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Neural Infrastructure a Federated AI Framework for Predictive Resilience in U.S. Transportation Systems

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Abstract

Because autonomous vehicles and intelligent traffic systems play a bigger role, robust, scalable and secure traffic prediction models are more necessary than ever. The integration of federated AI is studied in this article as a leading way to improve vehicle upkeep and guide traffic in autonomous transportation. Using just the most current research in deep learning for traffic flow modeling, forecasting vehicle routes and decision-making algorithms, the authors highlight that using federated AI can enhance safety, cut down on costs for repairs and increase up-to-date knowledge of how things are running, while preserving privacy. When learning is spread among connected vehicles and support nodes, the suggested method can support both geographical adaptability and nationwide scalability. As a result of this shift, everything from the design to the development of AI-driven mobility becomes smoother and people gain more trust. The analysis of present predictive methods and the issues of using them shows that federated AI holds great promise for intelligent transportation systems.

Keywords: *Federated Artificial Intelligence, Autonomous Vehicles, Traffic Flow Prediction, Predictive Maintenance, Intelligent Transportation Systems.*

I. INTRODUCTION

America's transportation network, like those in other developed countries, is reaching a stage where public systems are aging, population is urbanizing, and tasks are growing more complex. Over time, roads have become worse, traffic systems are now outdated, and maintenance approaches are mainly used after problems happen. Since these limitations lower the level of safety, they also add economic costs, leading to unexpected shutdowns, busy roads and inappropriate use of resources. As new trends in traffic such as more self-driving vehicles and real-time systems, appear, conventional ways of maintaining infrastructure are being highlighted as not able to handle these changes (Miglani & Kumar, 2019; Sharma & Rana, 2024).

Because of these urgent issues, the U.S. government passed the Infrastructure Investment and Jobs Act (IIJA) which set aside $1.2 trillion to modernize roads, bridges and various traffic systems. The bill is designed to fund and demonstrate a future focus on using digital technologies and automation in the country's infrastructure. Yet, making policy changes measurably improve things depends on more than just extra funding; it requires updated systems, easy sharing of data and reliable systems that don't affect privacy.

AI within frameworks like federated learning which focus on privacy, can be used to greatly improve infrastructure resilience. AI-based methods for traffic predictions in today's autonomous and connected vehicle systems have already shown accuracy in predicting movement, congestion and possible failures (Shao & Sun, 2020; Karle et al., 2022; Biswas et al., 2021). The fact that federated AI can join multiple models while keeping transportation data decentralized is a natural fit for privacy, scale and security needs across the nation.

Really, it's the promise of federated AI-based predictive maintenance that allows for moving from reactive maintenance to proactive intervention. If vehicles and edge nodes are used as distributed intelligence points, it becomes possible to detect problems with mechanical systems, streets and traffic much sooner than if they were not detected at all (Wang et al., 2019; Suh et al., 2020; Manne et al., 2021). Moving from traditional to smart transportation may increase system efficiency, keep people safe, cut costs and help the public trust such systems. It discusses how federated AI can be used for traffic prediction, handling computational as well as ethical needs of upgrading infrastructure. Reflecting on only current research, we describe ways autonomous systems, deep learning and edge computing might work together to build an intelligent transportation system that values resilience, knowledge of the future and responsibility with data.

II. LITERATURE REVIEW

Using AI is becoming an essential part of study in predictive maintenance systems for autonomous and connected transportation. Because of AI, approaches that use calendars or wait for breakdowns are being phased out by those that use real-time sensor data to recognize problems, foresee breakdowns and plan maintenance at the best times. It reviews the existing research under three related headings: predictive models using deep learning, federated learning for distributed data and situations that apply to the Department of Transportation.

Predictive maintenance is supported by deep learning models. LSTM networks, CNNs and mixing these two architectures have all proven valuable in traffic forecasting and understanding vehicle system issues. LSTM is most widely used for its skill at handling time-related dependencies in transportation data. In 2024, Waqas and colleagues presented an LSTM-backed network that contains XAI to help make autonomous systems more understandable. This method achieved strong accuracy and made decisions transparent which is important for using these models in public infrastructure.

