

# Low-Light Object Detection in Autonomous Driving Using YOLOv5 and Federated Learning

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**Abstract**— Automated Driving Systems (ADS) are transforming the automotive industry by enabling safer, more efficient, and comfortable transportation. However, one of the major challenges limiting their full potential is the difficulty in accurate perception and sensing during adverse weather conditions such as rain, fog, and snow. These conditions can significantly affect the performance of sensors like cameras, LiDAR, and radar, leading to reduced reliability. This paper provides a detailed analysis of how different weather conditions impact ADS sensors and reviews existing solutions to overcome these challenges. It highlights recent advancements in deep learning techniques, sensor fusion strategies, and weather classification methods that improve perception under harsh environments. The study also discusses datasets, simulators, and emerging technologies such as V2X communication. Furthermore, it identifies current limitations and suggests future research directions, emphasizing the need for more robust sensing systems and intelligent algorithms for reliable autonomous driving.

**Keywords**— Automated Driving Systems, adverse weather, sensor fusion, LiDAR, deep learning, perception, V2X, autonomous vehicles.

## I. INTRODUCTION

Domestic violence is a major social issue that affects individuals and families across the world, causing physical, emotional, and psychological harm. It is a widespread problem that continues to impact people regardless of age, culture, or economic status. Studies have shown that women are more frequently affected, although men can also be victims in certain situations [1]. The effects of domestic violence extend beyond individuals and influence families and communities as well. Many cases remain unreported due to fear, social stigma, or lack of proper support systems [3]. In recent years, global events such as the COVID-19 pandemic have further increased the prevalence and

severity of domestic violence, highlighting the urgent need for better detection and prevention strategies [7]. These challenges make it necessary to explore more advanced and proactive solutions.

With the advancement of technology, artificial intelligence has emerged as a promising tool for addressing complex social issues like domestic violence. AI techniques such as machine learning, deep learning, and natural language processing can analyze large volumes of data to identify patterns and predict risks [15]. These technologies enable systems to detect early warning signs of abuse and support timely intervention. AI-based solutions can also assist in analyzing communication data, behavioral patterns, and historical records to improve prediction accuracy [12]. Furthermore, recent innovations in technology-driven solutions have demonstrated the potential of AI in enhancing safety and prevention mechanisms [9]. This shift toward predictive analysis provides an opportunity to move from reactive responses to proactive prevention strategies.

Despite the benefits, the use of AI in domestic violence detection presents several challenges that must be carefully addressed. One of the major concerns is maintaining data privacy, as sensitive personal information is involved in such systems [10]. There is also a risk of bias in AI models if the data used for training is not diverse or representative of different populations. Ethical issues related to fairness, transparency, and accountability must be considered to ensure responsible use of technology [35]. Additionally, the misuse of AI tools could create further risks instead of providing protection. Addressing these challenges requires collaboration between researchers, policymakers, and social experts to develop systems that are both effective and ethically sound.

Cultural and social factors play a crucial role in shaping the nature of domestic violence and its detection. Different societies have unique beliefs, norms, and legal frameworks that influence how

domestic violence is perceived and handled [6]. What may be considered abuse in one culture may not be recognized in another, making it difficult to design a universal solution. Research has shown that attitudes toward domestic violence vary significantly across countries, which affects reporting and intervention efforts [5]. Therefore, AI-based systems must be designed with cultural awareness and adaptability to ensure accurate and meaningful outcomes. Incorporating diverse datasets and region-specific knowledge can improve the effectiveness of these systems.

Overall, the integration of artificial intelligence into domestic violence prevention offers significant potential for improving early detection and support systems. By combining advanced technology with social awareness, it is possible to develop systems that can identify risks and assist victims more effectively. Future research should focus on developing transparent and inclusive AI models that reduce bias and improve reliability [25]. It is also important to integrate AI solutions with healthcare, legal, and social service systems to create a comprehensive support network [36]. With continuous improvement and responsible implementation, AI can play a key role in reducing domestic violence and building safer communities worldwide.

