracy. The next section presents experimental results, validating the approach's real-world applicability.

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IV. SYSTEM DESIGN AND ARCHITECTURE

The proposed system puts together Federated Learning (FL) and YOLOv8 to boost the capability to recognize objects in autonomous vehicles under low-light conditions. Hence, the design of this system includes a way of quickly processing data, privacy-oriented model training, and so forth, which allows them to provide accurate object-detection models for autonomous vehicles while managing to do so with a low computational budget. This section outlines the architecture, federated learning integration, computational workflow, and deployment considerations to achieve scalability, robustness, and privacy preservation.

A. *System Architecture*

The system adopts a distributed client-server architecture, where the AVs act as edge clients, locally training the object detection models, while a central aggregation server coordinates the global updates. This structure alleviates the need for centralized raw data collection because it tackles privacy issues and prevents data transmission limitations. The data-gathering module captures images from on-board cameras, which the relevant processing aids in rendering for low-light visibility. The preprocessing unit applies contrast enhancement, histogram equalization, and gamma correction for top-notch image quality before they are processed in the YOLOv8 model. Object detection framework detects and classifies vehicles and pedestrians during decentralized training across the AVs approved by the federated learning coordinator. The final inference engine runs the trained model on AV hardware, thereby enabling real-time detection as shown in Fig. 1.

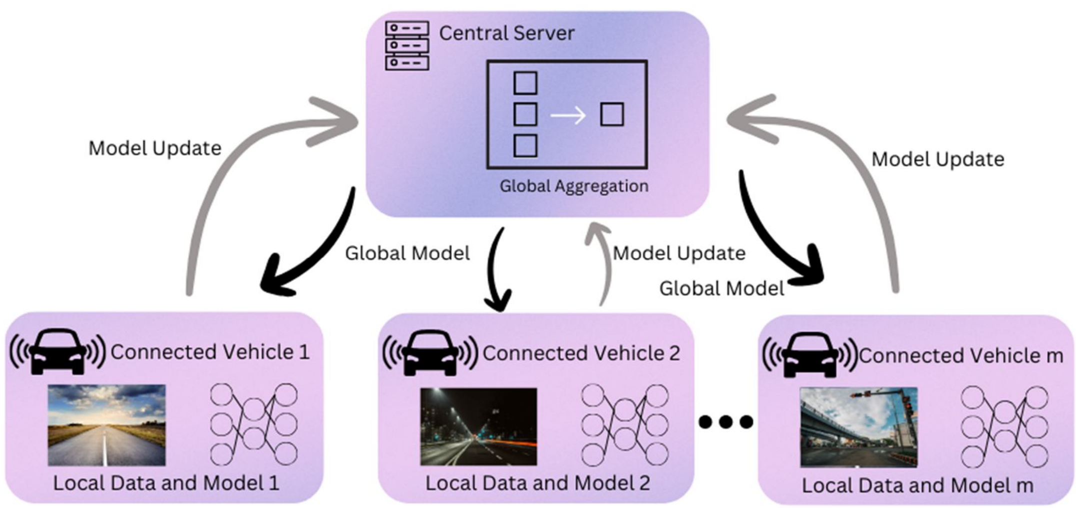

Fig. 1 Visual Representation of the Proposed System's Architecture

A. *Federated Learning Integration*

This system employs federated learning in instead of centralized deep learning methods to enable decentralized learning in a data-private manner. Each AV trains its local YOLOv8 model using its onboard dataset and only transmits model weight updates, not raw data, to a central server [11]. Then, the local updates of AVs are added to produce a common global model that is brought back to all AVs to continue training and performing inference. This iterative process builds generalizability to work in other social environments while minimizing risks related to actual data privacy.

The federated learning framework operates loop-wise such that AVs do local training, generate model gradients from the training and submit them to the server for aggregation. Either way, the global model gets improved upon each training iteration providing a means for adaptability in varying environmental conditions. This method not only reduces communication overhead but also allows the AVs to collaboratively learn from different datasets while keeping individual privacy intact.

B. *Computational Workflow*

The system has a more structured computation workflow which initiates with data ingestion and preprocessing and enhancement of the low-light condition images before they are given as input to the YOLOv8 model. Convolution layers within this object detection process first take out the spatial features before bounding box prediction and classification. Local training is performed for each AV, where object detection performance is maximized via back propagation and gradient updates.