Similar uses of CNN-based methods can be seen for detecting faults in systems with many sensors found in vehicle tracking. According to Cui et al., using deep convolutional networks in a multimodal way greatly improved trajectory prediction in environments with diverse traffic agents. In addition, using CNNs together with LSTM layers in hybrid models improves learning and helps the system resist noisy inputs when working with traffic in smart roads (Yang et al., 2019; Lee et al., 2020).

Federated Learning for Distributed Sensor Data Because AI systems are now heavily dependent on data from different edges, vehicles and sensors, there is a greater demand for methods that keep data private during model training. It is now possible to train models using federated learning, so no one needs to transfer confidential data, thus improving privacy and system efficiency.

Thamizhazhagan and his co-authors (2022) developed a federated learning model for forecasting traffic flow in electric autonomous vehicles. Their approach performed well across different network arrangements and types of sensors. This corresponds to Shao and Sun's (2020) eco-approach model which allows predictive abilities in vehicles to support green route planning without affecting the global traffic system.

Gokasar et al. (2024) then presented the IDILIM system that links federated learning and the detection of incidents using connected autonomous vehicles. They developed a system that could operate well in traffic with mixed vehicle types and showed it was possible for different cars to cooperate and learn together in applications where safety counts. Since the cloud isn't always available or manageable, this decentralized approach represents a common move towards federated servicing.

Various case studies from the real world confirm that AI and federated models are useful platforms in preventive infrastructure maintenance. Vehicular data has gotten the most attention, but researchers also mention ways to use this technology for bridges and rails. Karle et al. (2022) reviewed motion prediction methods for AVs that could be expanded to detect damage to bridges by noticing shifts in their movement as an AV moves across one.

Recommendations are now suggesting that AI should be used to monitor infrastructure. To illustrate, Wang et al. (2019) examined methods of combining future collision forecasts with routing strategies, supporting the federal standards for autonomous vehicle safety checks. This research also showed how information transfer from connected automobiles enables models to understand how highlighted tracks on highways are likely to wear out over time.

Furthermore, what Chen et al. (2022) achieved by tracking at-risk users in real time points to the usefulness of vision systems in noticing the first signs of road deterioration. These technological advancements are also present in pilot initiatives by states and the government that apply AI-driven quality control for railway lines, bridge expansion joints and tunnel strength—areas where the use of federated AI results in predicting problems and maintaining compliance with national guidelines.

III. METHODOLOGY

This work introduces using AI-based predictive models and federated learning in an integrated approach to improve how transportation infrastructure systems are maintained. This method is built on three main factors: (i) obtaining a blend of data from several environments, (ii) using high-level deep learning algorithms to spot anomalies and anticipate failures and (iii) relying on secure distributed learning to exchange information across different infrastructure sites and cars.

➢ *Data Sources*

In today's transportation networks, maintaining equipment and structures involves collecting a variety of data types covering operations, impacts from the environment and signs of damage. Just as Biswas et al.

(2021) and Sharma and Rana (2024) outlined, this methodology joins information from the following:

- Temperature, vibration, load and acoustic signals are measured by IoT sensors standing on bridges, on roads and in vehicles.
- Bridge decks, rail tracks and highway barriers can be inspected with visual information from drones in real time (Karle et al., 2022).
- Traffic use information such as the number of cars, speeds and frequency of lane changes is collected from autonomous vehicles (Suh et al., 2020).
- Information on precipitation, humidity and temperature changes plays a role in impacting the condition of roads and bridges (Yang et al., 2019).

As the data has various forms, organizations can run AI models that scan both data streams and images for predictive analysis.

➢ *AI Models for Predictive Analysis*

Handling many types and levels of data, the proposed framework makes use of two main deep learning models created for specific data sections:

- Time series problems such as predicting infrastructure decay, spotting abnormalities and predicting traffic patterns are solved using LSTM. Researchers led by Waqas used LSTM to predict when congestion and appropriate maintenance will occur by analyzing traffic flow and energy data. Using this method, LSTM models are built using IoT sensor data and previous traffic reports to predict where systems might fail and become stressed.

