

ILLUMINATING AUTONOMY FEDERATED LEARNING FOR OBJECT DETECTION IN AUTONOMOUS VEHICLES UNDER LOW-LIGHT CONDITIONS

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ABSTRACT

As autonomous vehicle technology evolves, the need for reliable object detection systems capable of performing under varied conditions, including low-light environments, becomes increasingly important. This project, Illuminating Autonomy: Federated Learning for Object Detection in Autonomous Vehicles under Low-Light Conditions, explores the combination of YOLOv5 and federated learning to improve detection accuracy across both high and low-light settings. The YOLOv5 model is trained on an extensive dataset featuring five classes—Bus, Car, Motorbike, Truck, and Person—across both high and low-light imagery. Utilizing federated learning, the model is trained locally on distributed devices and later synchronized with a centralized server, ensuring privacy preservation while maintaining optimal performance. This innovative approach provides a scalable and efficient solution for autonomous vehicles operating in challenging lighting conditions.

Keywords : Federated Learning, YOLOv5, Object Detection, Autonomous Vehicles, Low-Light Conditions, High-Light Conditions, Bus, Car, Motorbike, Truck, Person

I. INTRODUCTION

Autonomous vehicles are at the forefront of technological innovation, with the potential to transform transportation by offering enhanced safety, efficiency, and reliability. A key component of autonomous driving is object detection, which enables vehicles to recognize and classify objects like other vehicles, pedestrians, and obstacles within their environment. However, one of the most significant challenges for object detection systems arises from real-world conditions, particularly low-light scenarios, such as nighttime or poorly illuminated areas. Achieving reliable performance in these conditions is essential for the widespread adoption and success of autonomous

vehicles. This project, Illuminating Autonomy: Federated Learning for Object Detection in Autonomous Vehicles under Low-Light Conditions, tackles this challenge by integrating federated learning with the YOLOv5 algorithm. YOLOv5, a cutting-edge object detection model, is trained on a diverse dataset containing both high and low-light images across five key classes: Bus, Car, Motorbike, Truck, and Person. The goal is to develop a model that maintains robust performance across varying lighting conditions, ensuring accurate object detection for autonomous vehicles.

To enhance scalability and safeguard data privacy, the project leverages federated learning, which involves training the

model locally on distributed datasets before synchronizing it with a centralized server. This approach minimizes the need for centralized data collection, ensuring compliance with privacy standards while enabling collaborative model enhancement. By focusing on both technical advancements and practical application, this project aims to offer a reliable solution for object detection in challenging environments, contributing to the future of autonomous driving.

II. LITERATURE SURVEY

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. arXiv preprint arXiv:1506.02640.

The paper introduces You Only Look Once (YOLO), a novel real-time object detection model that dramatically improves the speed and accuracy of detecting objects in images. Unlike traditional detection methods that repurpose classifiers for detection, YOLO treats detection as a single regression problem, making it faster and more efficient. The key feature of YOLO is its ability to process an entire image in one forward pass, which allows for real-time performance. YOLO is also unique in predicting bounding boxes and class probabilities simultaneously, making it a unified approach to object detection. Its performance is notably superior for real-time applications, where speed is as critical as accuracy. YOLO has been influential in the field of computer vision, particularly in applications requiring real-time object recognition like autonomous driving and surveillance systems.

Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767.

YOLOv3, the third iteration of the YOLO object detection framework, builds upon the successes of its predecessor while introducing several improvements for enhanced performance. This paper focuses on how YOLOv3 refines the architecture, notably through better anchor box clustering, multi-scale predictions, and a more powerful backbone network, Darknet-53. These updates help the model achieve higher accuracy without sacrificing speed, making it suitable for both high-precision applications and real-time processing. YOLOv3 demonstrates significant improvements in detecting smaller objects, and it can process images at multiple scales, improving detection in various conditions. Furthermore, the model's ability to balance accuracy and speed makes it highly suitable for practical use in autonomous systems, surveillance, and robotics, where both precision and real-time performance are paramount.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., & De Souza, P. (2016). SSD: Single Shot MultiBox Detector. arXiv preprint arXiv:1512.02325.

