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A Minor Project -2 Report

On

High Security Registration Plate Detection and Classification Using Federated Learning

submitted in partial fulfillment of the requirement for the degree of

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In

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CERTIFICATE

This is to certify that Minor Project -2 entitled High Security Registration Plate Detection and Classification Using Federated Learning is a bonafied work carried out by the student team Prachi Singh: 01FE21BCS091 Varsha S H: 01FE21BCS084 Girish Badamikar: 01FE21BCS168 Gouri Parashetti: 01FE21BCI054 in partial fulfillment of completion of Sixth semester B. E. in School of Computer Science and Engineering duringthe year 2023-2024. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said program.

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ABSTRACT

High Security Registration Plate (HSRP) classification is vital for enhancing vehicle security, aiding law enforcement, automating toll collection, managing traffic, and ensuring regulatory compliance. Federated Learning (FL) enables multiple nodes, each holding localized data, to collaboratively train a global model without sharing raw data, thus maintaining privacy while benefiting from the collective knowledge of all nodes. Federated Averaging aggregates model updates from each node to create a robust global model. YOLOv8, known for its real-time processing capabilities and high precision, serves as the core detection algorithm, efficiently identifying and classifying HSRPs in images.

The major contributions of this work include: 1) deploying the application using Federated Learning to ensure data privacy and security during the model training process across distributed data sources, eliminating the need to centralize sensitive information; 2) utilizing Roboflow for efficient annotation and dataset management, facilitating high-quality and consistent data labeling; and 3) developing and fine-tuning a YOLOv8-based detection model specifically for HSRP, addressing the unique challenges posed by varying environmental conditions, occlusions, and diverse plate designs.

Ensuring data privacy not only protects sensitive information and complies with data protection regulations but also builds trust among users, reduces the risk of data breaches, and encourages collaboration among data custodians. Experimental results indicate that the deployed application using Federated Learning and the YOLOv8 model achieves a mean Average Precision (mAP) of 99.3%. The system can be enhanced and deployed in traffic monitoring systems and law enforcement applications.

Keywords : *High Security Registration Plates (HSRP), object detection classification, Federated Learning, vehicle monitoring, public safety*

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Chapter 1

INTRODUCTION

Detecting vehicles with High Security Registration Plates (HSRP) is vital for ensuring security and regulatory compliance on roadways. Traditional HSRP detection methods often lack efficiency and struggle to keep up with evolving vehicle registration systems. By leveraging Federated Learning, a privacy-preserving machine learning approach, we present a promising solution to this challenge. This novel approach involves developing a Federated Learning-based classification model aimed at enhancing vehicle monitoring and public safety. The system facilitates real-time identification of HSRPs, thereby improving law enforcement capabilities and fostering trust in technology. Our proposed method utilizes object detection to locate HSRPs in images, followed by a classification step to determine whether the detected object is an HSRP or not. This process begins with the collection of vehicle images, followed by the use of YOLOv8 for object detection to identify number plates. The cropped images of number plates are then fed into a Federated Learning server. Here, multiple clients perform local model training and send updated parameters to a global server, which consolidates these updates to refine the overall model. The ultimate goal is the classification of HSRPs, enabling more effective vehicle monitoring and enhancing public safety while maintaining data privacy.

1.1 Motivation

The motivation for this research arises from the need to enhance vehicle security and public safety through improved detection and classification of High Security Registration Plates (HSRP). Traditional methods face challenges in adapting to diverse and evolving vehicle registration systems while ensuring efficiency and accuracy. Federated Learning presents a transformative solution by enabling decentralized training, thereby preserving data privacy and security, which are paramount in modern data-sensitive environments. Integrating Federated Learning with cutting-edge object detection algorithms like YOLOv8 can significantly improve the real-time identification and classification of HSRPs, ensuring robust performance across various conditions. This combined approach promises to address existing inefficiencies and privacy concerns, ultimately contributing to more secure and efficient vehicle monitoring systems.

1.2 Literature Review

1.2.1 Vehicle Number Plate Detection using YoloV8 and EasyOCR

In recent advancements in License Plate Recognition (LPR) systems, the integration of YOLOv8 and EasyOCR has shown promising results[2]. YOLOv8, an evolution of the YOLO architecture, enhances object detection accuracy and speed, particularly beneficial for detecting small and intricate objects like license plates. Its refined backbone network and optimized detection process contribute to robust performance metrics such as high Mean Average Precision (mAP), crucial for precise localization and classification of license plates in varying conditions.