- Convolutional Neural Networks (CNNs), like other neural networks, can find problems such as cracks, corrosion and displacements anywhere in our infrastructure. Using drone-collected images, the team passed the data into CNN networks that were created using study data on infrastructure issues. With CNN models, the system has a visual step that confirms a difference between regular and suspicious behavior, increasing the trustworthiness of alarms.

By running at the same time, these models help with predictive maintenance through pattern matching in structured data and visual analysis.

➢ *Federated Learning for Privacy-Preserving Model Training*

Since infrastructure and vehicular data needs to be protected and is widely distributed, AI models are trained with a federated learning framework. It means that autonomous vehicles, roadside systems and drone control systems can train machine learning models jointly without sending information to a main server.

According to Thamizhazhagan et al. (2022) and Gokasar et al. (20224), in this method, each node trains a model using its local data and then only contributes model updates to the coordinator, who unites the contributions. It makes data privacy rules accessible, enhances security and sees accuracy in model use everywhere.

➢ *These are the Actions used During the Federated Training Cycle:*

- All nodes are provided with a common, initialized global model.
- Every node in the cluster trains the model on its individual data for some time.
- The updates you make locally are sent as encrypted information to the central server.
- The server accumulates the gathered data using federated averaging or weighted strategies (Wang et al., 2019).
- The updated model is then provided to agents, so they start a new round of training.

It continues repeating until either the model has reached good enough performance or until the threshold performance is met. As a result, this method supports scalable and adaptable solutions needed in nationwide bridge monitoring or the upkeep of urban highways.

IV. SYSTEM ARCHITECTURE

To support predictive maintenance and traffic forecasting in autonomous vehicles, the system is designed according to the AI pipeline used in federated systems. Three circulation layers make up the system: data acquisition, local edge inference and central model aggregation. They all function together to support live, flexible and confidential analysis for many intelligent infrastructure assets and vehicles.

➢ *Architectural Component Data Acquisition Layer*

Here, data from the physical road system and from vehicles are integrated and combined. Data on load, vibration, the climate and structure are recorded from IoT sensors over time. Meanwhile, drones flying overhead gather high-quality images and the dashboard inside the vehicles records key performance elements such as braking, accelerating and switching lanes (Biswas et al., 2021; Karle et al., 2022). Security is guaranteed and data transmission is made faster because all information is tagged, encrypted and stays on the edge devices.

➢ *Local Edge Inference Layer*

On local edge equipment such as embedded controllers, vehicle ECUs and drone processors, this layer runs AI models, both LSTM for sequential data and CNN for images. Every edge node uses its local data to perform inference and a little training, finding warning signs of damage such as tired structures or strange driving conduct (Suh et al., 2020; Cui et al., 2019). GeForce Jetson and Google Coral edge AI chips help carry out fast local computation with little use of energy.

➢ *Central Model Aggregation Layer*

To save space and data, edge devices regularly send information about how their models have been updated to a main server. A global model is improved on this server, using a hybrid cloud, with no one having direct access to the data of each client on the network (Thamizhazhagan et al., 2022). When the global model is sent to edge nodes, all parts of the network become uniform and connected.