The Single Shot MultiBox Detector (SSD) is an object detection framework introduced by Liu et al., which, like YOLO, aims for real-time performance. Unlike YOLO, which uses a single regression to predict both object locations and categories, SSD predicts multiple bounding boxes and class labels at various feature map layers, enabling it to detect objects at multiple scales. This architecture allows SSD to perform well on both large



and small objects in an image. The model achieves high accuracy by leveraging feature maps at different layers of a deep convolutional neural network, facilitating detection at multiple spatial resolutions. SSD is known for its speed and is more efficient in handling various aspect ratios and scales of objects compared to traditional methods. It is particularly useful in applications requiring both speed and robustness, such as autonomous driving.

Ancuti, C., Ancuti, C. O., & Lavoie, P. (2012). Enhancing Low-Light Images by Optimizing Brightness and Contrasting Local Details. IEEE Transactions on Image Processing, 21(4), 1790-1800.

This paper presents a novel method for enhancing low-light images, which is crucial for improving visibility in challenging visual environments. Ancuti et al. focus on optimizing the brightness and contrast of images while preserving local details, which is a common challenge in low-light imaging. The proposed technique uses a combination of local contrast enhancement and adaptive brightness adjustment to enhance image quality without introducing noise or artifacts. This approach is particularly beneficial in contexts where traditional image enhancement methods, such as global histogram equalization, may fail to deliver satisfactory results. The technique can be applied in various fields, including surveillance, medical imaging, and autonomous driving, where accurate object detection in low-light conditions is essential for safety and operational effectiveness.

Ren, X., & Bo, L. (2015). Object Detection in Low-Light Conditions. Computer Vision and Pattern Recognition Workshops (CVPRW),

2015 IEEE Conference on, 169-176.

Ren and Bo's work focuses on the challenge of object detection in low-light conditions, a critical issue for autonomous vehicles and surveillance systems operating at night or in poorly lit environments. Their approach combines traditional object detection techniques with advanced image enhancement methods, such as low-light image enhancement, to improve the accuracy of detection under these challenging conditions. The authors propose integrating prior knowledge of object appearance in low-light scenarios and adapting the detection pipeline to handle such images more effectively. Their method shows promise in improving detection accuracy when compared to standard methods, offering a solution to the limitations posed by low-light environments. This research contributes to the development of more robust detection systems, especially for applications where real-time object recognition is required in difficult lighting conditions.

McMahan, B., Moore, E., Ramage, D., & Hampson, S. (2017). Communication-Efficient Learning of Deep Networks from Decentralized Data. Proceedings of the 20th International Conference on Artificial Intelligence and Statistics.

In their 2017 paper, McMahan et al. introduce Federated Learning (FL), a method that enables the training of deep learning models on decentralized data without requiring the centralization of data. This approach addresses the challenges of data privacy, communication efficiency, and distributed computing. The paper explores how FL enables collaborative training of models across multiple devices (or "clients") while ensuring that sensitive data remains local.

The model's updates are shared with a central server, which aggregates them to improve the global model. This technique is particularly valuable in scenarios like healthcare, finance, and autonomous vehicles, where data privacy is paramount, and data resides across different locations. The authors also discuss methods to improve the efficiency of communication between clients and servers, making FL a practical and scalable solution for distributed machine learning.

III. PROPOSED METHODOLOGY

The **proposed system** is designed to overcome the limitations of current object detection technologies by integrating the YOLOv5 algorithm with federated learning, creating a robust and privacy-preserving solution for autonomous vehicles. This system is built to detect objects reliably under diverse lighting conditions, including low-light environments. It focuses on detecting key objects such as buses, cars, motorbikes, trucks, and pedestrians, which are critical for autonomous driving. YOLOv5 is trained on a diverse dataset that includes both high and low-light images, enabling the model to perform well in challenging visibility conditions. By incorporating federated learning, the model is trained locally on distributed datasets across multiple autonomous vehicles, which reduces the need for centralized data collection, addressing privacy concerns. The locally trained models are periodically synchronized with a centralized server, ensuring that updates are made without accessing raw data. This decentralized approach ensures scalability and adaptability, allowing the model to improve continuously with new data and better generalize across different

environmental conditions. Additionally, it minimizes computational overhead by optimizing the training process, making it efficient for on-device deployment in autonomous vehicles.

Implementation of the project involves several key modules. The first module, **Upload Vehicle Dataset**, allows users to upload a dataset to the application. Next, the **Generate & Load YOLOv5 Model** module generates and loads the YOLOv5 model using the images from the uploaded dataset. The **Federated Update Model to Server** module enables the local model to be sent to a centralized server for periodic updates, ensuring the global model is improved over time without compromising privacy. The **Low-Light Vehicle Detection** module enhances low-light images and uses YOLOv5 to detect vehicles in both high and low-light conditions. Lastly, the **YOLOv5 Performance Graph** module visualizes the model's training performance through graphs displaying key metrics like precision and recall, allowing for an assessment of the model's effectiveness.