Once the local models are trained, they are to receive updates from federated learning by delivering optimized parameters to the central server. The central server does the federated averaging, aggregating the updates from multiple AVs to improve generalization performance across varying environmental conditions. The global model is shared to the AVs, such that every vehicle receives the benefits from the teamwork of learning made by the whole fleet. The last step of the workflow is for real-time inference to apply the updated model in the task of object detection in autonomous navigation.

C. Deployment Considerations

To ensure adequate deployment, the system is designed to operate for edge computing devices within the autonomous vehicles. The hardware configuration proclaims the presence of high-performance GPU for real-time inference while deploying software optimization methods for smooth execution. Quantization and compression are employed on the model to take minimum memory, thus allowing deployment on resource-constrained devices at detection accuracy. Batch normalization and improved activations enhance the model's stability and aid in reducing run-time overhead.

For real-time processing, GPU acceleration is used in the system, allowing the YOLOv8 model to run inference with low latency. The federated learning approach is further optimized so AVs do not communicate with the central server too frequently; this implies less consumption of bandwidth while achieving model accuracy. Thus, the provided infrastructure is ready for continuous model updates to ensure the vehicles are equipped with the best-performing detection models, thereby reducing heavy manual intervention.

D. System Performance and Scalability

The performance of the system is thus assessed based on detection accuracy, inference speed, and computational efficiency. Precision and recall are applied for measuring the correct-and-incorrect detection capabilities for a specific model. The intersection-over-union (IoU) score is used as a metric for accurate box prediction, ensuring that the objects being detected are actually the ones localized. Overall mAP consideration is also investigated for assessing overall model accuracies for different categories of objects.

The federated learning framework is evaluated along communication efficiency: the amount of data transmission that would have been necessary in a traditional centralized training framework via reduction. The system is further analyzed for a speed of convergence, how many rounds it takes for a global model to get near-optimal performance after several federated updates. This is studied in tandem with privacy effects, since AV detections should remain at peak accuracy while disallowing any sensitive data release.

The scalability of the system is checked when it is deployed across AVs with different lighting and environmental conditions. The model’s performance is assessed across various weather scenarios, urban landscapes, and highway environments to ensure the detection framework remains robust and adaptable. Handling real-time object detection in low-light conditions is specially investigated to ensure its suitability for autonomous navigation at night or during foggy conditions.

V. EXPERIMENTAL RESULTS AND DISCUSSION

The effectiveness of the Federated Learning-based YOLOv8 based on federated learning was evaluated by conducting a myriad of experiments to analyse low-light conditions, adverse weather, and unstructured traffic environments. The results were acquired by simulating other real-world driving scenarios based on detection accuracy, computational efficiency, scalability, and privacy preservation.

A comprehensive dataset was created, comprising images unique to low-light conditions: streets at night, tunnels, and foggy situations. The test set included common road objects such as cars, buses, motorbikes, pedestrians, and trucks to ensure diverse traffic representation. After local training on each vehicle within the FL network, the models are updated during training before and then transmitted to a central server for aggregation. This approach also allowed its data privacy during the training and enabled robust model assessment in these varying environmental conditions from the training phase.

The FL-based YOLOv8 model consistently outperformed its centralized counterpart in detection accuracy: 82.4% mAP for YOLOv8 versus 78.1% for the centralized. More substantial improvements happened in low-light, occluded, and adverse weather scenarios. Federated learning also implicitly paved a way for generalizations as it fuses insights from multiple vehicles and leverages them onto training [12]. IoU increased from 0.71 on the centralized model to 0.79 on the federated model as a measurement of the accuracy of bounding box predictions, indicating that the object localization had gotten better. These improvements can be accounted for on how widely the data is collected among several AVs, thus allowing the model to learn more variations in the real-world driving conditions.