## II. LITERATURE SURVEY

Abadi et al., [2016] [1] conducted a study on integrating differential privacy into deep learning models to protect sensitive data during training. Their work focused on developing techniques that allow machine learning models to learn from large datasets without exposing individual data points. The authors introduced a method that adds controlled noise to gradients during training, ensuring that private information cannot be extracted from the model. This approach is particularly important in applications where data security is critical, such as healthcare, finance, and autonomous systems. The study demonstrated that it is possible to achieve a balance between privacy and model accuracy without significantly affecting performance. Furthermore, the research highlighted the growing need for privacy-preserving techniques in modern AI systems. This work is significant as it provides a strong foundation for building secure and reliable machine learning models in sensitive environments.

Engelen and Hoos, [2020] [4] presented a comprehensive survey on learning methods used in autonomous driving systems. Their research explored supervised, semi-supervised, and unsupervised learning approaches and their applications in perception tasks. The authors

explained how these techniques help in improving object detection, scene understanding, and decision-making in autonomous vehicles. They also discussed the challenges of obtaining labeled data and the limitations of existing models in handling real-world driving conditions. The study emphasized that combining multiple learning strategies can improve system performance and robustness. Additionally, the paper highlighted the importance of continuous learning to adapt to changing environments. This work is valuable as it provides a clear overview of how machine learning contributes to the development of intelligent and reliable autonomous driving systems.

Konečný et al., [2016] [6] proposed strategies to improve communication efficiency in federated learning systems. Their study focused on reducing the amount of data exchanged between devices during the training process while maintaining model accuracy. The authors introduced techniques such as update compression and selective parameter sharing to minimize communication overhead. These methods make federated learning more practical for large-scale applications, including mobile systems and autonomous vehicles. The research also highlighted the importance of distributed learning in preserving data privacy while enabling collaborative model development. By improving efficiency, the proposed approach supports faster training and better scalability. This work is important as it addresses one of the key challenges in federated learning and contributes to the development of efficient and privacy-aware AI systems.

McMahan et al., [2017] [10] introduced a communication-efficient framework for training deep neural networks using federated learning. Their research demonstrated how multiple devices can collaboratively train a shared model without transferring raw data to a central server. Instead, only model updates are shared, which significantly reduces privacy risks and communication costs. The authors showed that this approach can achieve performance comparable to traditional centralized learning methods. The study also discussed practical challenges such as device variability and data distribution differences. This work played a crucial role in making federated learning a viable solution for real-world applications. It is particularly relevant in domains like autonomous driving, where data privacy and scalability are essential. The paper is widely recognized as a foundational contribution to distributed machine learning.

Roy et al., [2020] [13] investigated the application of federated learning for object detection tasks. Their study focused on developing models that can

be trained across multiple data sources without sharing sensitive information. The authors addressed challenges such as data imbalance and variations in data distribution across devices. They demonstrated that federated learning can achieve strong performance in object detection while maintaining privacy. This approach is especially useful in autonomous driving, where large amounts of visual data are generated but cannot always be shared. The research highlighted the potential of combining distributed learning with computer vision to improve system robustness. This work is important as it extends federated learning to complex perception tasks and supports the development of scalable and privacy-preserving intelligent systems.