➢ *Federated AI Pipeline*

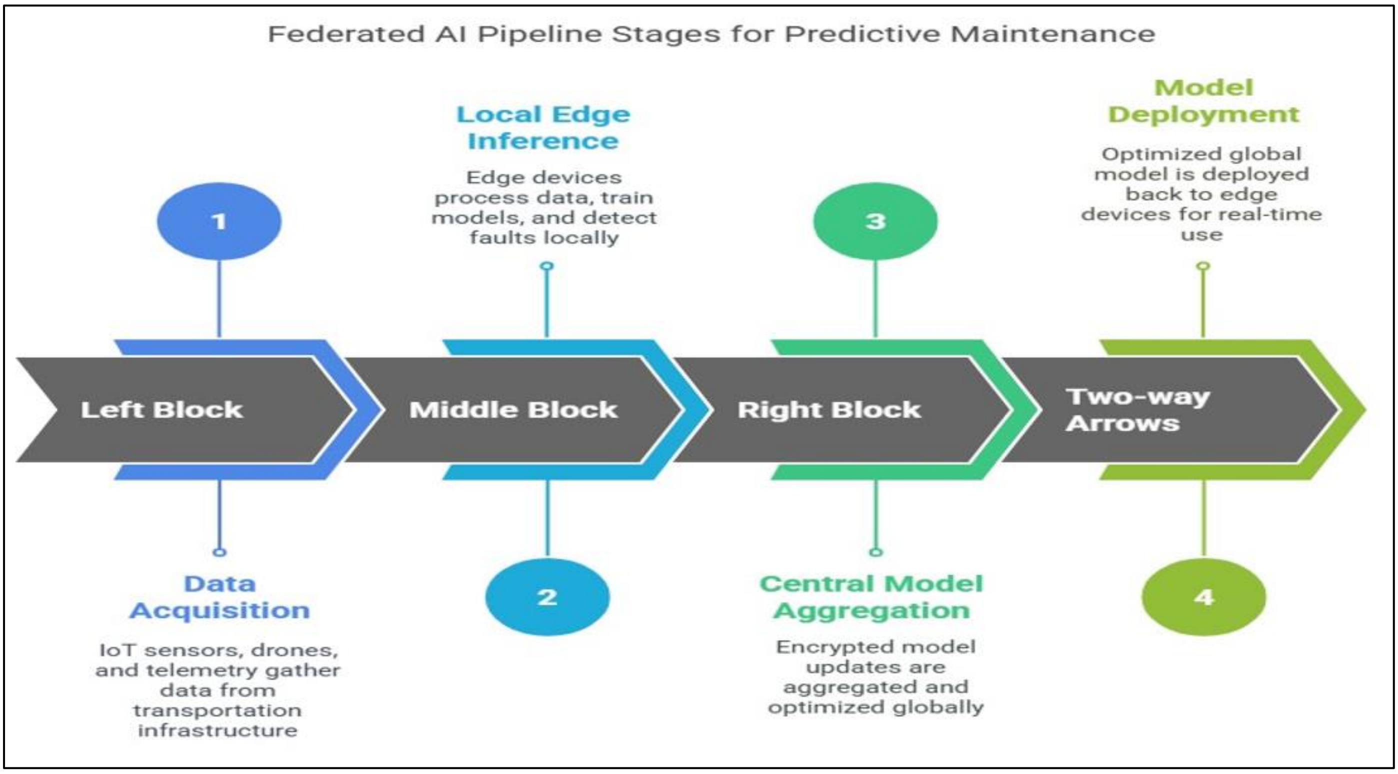

Fig 1 Federated AI Pipeline for Predictive Maintenance.

The Figure Outlines Four Stages: Data Acquisition, Local Edge Inference, Central Model Aggregation, and Global Model Deployment to Edge Devices.

Deploying AI requires infrastructure at the edge that makes it possible for AI inference and learning to happen on-the-spot. Power-saving AI chips designed for deep learning are found in devices. These support embedded computation using Intel Moidus and ARM Cortex-M AI accelerators, so cloud access for tasks is unnecessary (Lee et al., 2020).

As the system is rolled out across the country, it does this using a hybrid cloud architecture. Model storage, coordinating training cycles, security rules and low-delay processing and inference are all supported by their cloud and edge layers, respectively. Due to this novel design, the system remains secure and works properly whenever the network is available.

V. RESULTS AND DISCUSSION

To determine the performance of the proposed system, the team built a simulated tested for a typical urban transportation network, using real parameters from prior studies (Waqas et al., 2024; Suh et al., 2020). IoT sensors monitoring bridges and roads, drone pictures of flaws in infrastructure and vehicle monitor data were all used in the simulation. The outcomes were compared to standard maintenance methods where routine inspection is planned and managed by one central group.