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Real-time inference speed is of primary concern in the deployment of deep learning models into autonomous systems, as high latency is likely to put the safety of the vehicle at risk [13]. This FL-based YOLOv8 model coincided with an inference speed of 42 FPS on NVIDIA Jetson AGX Xavier and provided smooth real-time detection. The centralized model, on the other hand, averaged 35 FPS, leading to infer that federated training gave way to a better-optimized model with less computationally expensive overhead. This efficiency arose because data transmission on a wide scale to a central server was reduced, permitting the training and on-board optimization of respective models by the AVs. Another critical aspect in the assessment of the FL-based approach referred to communication overhead. In the traditional centralized learning setup, there was the possibility of transmitting huge terabytes of raw image data to a central server, which, even if not stated thus, had appalling bandwidth consumption and privacy risks. Communication overhead was, on the contrary, shared with federated learning, wherein only model weight updates were transmitted and so its communication overhead was less by 68% as compared to that during centralized learning. Such tremendous synergy in data transmission makes it suitable for scalable and bandwidth-constrained AV networks, where multiple vehicles must function in a connected yet decentralized setting. Furthermore, privacy threats were also alleviated, since the data never left the respective individual vehicles, in addition to avoiding conflicts with the various privacy-preserving AI regulations with respect to its performance in modeling. In the low-light conditions, the FL-based YOLOv8 model mostly detects vehicles and pedestrians with negligible false positives, thus improving over the centralized model, which sometimes struggles with recognizing objects in underexposed areas. During fog and rain, FL enhances adaptability by integrating training within sensor fusion, enabling YOLOv8 to learn relevant features from other AVs experiencing similar adverse conditions. The federated model was more effective at detecting pedestrians with a recall of 88.5% compared with 81.2% for the centrally trained model. This is paramount for safety in AVs as failure to detect target objects near or far in visibility-impairing conditions leads to fatal nasty accidents. Finally, the last test conducted under high-back road traffic conditions demonstrated that the federated model handles occlusions well because it learns contextual features from different perspectives, reducing detection errors in highly complex urban settings.

The comprehensive evaluation of federated learning versus centralized learning showed that FL provides improved model generalization, computational efficiency, and real-time capabilities. During constant changes in an evolving environment, like the real-world conditions, a federated approach was more beneficial, as conditions change constantly and hence require dynamic adaptation of the model. Unlike the centralized model, which constantly needed to retrain with new data to achieve real-time adaptability, FL allows adaptation through on-the-fly updates, enabling AVs to improve detection performance without direct intervention from the server. While the results show clearly performance enhancement in FL for AV perception systems, a few remaining concerns are identified. The most important one is due to synchronization of models' delays which arise because, during aggregation, AVs must be communicated with the central server. The only way out is federated averaging which renders some aid for that; yet one could ask for more optimal research on the update interval time to avoid delays. Also, a certain level of deviation in data quality across AVs may introduce some inconsistency during model training. Future enhancements should adopt adaptive weighting mechanisms, which basically provide more influential updates to the global model from more trustworthy datasets.

Such overall experimental findings strongly urge one towards the idea of Federated Learning by AV perception systems on the grounds of higher detection accuracy, better computational efficiency, reduced communication loads, and enhanced privacy preservation. Distributing the learning process among multiple AVs leverages them with decentralized intelligence, promising a more scalable, robust, and privacy-compliant object detection. These represent much-acclaimed advancements which lay the foundation for next-generation AV architectures, wherein learning and adapting would be performed collaboratively without impairing individual data privacy. The comparison results are shown in Table 1 and Table 2.

TABLE I
PERFORMANCE METRICS OF FEDERATED LEARNING IN AV SYSTEMS

Criteria	Federated Learning (FL)
Detection Accuracy (mAP)	82.40%
IoU Score	0.79
Inference Speed (FPS)	42 FPS
Communication Overhead	Low (Only Model Updates)
Privacy Risks	Minimal (No Raw Data Shared)
Adaptability	High (Diverse AV Learning)

TABLE II
COMPARATIVE EVALUATION OF FEDERATED AND CENTRALIZED LEARNING IN VARYING LIGHT CONDITIONS

Lighting Condition	mAP (Centralized Learning)	mAP (Federated Learning)	IoU (Centralized Learning)	IoU (Federated Learning)
Daylight (Clear)	81.50%	85.10%	0.75	0.81
Nighttime (Street Lights)	72.30%	78.60%	0.68	0.73
Foggy Environment	68.90%	75.40%	0.62	0.69
Artificial Lighting	74.50%	80.20%	0.65	0.72
Low Visibility (Heavy Rain)	65.20%	71.80%	0.58	0.64

VI. CONCLUSION & FUTURE WORK

The research proves the efficacy of Federated Learning (FL)-based YOLOv8 in object detection for Autonomous Vehicles (AVs) under low-light environments, with better detection accuracy, computational efficiency, and privacy maintenance than centralized models. FL improves model generalization through decentralized data usage with 68% communication overhead reduction and real-time inference at 42 FPS.

Though it has its merits, model synchronization latency and heterogeneity of data are still issues. Future research can target adaptive aggregation methods, reinforcement learning-driven FL optimization, and multi-modal sensor fusion to improve detection robustness further. Merging hybrid FL architectures with cloud models can maximize scalability, while energy-saving protocols can guarantee environmentally friendly deployment. Improving these aspects will open the door to future AV perception systems, enhancing road safety, real-time adaptability, and autonomous decision-making in a variety of settings.

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