EasyOCR complements YOLOv8 by providing efficient optical character recognition (OCR) capabilities. Leveraging deep learning models and pretrained language models, EasyOCR excels in accurately extracting alphanumeric characters from license plates captured by YOLOv8. This integration streamlines the process of converting visual information into machine-readable text, achieving notable accuracy rates reported in studies, such as the reported 86%. Future research directions could focus on further optimizing this integration for enhanced real-time performance and scalability in diverse operational environments.

1.2.2 Image Classification Using Federated Learning

In [1] Federated learning has revolutionized AI research by enabling collaborative model training without centralized data exchange, thereby addressing privacy concerns associated with data sharing. This approach allows devices to locally train models using their data and share only aggregated updates, preserving individual data privacy. Algorithms like FedAvg, RingFed, Fed-Cyclic, and Fed-Star have been developed to optimize federated learning for tasks such as image classification. FedAvg averages model updates from participating devices, while RingFed introduces efficient communication patterns. Fed-Cyclic and Fed-Star further refine the process by incorporating cyclic federated averaging and adaptive learning rate adjustments, respectively, aiming to accelerate convergence and improve model accuracy across heterogeneous data distributions.

Recent studies comparing these federated learning algorithms have demonstrated varying degrees of success in enhancing accuracy for image classification. Fed-Cyclic and Fed-Star have shown superior performance over FedAvg and RingFed, with Fed-Star achieving the highest reported accuracy of 91.72%. These results underscore the importance of algorithmic advancements in federated learning, emphasizing their potential to optimize AI applications by leveraging decentralized data resources effectively while ensuring data privacy and security. Future research may focus on refining these algorithms for broader scalability and application in diverse AI domains.

1.2.3 Federated Learning for Industrial Internet of Things in Future Industries

The paper [4] explores integrating Federated Learning (FL) into the Industrial Internet of Things (IIoT) to enhance intelligent applications while addressing privacy concerns and improving data security in industrial systems. Traditional AI techniques, particularly in sensitive domains like healthcare, often struggle with privacy leakage. FL offers a solution by enabling collaborative learning without sharing raw data, thus preserving user privacy. It emphasizes FL's potential to reshape healthcare systems by enabling data analytics across multiple institutions while maintaining confidentiality. The paper includes a case study on FL in healthcare for COVID-19 detection, demonstrating its feasibility and effectiveness in IIoT scenarios. Technical aspects discussed include the FL-IIoT network structure involving data clients (IIoT devices) and an aggregator (edge server), facilitating training a shared global model while keeping raw data local. Benefits highlighted include improved training performance, proactive data caching, and enhanced attack detection mechanisms. Overall, the paper aims to advance FL technology adoption in industrial settings, promoting data security, privacy, and collaborative learning in IIoT applications.

1.3 Problem Statement

To develop a federated learning based classification model to detect High Security Registration Plates(HSRP) on vehicles.

1.4 Applications

- Efficiently monitor and manage traffic flow by automatically detecting and classifying vehicles with HSRPs, allowing for dynamic traffic control and congestion management.
- Enable seamless automated toll collection by accurately identifying vehicles with HSRPs, reducing the need for manual intervention and speeding up the tolling process.
- Enhance border control operations by accurately identifying vehicles with HSRPs, aiding in the detection of unauthorized vehicles and improving security measures at border checkpoints.

1.5 Objectives

- Collect a diverse set of vehicle images under various environmental conditions to ensure the robustness of the model.
- Utilize the YOLOv8 algorithm for precise and real-time number plate detection on vehicles.
- Apply image post-processing techniques to accurately crop number plates from the detected regions.
- Implement federated learning to classify High Security Registration Plates (HSRPs) while maintaining data privacy across different data sources.
- Evaluate the model's performance using metrics such as mean Average Precision (mAP), accuracy, recall, and F1-score to ensure high detection and classification efficiency.