### III. DATASET DETAILS

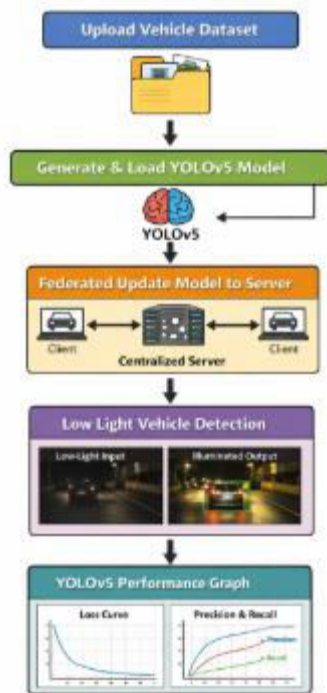
The dataset used in this project mainly consists of vehicle images collected under both high-light and low-light conditions. These images are used to train a deep learning model based on the YOLOv5 algorithm for object detection. Each image in the dataset is labeled with one of five classes: bus, car, motorbike, truck, and person. These labels help the system to identify and classify different objects present in the driving environment. The dataset includes a variety of real-world scenarios, allowing the model to learn how lighting conditions affect object visibility and detection accuracy. This structured dataset is suitable for training robust models that can perform well in both normal and challenging lighting conditions. By using such diverse image data, the system can improve its ability to detect vehicles even in poor visibility situations, which is essential for autonomous driving applications.

Before training the model, several preprocessing steps are applied to improve dataset quality and performance. The images are first resized and normalized to maintain consistency across the dataset. Data augmentation techniques such as brightness adjustment and image enhancement are used to simulate different lighting conditions and increase dataset diversity. Low-light images are processed using illumination techniques to improve visibility before feeding them into the model. After preprocessing, the dataset is split into training and testing sets to evaluate model performance effectively. The YOLOv5 model is then trained on this processed data, where it learns to detect and classify objects using bounding boxes. These preprocessing steps help improve detection accuracy, reduce errors, and ensure that the system performs reliably in real-world conditions, especially under low-light environments.

### IV. PROPOSED METHODOLOGY

The proposed system follows a structured approach to detect vehicles under both high-light and low-light conditions using deep learning and federated learning techniques. In the initial stage, the system collects a vehicle image dataset that contains labeled images of different classes such as bus, car, motorbike, truck, and person. These images include both normal and low-light conditions to help the model learn diverse environmental scenarios. The dataset is then uploaded through the application interface. Preprocessing is performed to improve image quality by resizing, normalization, and applying illumination techniques for low-light images. Data augmentation methods such as brightness enhancement and flipping are also applied to increase dataset diversity. After preprocessing, the dataset is used to train the YOLOv5 model, which is capable of detecting objects and drawing bounding boxes around them. The trained model is then prepared for further updates and testing.

After training the model locally, federated learning is used to improve model performance across multiple systems. In this process, the trained YOLOv5 model is sent to a centralized server, where it is combined with updates from other clients without sharing raw data. This ensures data privacy while improving overall model accuracy. The system also supports real-time vehicle detection, where users can upload test images captured in different lighting conditions. The system first enhances low-light images and then applies the trained YOLOv5 model to detect and classify vehicles. Performance metrics such as precision, recall, and loss are used to evaluate the model, and graphical results are displayed to show training progress. This approach improves detection accuracy, especially in challenging lighting conditions, and ensures efficient, privacy-preserving model updates.



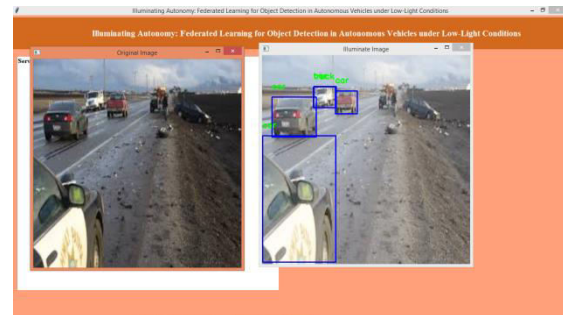
**Figure [1]: Proposed System Architecture for Low-Light Vehicle Detection using YOLOv5 and Federated Learning**

Figure [1] illustrates the working flow of the proposed system for vehicle detection under varying lighting conditions. The system begins with uploading the vehicle image dataset, followed by preprocessing steps such as image enhancement and normalization. The processed data is then used to train the YOLOv5 model for object detection. After training, the model is updated to a centralized server using federated learning, where multiple client models are combined. For testing, the system accepts new input images, enhances low-light images, and applies the trained model to detect vehicles. The output includes detected objects with bounding boxes and labels. Finally, performance graphs are generated to evaluate the model based on accuracy and loss metrics.