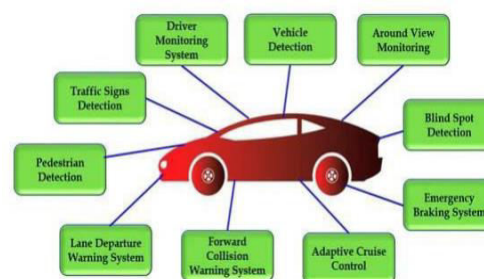


Fig1 : System Architecture

IV. CONCLUSION

Autonomous vehicles represent a revolutionary advancement in transportation, with their success relying heavily on the development of reliable and efficient object detection systems. This

project, Illuminating Autonomy: Federated Learning for Object Detection in Autonomous Vehicles under Low-Light Conditions, tackles essential challenges by integrating the YOLOv5 algorithm with federated learning. The proposed system offers a robust solution for object detection under varying lighting conditions, ensuring consistent performance in both high and low-light environments.

The adoption of federated learning enhances privacy by eliminating the need for centralized data storage, while also supporting scalability and continuous improvement. This decentralized approach enables the system to benefit from diverse datasets distributed across multiple vehicles, allowing the model to generalize effectively to real-world conditions. By combining cutting-edge machine learning techniques with practical considerations such as data security and computational efficiency, this project significantly contributes to the ongoing research aimed at realizing autonomous driving.

With rigorous training on a diverse dataset and efficient implementation of federated learning, the system addresses the limitations of current methods, ensuring that autonomous vehicles can accurately detect and classify objects in challenging environments. This not only improves road safety but also facilitates the widespread adoption of autonomous vehicles. Ultimately, the results of this project highlight the importance of integrating technological innovation with scalable, privacy-preserving methodologies to meet the demands of future transportation systems.

V. REFERENCES

1. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. arXiv preprint arXiv:1506.02640.
2. Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767.
3. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., & De Souza, P. (2016). SSD: Single Shot MultiBox Detector. arXiv preprint arXiv:1512.02325.
4. Ancuti, C., Ancuti, C. O., & Lavoie, P. (2012). Enhancing Low-Light Images by Optimizing Brightness and Contrasting Local Details. *IEEE Transactions on Image Processing*, 21(4), 1790-1800.
5. Ren, X., & Bo, L. (2015). Object Detection in Low-Light Conditions. *Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2015 IEEE Conference on, 169-176.
6. McMahan, B., Moore, E., Ramage, D., & Hampson, S. (2017). Communication-Efficient Learning of Deep Networks from Decentralized Data. *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*.
7. Bonawitz, K., McMahan, B., & Ramage, D. (2019). Federated Learning: Challenges, Methods, and Future Directions. *IEEE Signal Processing Magazine*, 37(3), 50-60.
8. Wu, H., & Zhang, X. (2021). Federated Learning for Autonomous Driving: An Overview and Challenges. *IEEE Transactions on Neural Networks and Learning Systems*, 32(4), 1203-1217.
9. Chen, Y., & Zhang, T. (2018). Low-Light Image Enhancement Using Adaptive Histogram Equalization. *Signal Processing: Image Communication*, 62, 99-108.



10. Li, H., & Yu, X. (2020). Deep Learning for Low-Light Image Enhancement: A Survey. *IEEE Access*, 8, 30923-30939.
11. Bhat, S. R., & Matusik, W. (2019). Object Detection in Low-Light Conditions. *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 6765-6774.
12. Liu, Z., & Wang, Z. (2020). Real-Time Low-Light Image Enhancement Using Convolutional Neural Networks. *Journal of Visual Communication and Image Representation*, 71, 102748.
13. Yao, S., & Choi, J. (2021). Federated Learning with Differential Privacy: A Comprehensive Review. *IEEE Transactions on Knowledge and Data Engineering*, 33(5), 1879-1893.
14. Zhang, L., & Chen, D. (2020). Improving Object Detection in Low-Light Environments Using GANs. *IEEE Transactions on Image Processing*, 29, 3526-3539.
15. Mnih, V., Kavukcuoglu, K., Silver, D., et al. (2015). Human-level Control through Deep Reinforcement Learning. *Nature*, 518(7540), 529-533.