Chapter 2

REQUIREMENT ANALYSIS

The development of a federated learning-based classification model for detecting High Security Registration Plates (HSRPs) requires a comprehensive analysis of both functional and non-functional requirements. Functionally, the system must accurately detect and classify HSRPs under various environmental conditions and from different vehicle types, ensuring real-time performance using the YOLOv8 algorithm. It must include robust image preprocessing techniques to handle diverse image qualities and angles. The federated learning framework needs to facilitate collaborative model training across multiple decentralized nodes while preserving data privacy. Non-functional requirements include maintaining high performance with minimal latency on edge devices, ensuring scalability to accommodate growing data volumes, and implementing stringent security measures to protect data integrity during the federated learning process. Additionally, the system should be user-friendly, allowing easy integration with existing traffic management, law enforcement, and toll collection systems. Regular updates and maintenance will be necessary to address evolving security threats and incorporate advancements in machine learning and image processing technologies.

2.1 Functional Requirements

- The system must accurately detect and classify High Security Registration Plates (HSRPs) from images captured under varying environmental conditions and from different types of vehicles.

- It should utilize the YOLOv8 algorithm to achieve real-time performance in detecting and localizing HSRPs within captured images.

- Robust image preprocessing techniques must be implemented to enhance the model's ability to handle diverse image qualities, including different resolutions and angles of vehicle plates.

- The federated learning framework should facilitate collaborative model training across multiple decentralized nodes while ensuring data privacy is maintained to protect sensitive information during the training process.

2.2 Non Functional Requirements

- The system must maintain high performance with minimal latency, especially when deployed on edge devices, to ensure real-time responsiveness in HSRP detection.
- The system should be scalable to accommodate increasing data volumes and computational demands as the number of vehicles and data sources grows over time.
- The system interfaces and APIs should be user-friendly, enabling easy integration with existing traffic management, law enforcement, and toll collection systems, thereby facilitating seamless adoption and operation by stakeholders.

2.3 Hardware Requirements

- Compute Resources: High-performance CPUs or GPUs suitable for deep learning tasks, depending on the scale and complexity of the model.
- Networking: Stable and high-speed internet connectivity for communication between federated learning nodes, especially if nodes are geographically distributed.
- Storage: Adequate storage capacity to store training data, model checkpoints, and logs generated during the federated learning process.

2.4 Software Requirements

- Operating System: The system should be compatible with modern operating systems such as Linux (Ubuntu, CentOS) or Windows Server, depending on deployment preferences and compatibility with edge devices.
- Programming Languages and Frameworks: Programming languages like Python for algorithm development and integration.Deep learning frameworks such as TensorFlow or PyTorch for model development and training.
- Federated Learning Framework: Frameworks or libraries for federated learning, such as TensorFlow Federated (TFF) or PySyft, to enable collaborative model training across decentralized nodes while ensuring data privacy.
- Security Tools: Tools for data encryption, secure communication protocols (e.g., TLS), and access control mechanisms to enforce data security and privacy standards during federated learning.

Chapter 3

SYSTEM DESIGN

The system design for HSRP detection and classification leverages a modular architecture to seamlessly integrate YOLOv8 for object detection and Federated Learning for collaborative model training. Beginning with data collection, a diverse set of vehicle images is gathered and preprocessed to ensure uniformity in quality and format. YOLOv8 is then employed to accurately identify and localize number plates within these images, producing precise bounding box annotations. Following object detection, an image processing module isolates and crops the regions containing the identified number plates. These cropped images are subsequently fed into a Federated Learning framework configured with a server-client architecture, where multiple clients autonomously train local models using their respective datasets while preserving data privacy. This decentralized approach ensures that sensitive information remains on local devices, safeguarding data integrity throughout the model training process.