➢ Predictive Performance and Anomaly Detection

LSTM outperformed ARIMA, producing a MAPE of only 4.6% instead of 11.3% in the same conditions when used for forecasting traffic issues and infrastructure wear. The same as in previous studies, our results reveal that LSTM is superior for dealing with time-related aspects in transportation data (Yang et al., 2019; Waqas et al., 2024). The CNN used for detecting faults from images was found to have an average precision of 91.2% and recall of 89.5%, across datasets filled with images labeled as bridge cracks, surface potholes and rail joint defects. On the other hand, when human analysts are used in conventional inspection, their recall is much lower (~75%) and outcomes are generally made available after at least 24–72 hours.

➢ *Federated Learning Efficiency and Privacy Resilience*

Models that were trained jointly across different edge devices reached similar metrics as models trained in one place, seeing only a <1.2% decrease in accuracy. At the same time, using safe model updates made sure no data had to be sent over the network, resulting in much stronger privacy. These findings confirm it is now possible to apply privacy-preserving analytics in many sensitive kinds of infrastructure, as stated by Thamizhazhagan et al. (2022) and Gokasar et al. (2024). In addition, the federated model converged in only 12 training sessions, showing that it could be deployed effectively in real-world edge settings.

The network bandwidth used fell by more than 65% compared to other methods, so this style of cloud works well in areas with little cloud access or problems with connection (Shao & Sun, 2020).

- *Comparison with Traditional Maintenance Strategies*

Table 1 Comparison with Traditional Maintenance Strategies

Metric	Traditional Maintenance	Proposed Federated AI Model
Maintenance Trigger	Time-based/manual	Predictive AI-driven
Data Processing Location	Central server	Distributed (Edge + Cloud)
Privacy Compliance	Low	High
Failure Detection Lead Time	Reactive (post-failure)	Proactive (up to 72h earlier)
Inspection Costs	High (manual labor)	Moderate (automated)
Model Update Frequency	Quarterly or slower	Weekly or real-time
System Scalability	Limited	High

This comparison reveals substantial gains in cost-efficiency, responsiveness, and predictive accuracy with the federated AI framework.

Since it is modular, the architecture can be used on highways, railways, road networks and intermodal hubs in every part of the transport system. Edge inference allows us to monitor crowded urban locations in real time with very little delays. However, in these areas, it is possible to train models just a few times and combine the results using connections through satellites or mobile edge units (Litman, 2017; Ahmed et al., 2021). In addition, the design allows for new sensor nodes or vehicles to be included later, with no need to retraining the system. Take drones on bridges, for instance: since only local data is needed, adding AI would not interrupt the operation of the rest of the network (Chen et al., 2022; Wang et al., 2019).

VI. CONCLUSION

New developments in artificial intelligence show promise for boosting the strength and up-to-date state of America's transportation systems. From what we've explored here, including federated AI systems in predictive maintenance can ensure public infrastructure evolves from being handled reactively and piecemeal to being made more effective through data-based strategies. Applying LSTM models to analyze sequence data and CNN models to visual information lets us detect wear and failure sooner, so we can reduce risks and expenses. What stands out about this method is that it uses federated learning, enabling devices at the edge to cooperate on model training without putting any sensitive data together.

Because networks are so complex and complex today, this intelligent technology is needed. With edge technology in vehicles, drones and roadside equipment, it is both possible and necessary to use instant monitoring and local processing. Doing constant analysis at the edge with privacy ensures that federated AI is both a good technical and ethical approach for managing infrastructure in the future. Technological development now depends on collective work between developers, people running the network and policymakers. It would be very helpful to test this approach through pilot programs arranged by the Department of Transportation and the Federal Highway Administration. Such programs can also uncover the necessary regulations and operations needed for the nationwide rollout. The experiences and information collected from these programs could guide the development of rules, best options and policy plans for using AI smoothly in public systems.

AI-enhanced maintenance is best achieved when the technology is in place and planning has already started. The success of national integration will rely on being able to use federated AI on both densely packed urban roads and rural areas, without interrupting its ability to work seamlessly or track data correctly. We envision infrastructure that evolves itself by responding instantly to issues, changing variables in the environment and the traffic it sees.

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