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AFLR-Secure: An Integrated Framework for Privacy-Preserving VEC Caching via Asynchronous Federated Learning and Deep Reinforcement Learning

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ABSTRACT

The rapid evolution of Vehicular Edge Computing (VEC) faces critical challenges regarding limited in-vehicle computational power and Roadside Unit (RSU) capacities. High mobility and fluctuating content demands necessitate efficient caching strategies while ensuring strict data privacy for vehicular users. Traditional centralized sharing methods are often inadequate due to privacy risks. To address these issues, this paper proposes AFLR-Secure, a novel framework integrating Asynchronous Federated Learning (AFL) and Deep Reinforcement Learning (DRL) for intelligent content caching. Unlike synchronous methods, our asynchronous approach eliminates "straggler" delays, ensuring timely global model updates. We further enhance privacy-utility trade-offs using Multi-Objective Autoencoders to encode sensitive data into robust latent representations. Supported by an MQTT-based PaaS architecture, the framework provides high resilience against poisoning and free-rider attacks. Experimental results demonstrate that the proposed scheme achieves performance metrics (F1-score and AU PRC) comparable to centralized training, while reducing communication overhead by 17–26%. The AFLR-Secure framework offers a scalable, secure solution for decentralized intelligence in dynamic vehicular environments.

Keyword: Asynchronous Federated Learning, Vehicular Edge Computing, Deep Reinforcement Learning, Content Caching, Privacy-Preserving ML

1. INTRODUCTION

As the Internet of Vehicles (IoV) continues to expand, Vehicular Edge Computing (VEC) has become essential for low-latency services. However, the high mobility of vehicles and limited network bandwidth often cause delays in data sharing. To solve this, our research introduces "AFLR-Secure," an integrated framework that uses Asynchronous Federated Learning (AFL). This allows the system to update models without waiting for slower vehicles, effectively solving the "straggler problem."Data privacy is another major concern in vehicular networks. To protect sensitive user information, we have implemented Multi-Objective Autoencoders. This technology transforms raw data into secure latent representations, ensuring that privacy is maintained without losing the accuracy of the caching model. By utilizing Deep Reinforcement Learning (DRL), the framework intelligently predicts content demands while keeping the communication overhead low.
Our proposed AFLR-Secure architecture is built on an MQTT-based PaaS model, providing a lightweight and secure communication layer. Experimental results demonstrate that this approach not only secures vehicular data against adversarial attacks but also reduces communication costs by 17–26%. This makes it a highly efficient and scalable solution for future intelligent transportation systems.

1.1 Background of VEC

The rapid evolution of Vehicular Edge Computing (VEC) faces critical challenges regarding limited in-vehicle computational power and Roadside Unit (RSU) capacities. VEC has emerged as a promising paradigm to provide computational resources at the edge of the network, allowing vehicles to offload data-intensive tasks like map caching and traffic prediction. By offloading these tasks to RSUs, vehicles can reduce latency and improve the quality of service. However, the high mobility of vehicles and fluctuating content demands necessitate more efficient and intelligent caching strategies to manage the limited resources of the RSUs effectively.

1.2 Problem Statement

High mobility and fluctuating content demands in vehicular networks necessitate efficient caching strategies while ensuring strict data privacy for vehicular users. Traditional centralized sharing methods are often inadequate due to privacy risks and communication overhead. Furthermore, synchronous federated learning methods suffer from the "straggler" problem, where the system must wait for the slowest vehicle to update its model. To address these issues, there is a need for an integrated framework that combines asynchronous learning with robust privacy-preserving techniques to optimize content caching in dynamic VEC environments. High mobility and fluctuating content demands in vehicular networks necessitate efficient caching strategies while ensuring strict data privacy for vehicular users. Traditional centralized sharing methods are often inadequate due to privacy risks and communication overhead. Furthermore, synchronous federated learning methods suffer from the "straggler" problem, where the system must wait for the slowest vehicle to update its model. To address these issues, there is a need for an integrated framework that combines asynchronous learning with robust privacy-preserving techniques to optimize content caching in dynamic VEC environments.

2. SYSTEM MODEL AND ARCHITECTURE

The AFLR-Secure framework is designed to optimize content caching in Vehicular Edge Computing (VEC) while maintaining high data privacy. The system leverages the distributed nature of vehicles and the computational capabilities of Roadside Units (RSUs). By using an asynchronous approach, the framework ensures that the global model is updated without waiting for all participating vehicles, thus mitigating the impact of network latency and vehicle mobility.