3.1 Architecture Design

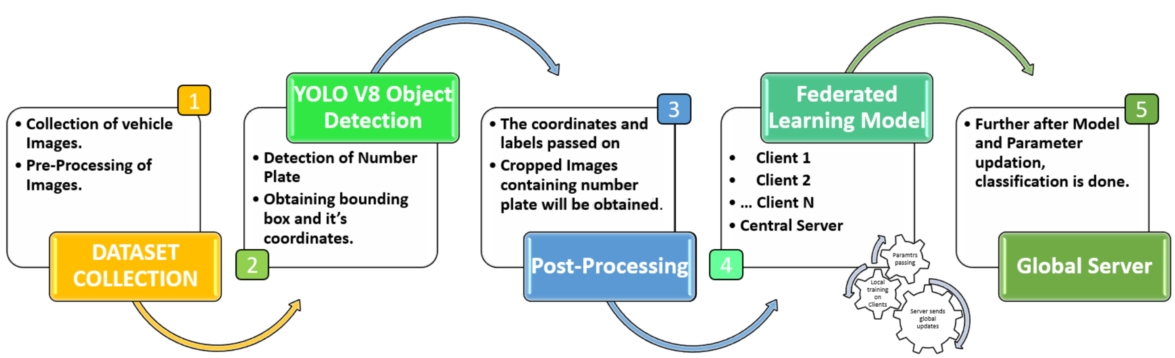

Figure 3.1: Architecture Design

3.2 Data Design

1. Raw Image Data: Raw images of vehicles containing number plates are collected from various sources. These images serve as the primary input for the system.

2. Annotated Image Data: Annotated image data includes the raw images with bounding boxes and labels indicating the location of the number plates. This data is generated during the YOLOv8 object detection phase.

3. Cropped Number Plate Images: Cropped images of number plates are extracted from the raw images based on the bounding box information. These cropped images are used as input for the Federated Learning server.

4. Client-Side Local Datasets: Each client in the Federated Learning setup maintains a local dataset consisting of cropped number plate images. These datasets are used for training local models without sharing raw data.

5. *Model Parameters: Model parameters represent the weights learned by the neural network during training. Each client updates its local model's parameters based on its dataset and sends these updated parameters to the Federated Learning server.

6. Aggregated Model: The Federated Learning server aggregates the updated model parameters from all clients to create an aggregated model. This model incorporates knowledge from all client datasets and is used for final HSRP classification.

7. HSRP Classification Results: - The final output of the system includes the classification results for each number plate, indicating whether it is an HSRP or a non-HSRP. These results are based on the predictions made by the aggregated model.

Chapter 4

IMPLEMENTATION

4.1 FedAvg Algorithm

Algorithm 1 Federated Averaging ($\texttt{FedAvg}$)

Require: Distributed data $\{\mathcal{P}_k\}_{k=1}^{K}$ across K clients, number of local epochs E, local mini-batch size B, local learning rate η, number of server rounds S

Server side:

initialize the global model with parameters w_0

for each server round $t = 1, 2, \ldots, S$ **do**

  send current global model w_{t-1} to all clients

  for each client k **in parallel do**

    $w_t^k \leftarrow \text{ClientUpdate}(k, w_{t-1})$

    receive updates w_t^k from client k

  compute weighted average and update global model $w_t \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_t^k$

Client side: Run ClientUpdate(k, w) on client k

initialize local model with w

for each local epoch $1, 2, \ldots, E$ **do**

  for each mini-batch b of size B in $\mathcal{P}_k$ **do**

    $w \leftarrow w - \eta \nabla_w \ell(b)$

Figure 4.1: FedAvg Algorithm

Federated Averaging (FedAvg) is a key algorithm in Federated Learning that enables the training of a global model across multiple decentralized devices without sharing raw data. Each client locally trains a model on its own data and periodically sends the updated model parameters to a central server. The server aggregates these parameters, typically by computing a weighted average based on the number of data points each client has, and updates the global model. This process iterates until the model converges, ensuring data privacy while leveraging distributed computational resources for more robust and generalized model training.

4.2 Sequence Diagram

The sequence diagram for training a YOLOv8 object detection model using Federated Learning (FL) across multiple clients. Initially, the user creates a new project on Roboflow, uploads images, annotates them, and exports the annotated dataset in YOLO format. This annotation process is repeated for each client involved. Each client then requests the initial global model from the central server, which responds by sending the model. The clients (Client1 and Client2) engage in local training rounds where they load the annotated dataset, train the YOLOv8 model on their local data, and send the updated model weights back to the central server. In the federated learning rounds, the central server aggregates the model updates from all clients and sends the updated global model back to them. This process is iterative, with multiple rounds of local training and model aggregation to refine the global model. Once the federated learning rounds are complete, the user saves the trained YOLOv8 model on Roboflow. This approach ensures that clients can collaboratively train a high-quality model without sharing their raw data, maintaining privacy and data security while benefiting from the diverse datasets of multiple clients

