GROUP - 01

Edge-Enabled Digital Twin Framework for DRL-Based Cooperative Perception in Autonomous Vehicles

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Theme : Autonomous Vehicles

Challenge : Task Scheduling

PROBLEM STATEMENT

Autonomous vehicles depend on on-board sensors to understand their surroundings, but these sensors have limitations — they can be blocked, have short range,may miss critical objects

Cooperative perception solves this by allowing vehicles to share sensing data with each other. However, selecting the right helper vehicles (CoVs) and allocating bandwidth efficiently is difficult because vehicles are moving, data quality changes over time, and delays must be minimal.

Our project uses a Digital Twin at the RSU to predict vehicle positions with LSTM models trained at the edge and to make intelligent CoV selection and bandwidth allocation decisions using Deep Reinforcement Learning. This ensures timely, high-quality perception for safer autonomous driving.

WHY IS THIS A EDGE PROBLEM

Latency and Privacy:

In cooperative perception, autonomous vehicles need to process and share sensor data in milliseconds to make driving decisions.

Sending all data to a remote cloud would introduce high latency and risk outdated information. Instead, our system uses edge and fog computing:

- **Edge layer** (Vehicles) → Run LSTM models locally to predict their own future positions without sending raw data.
- **Fog layer** (RSU) → Hosts the Digital Twin and runs DRL to select the best Cooperative Vehicles (CoVs) and allocate bandwidth.

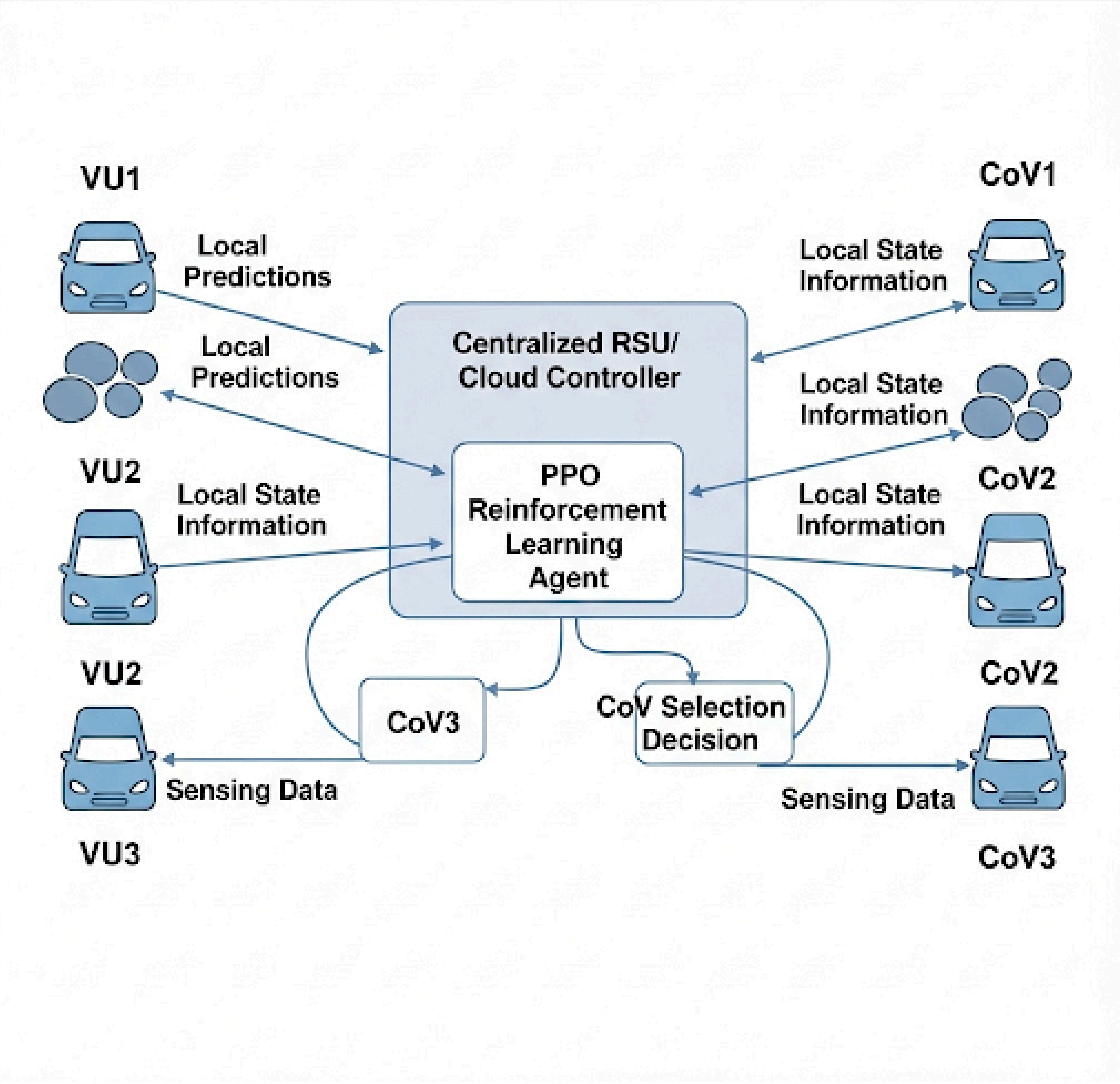
Processing at the edge and fog levels ensures low latency, reduced bandwidth usage, and real-time decision-making, which are essential for safe autonomous driving.Since the LSTM model is running locally sensitive data of the user such as users’s location stays localy in the car itself.