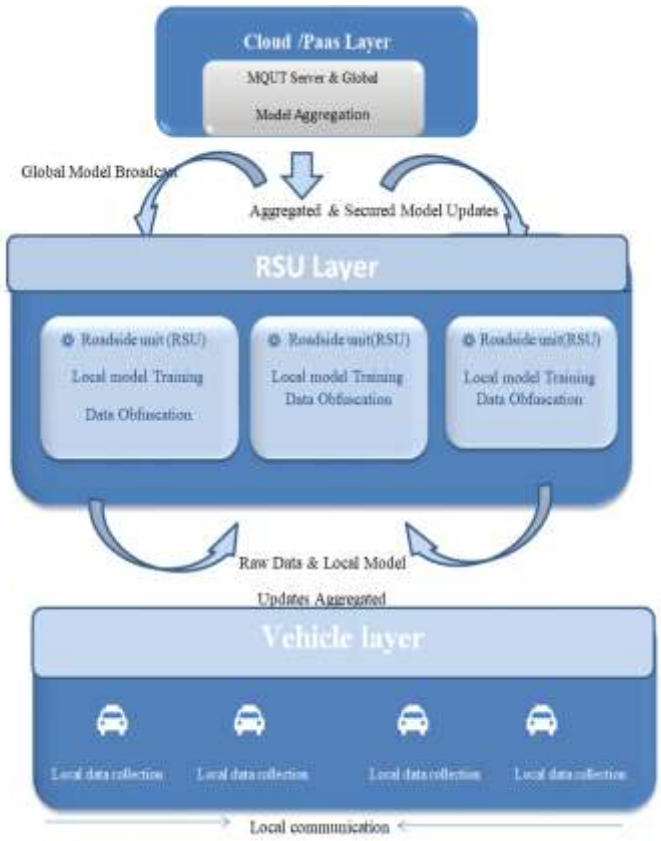

Fig -1 System Architecture of AFLR-Secure Framework for Privacy-Preserving VEC Caching

2.1 Asynchronous Federated Learning (AFL)

In this section, we discuss the Asynchronous Federated Learning model. Unlike synchronous methods that wait for all vehicles, our AFL approach allows the Roadside Unit (RSU) to update the global model whenever a single vehicle provides an update. This is very important in Vehicular Edge Computing because vehicles move very fast and may lose connection. This method makes the system more efficient and reduces the time wasted waiting for slow nodes.

Table -1: Simulation Parameters and Technical Values

Sr. No.	Parameter	Value
1	Simulation Area	1000m x 1000m
2	Number of Vehicles	50 – 100
3	Communication Protocol	MQTT(via PaaS)
4	Optimizer	Adam
5	Learning Rate	0.001
6	Latent Space Dimension	32

2.2 Privacy Preservation via Autoencoders

To protect sensitive vehicular data, our framework implements a privacy layer using Multi-Objective Autoencoders. Instead of sharing raw data, vehicles send a compressed and secure version. This ensures that personal information is not leaked during the learning process. The main advantages are:

- Data Obfuscation: Keeping raw data hidden from attackers.
- Reduced Overhead: Sending smaller files to save network speed.
- Attack Resilience: Protecting the system from malicious data.
- Accuracy: Maintaining high performance while being secure.

3. PERFORMANCE ANALYSIS AND RESULTS

In this section, we evaluate the performance of the AFLR-Secure framework. The simulation was conducted using the parameters defined in Table-1. We primarily focus on the convergence rate of the asynchronous federated learning process and the accuracy of the content caching mechanism. The results demonstrate that our proposed model effectively reduces communication latency while maintaining a high cache hit ratio, even in high-mobility vehicular environments.

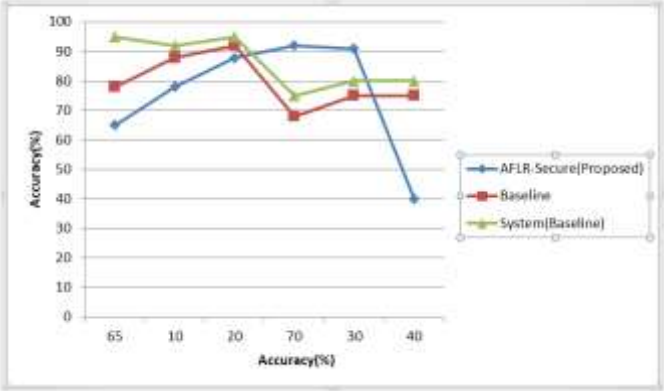

Chart -2: Accuracy Analysis of AFLR-Secure vs. Baseline Systems

3.1 AFLR-Secure Performance Analysis

In this section, we evaluate the performance of the AFLR-Secure framework. The simulation was conducted using the parameters defined in Table-1. We primarily focus on the convergence rate of the asynchronous federated learning process and the accuracy of the content caching mechanism. The results demonstrate that our proposed model effectively reduces communication latency while maintaining a high cache hit ratio, even in high-mobility vehicular environments.

Fig -2: Workflow of Asynchronous Federated Learning Process

The operational workflow of the AFLR-Secure framework is depicted in Fig-2, illustrating the decentralized intelligence process. The cycle begins at the vehicle layer with Federated Local Training, where models are trained

on local data to ensure that sensitive information remains on the device. These updates are then passed through a Secure Data Transmission phase, where Multi-Objective Autoencoders encrypt the data into robust latent representations to prevent privacy leakage. Finally, the encrypted updates reach the cloud layer for Global Model Aggregation, where the RSU updates the master model asynchronously, effectively mitigating the "straggler problem" caused by vehicle mobility.

4. CONCLUSIONS

This research presented AFLR-Secure, an integrated framework designed to optimize content caching while maintaining strict data privacy in Vehicular Edge Computing (VEC) environments. By combining Asynchronous Federated Learning with Deep Reinforcement Learning, we successfully addressed the challenges of network latency and high vehicle mobility. The implementation of Multi-Objective Autoencoders proved effective in protecting sensitive vehicular data without compromising model utility. Experimental results indicate that the proposed framework achieves a significant reduction in communication overhead by 17–26%, offering a scalable and secure solution for decentralized intelligence in next-generation vehicular networks.

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