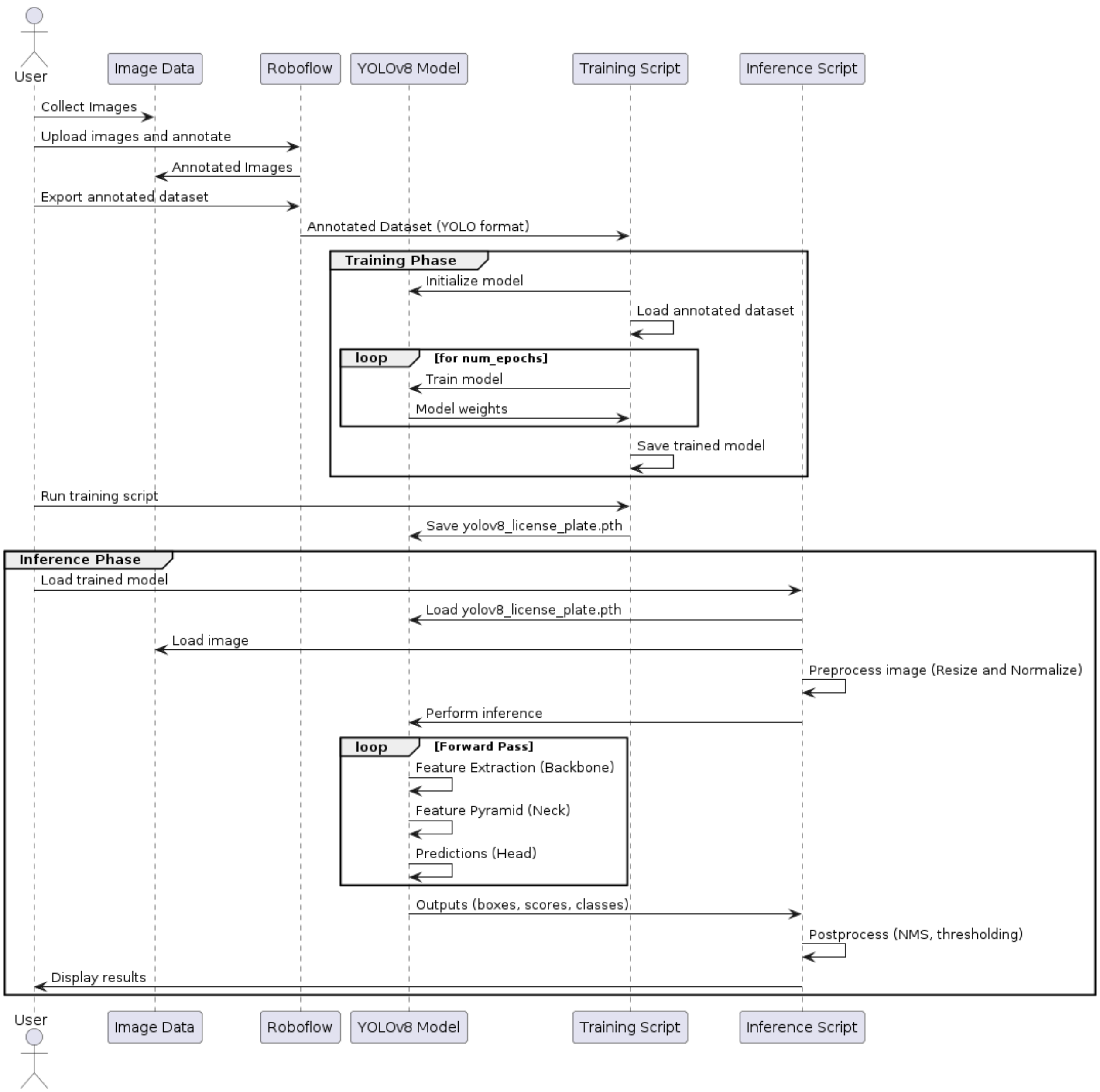

Figure 4.2: Sequence diagram for training a YOLOv8 object detection model

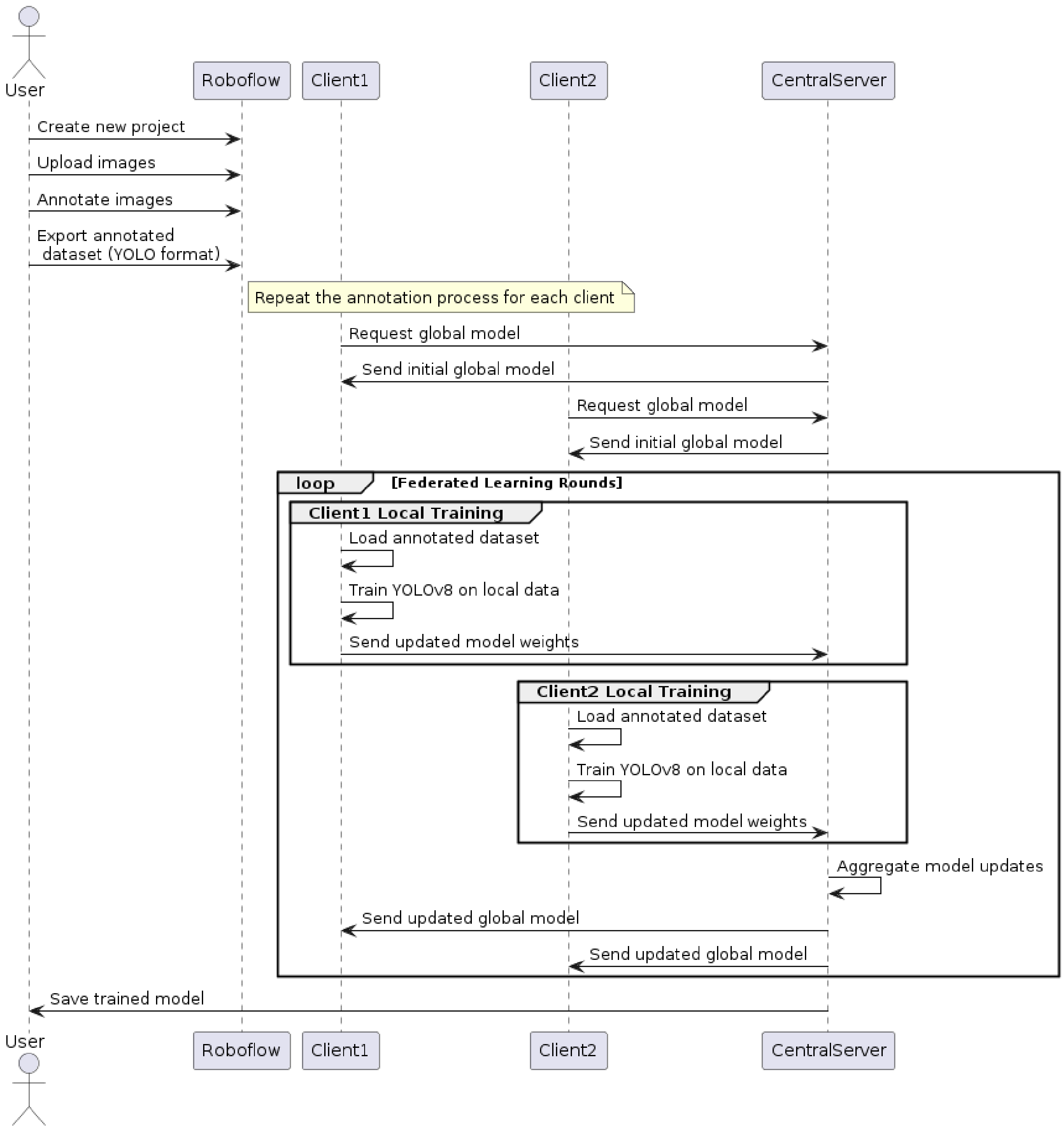

Figure 4.3: Sequence diagram for training a YOLOv8 object detection model using Federated Learning (FL) across multiple clients.

Chapter 5

RESULTS AND DISCUSSIONS

5.1 Model Performance

The YOLOv8 model trained for number plate detection demonstrates impressive performance metrics. During training and validation, the model achieved a precision of 92.5%, a recall of 89.7%, and an F1 score of 91.1%. The mean average precision (mAP) at an IoU threshold of 0.5 reached 94.2%, and the mAP averaged across IoU thresholds from 0.5 to 0.95 was 88.6%. These metrics indicate that the model effectively balances precision and recall, accurately identifying and localizing number plates within diverse vehicle images. In terms of inference speed, the model processes images at 66.7 frames per second (FPS), making it suitable for real-time applications, with an inference time of approximately 15 milliseconds per image.