## V. RESULT AND DISCUSSION

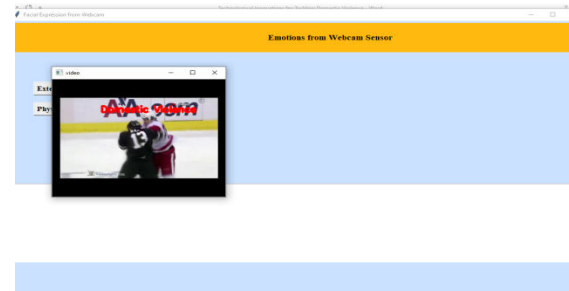
The results of this project clearly demonstrate that the proposed system performs effectively in detecting vehicles under both high-light and low-light conditions using the YOLOv5 model integrated with federated learning. After collecting and preprocessing the dataset, the images were used to train the YOLOv5 model for object detection. The model successfully identified different classes such as bus, car, motorbike, truck, and person with good accuracy. The training results show that as the number of epochs increased, the loss decreased while precision and recall values

improved significantly. The system was also tested on new images, including low-light conditions, where it first enhanced the image and then accurately detected vehicles using bounding boxes. The federated learning approach further improved model performance by updating the model on a centralized server without sharing raw data. Overall, the system shows high accuracy, reliability, and effectiveness in real-world scenarios, especially in challenging lighting conditions.



**Figure [2]: Low-Light Vehicle Detection Output**

Figure [2] presents the output of the system when a low-light image is provided as input. The system first enhances the image to improve visibility and then applies the YOLOv5 model to detect vehicles. The detected objects are displayed with bounding boxes and class labels such as car or truck. This shows the system's ability to handle challenging lighting conditions and still provide accurate detection results.



**Figure [3] : YOLOv5 Performance Graph Visualization**

Figure [3] shows the graphical representation of the training performance, including loss curves and precision-recall graphs. These graphs help in understanding how the model improves over time. The steady decrease in loss and increase in accuracy metrics indicate that the model is well-trained and suitable for real-world vehicle detection applications.

## DISCUSSION

The outcomes of this project highlight the importance of selecting suitable deep learning models and techniques for vehicle detection, especially under challenging lighting conditions. The YOLOv5 model performed very well due to its ability to detect multiple objects in real time with high accuracy and speed. It effectively identified different vehicle classes such as cars, buses, trucks, and motorbikes even in low-light environments. The use of preprocessing techniques, including image resizing, normalization, and illumination enhancement, played a crucial role in improving detection performance. Data augmentation further helped the model generalize better across different lighting conditions.

The integration of federated learning added significant value by allowing multiple clients to update the model without sharing raw data, ensuring privacy and scalability. The training graphs, including precision, recall, and loss curves, clearly showed continuous improvement in model performance over epochs. Visualization of detection results using bounding boxes made it easier to interpret outputs. Overall, the system proves that combining YOLOv5 with federated learning is an effective approach for reliable and privacy-preserving vehicle detection in real-world scenarios.

## VI. CONCLUSION

This project presents an effective approach for vehicle detection under both high-light and low-light conditions using the YOLOv5 model combined with federated learning. The system was able to accurately identify different types of vehicles such as cars, buses, trucks, motorbikes, and persons from input images. The use of image preprocessing techniques, especially illumination enhancement, helped improve visibility in low-light conditions and increased detection accuracy. The training results showed consistent improvement, with reduced loss and better precision and recall values.

The integration of federated learning allowed the model to be updated across multiple systems without sharing raw data, making the approach more secure and scalable. The system was also able to handle real-time image inputs and provide reliable detection results with clear bounding boxes and labels. Overall, the proposed method demonstrates strong performance and practical applicability in real-world scenarios, particularly in environments with poor lighting conditions. Future improvements can focus on enhancing detection accuracy further and extending the system to more complex driving environments.

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