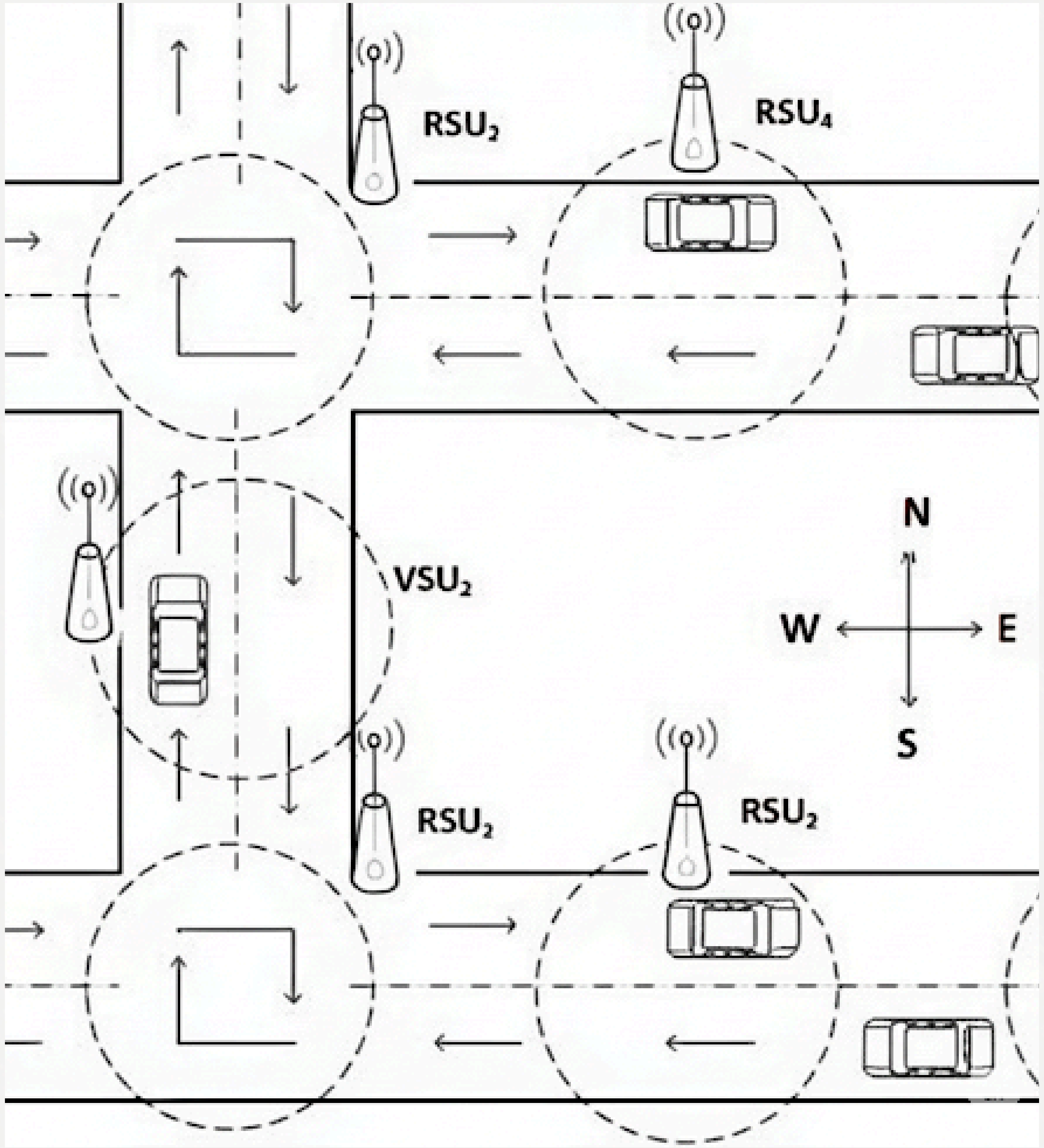
Scalability:

Vehicles constantly move in and out of RSU range Only an edge-based system can adapt instantly to these topology changes.

- Multiple RSUs (fog nodes) can serve different road segments independently.
- Avoids bottlenecks from a single centralized cloud server.

ARCHITECTURE DIAGRAM





STATE OF THE ART LITERATURE

Paper	Key Idea	Limitations	Why Our Paper Is Better
Vehicular Cooperative Perception Through Action Branching and Federated RLMohamed K. Abdel-Aziz et al., 2020	RL-based vehicle association, resource allocation, and content selection with FL.	No Digital Twin or mobility prediction; bandwidth allocation not adaptive.	We use Digital Twin + LSTM for proactive mobility prediction and DRL for adaptive bandwidth allocation.
Federated DRL-Based Task Offloading with Power Control in Vehicular Edge Computing Sungwon Moon & Yujin Lim, 2022	Combines FL with DDPG for power-controlled task offloading to edge servers.	Focuses on task offloading & power control, not cooperative perception; lacks Digital Twin or mobility-aware networking.	Our method is perception-oriented, using DT + LSTM predictions and scheduling via DRL for real-time CoV selection
Towards Cooperative Perception Services for ITS: Digital Twin in the Automotive Edge Cloud	Real-time Digital Twin visualization of vehicle surroundings using LiDAR and infrastructure sensors.	Lacks mobility forecasting and decision-making algorithms (no LSTM or DRL-based scheduling).	We advance this by integrating real-time DT with predictive LSTM modeling and DRL-driven CoV selection
Federated Learning for Digital Twin-Based Vehicular Networks: Architecture & Challenges	Conceptual architecture combining FL with Digital Twins in vehicular networks.	The work is high-level and lacks implementation of resource optimization or real-time scheduling.	Our approach is fully implementable, combining DT, LSTM, and DRL to deliver real-time cooperative perception.

IMPLEMENTATION AND WORKFLOW

Simulation: SUMO for traffic; CARLA for LiDAR & camera

LSTM Model: Many-to-Many PyTorch LSTM (64 units) predicting next-step vehicle coordinates from recent mobility data.

DRL: PPO in Stable-Baselines3 for CoV selection + bandwidth allocation using DT state as input

Communication Network: V2V link over IEEE 802.11p (DSRC) or C-V2X, modeled with bandwidth/delay constraints in simulation.

Git Repo : github.com/23CSE362-edge-computing-2025-26-odd/capstone-project-01_epicfailures

WORK SPLIT

TEAM MEMBER	CONTRIBUTION
Ragul	Working SUMO + CARLA simulation with synced vehicle movements and sensor data output.
Dheemant	LSTM model code, trained weights, and integrated prediction module.
Raksha	RSU Digital Twin system with live updates for all vehicles in simulation.
Vishal	DRL agent code, trained policy, bandwidth allocation logic, and fusion results.