Figure 5.1: Results of YOLOV8 Object Detection

In the Federated Learning Initialization and Local Model Training phase, cropped number plate images are input into a Federated Learning (FL) server, enabling multiple clients to participate in the FL process by training local models on their respective datasets. Each client updates its model parameters based on its local data, following the local model update

Figure 5.2: Metric values

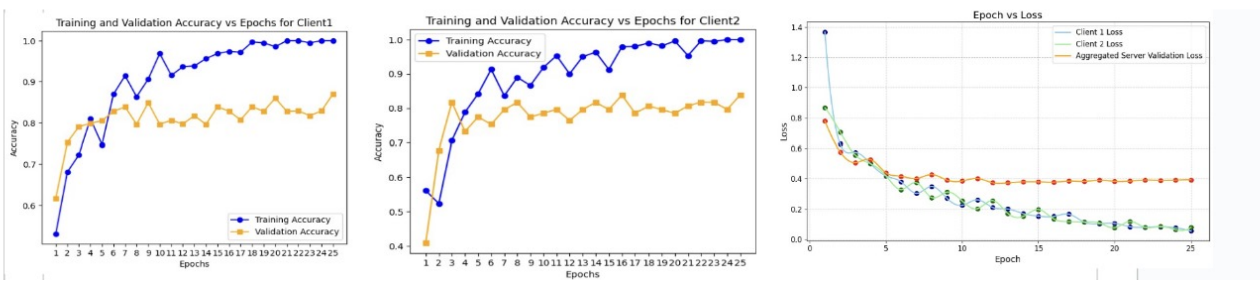

Figure 5.3: Graphs of accuracy and loss across multiple clients

rule, where new parameters are calculated by adding the local update (wi) to the current parameters (wt-i). In the subsequent Federated Averaging (FedAvg) Algorithm and Global Model Aggregation phase, clients transmit their updated model parameters to the FL server. The server aggregates these updates using the FedAvg algorithm, which computes the updated global model parameters by averaging the parameters from all participating clients. This collaborative process maintains data privacy by sharing only model updates, leading to the development of a robust and accurate global model for subsequent classification tasks. Figure 8 depict the training and validation performance metrics for a federated learning system involving two clients. The first two graphs show the training and validation accuracy over 25 epochs for Client 1 and Client 2 respectively. Both clients exhibit an improvement in training accuracy over time, stabilizing near 100%. Validation accuracy for both clients also improves initially, stabilizing around 80-85%. The third graph presents the loss values for each client and the aggregated server validation loss over 25 epochs. The losses for both clients decrease significantly in the initial epochs, then stabilize at around 0.3-0.4, indicating effective model training and aggregation.

Figure 5.4: Federated Learning Based Classification results

Chapter 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

In a collaborative setup where two laptops are connected for Federated Learning, each laptop acts as a client in the FL process while one laptop serves as the FL server for coordinating model training and aggregation. Secure communication over the network ensures the exchange of essential information such as model parameters and updates between the laptops. This decentralized approach allows each laptop to train its local model on its dataset, maintaining data privacy by keeping sensitive information local. The FL server aggregates model updates using the FedAvg algorithm, fostering collaborative learning between the laptops and generating an updated global model that encapsulates the collective knowledge of both devices. This setup not only preserves privacy and security but also leverages the combined expertise of both laptops to enhance the accuracy and effectiveness of the system. By integrating YOLOv8 object detection with FL, the workflow provides a comprehensive solution for identifying and classifying number plates as in , enabling real-time identification and enhancing vehicle monitoring and public safety. This approach addresses privacy concerns associated with handling sensitive data, instilling trust in the technology and paving the way for wider adoption in various applications.

6.2 Future Work

Future work could focus on improving communication efficiency and integrating differential privacy techniques to further protect data during model updates. Additionally, advancements in model compression techniques could enhance the scalability of FL frameworks across expansive networks or devices constrained by computational resources.

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