A Scalable IoT-Driven Framework for Real-Time Traffic Management and Accident Prevention Using Edge Intelligence and Adaptive Safety Analytics

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Abstract: The urban traffic is becoming more and more complex, and requires intelligent and adaptive transportation systems for safety, efficiency and sustainability. This study presents a novel scale able IoT-based framework using edge intelligence and real-time analytics for controlling traffic flow and for preventing accidents in a proactive manner. Contrary to classical approaches, we resort to low-latency edge processing, federated learning and predictive modeling to dynamically respond to variations occurring on the road. Real traffic and sensor datasets are used to train and validate the model at different intersections. The system also includes built-in support for pedestrian safety, emergency vehicle response, as well as cloud-edge setup for easy deployment. The experimental results show that the response time and traffic congestion are significantly reduced in the presence of an accident, indicating that the proposed approach can effectively improve urban mobility.

1 INTRODUCTION

Urban mobility is at a transformative point, one that is being driven by the coalescence of IoT (Internet of Things), AI (Artificial Intelligence) and edge computing. As urban areas grow and traffic on the roads becomes increasingly congested, so have the issues surrounding traffic management and road safety. Conventional traffic control strategies, which are based on pre-determined signals and centralized data analysis, tend to be inadequate for real-time traffic dynamics and accident prevention. This constraint requires future-generation ITS to become more responsive, predictive and adaptive.

Recent developments in IoT make it possible to deploy connected sensors, cameras and actuators along the road network, establishing an environment in which real-time data is gathered and processed in real-time. Edge computing supplements this infrastructure by moving processing closer to the source, decreasing latency and making quicker decisions possible. And when combined with predictive analytics and federated learning, these other technologies are part of a core platform for dynamic traffic management and accident avoidance.

The work introduces a scalable and robust framework with IoT and edge intelligence for addressing the vital transportation issues. By incorporating cloud-edge coordination, adaptive learning-based algorithms, multi-source sensor data fusion, the proposed system has the capability to minimize congestion, hazard detection, and fast response to avoid accidents. The architecture additionally includes intelligent routing for priority vehicles and can accommodate heterogeneous traffic

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conditions, rendering it applicable to various urban areas. The study, which uses a novel approach, aims to help create safer, smarter and more efficient transportation systems.

2 PROBLEM STATEMENT

Despite the fast advancements in smart city technologies, urban centres still face some recurring problems such as traffic congestions, slow emergency response rates, and increasing road accidents. Mature traffic control systems are usually reactive, central, they don't support the dynamic and heterogeneous vision of the real-time roads. These are not adaptable to analysing sensor data on such a large scale with low latency, and are unable to provide predictive analytics on how to avoid traffic disruption or accidents. Moreover, the current solutions have few facilities to adapt the taken security measures and edge-based intelligence, and multi-modal analysis of the traffic data which minify the efficiency in an intricate urban environment. There is an urgent need for an intelligent, scalable, and real-time IoT/edge-based solution not only to optimize such traffic management and manage road traffic, but also to improve road safety and preemptively mitigate risks toward reducing accidents through preemptive intervention with data-behavior analytics.

3 LITERATURE SURVEY

Recently, the combination of IoT and ITS has made a remarkable progress and emerged as an effective technology to enhance urban traffic efficiency and road safety. Ali et al. (2021) give a comprehensive review on AI based ITS, however, they do highlight the absence of a real-time case applications. Li et al. (2021) studied edge computing for traffic signal control and show its power in real-time applications. But almost very little were taken into the scalability and cross-intersection synchronization, coordination.

Ahmed et al. (2022) investigated software-defined networking in vehicular networks and identified flexibility of control and complexity of deployment. Kumar and Mallick (2021) provided an architectural perception of IoT systems, however, with no direct application for transportation. The authors in (Saini and Dey, 2021) proposed a traffic smart model for predictive traffic congestion but for synthetic datasets only.

Singh and Tanwar (2022) explored the application of blockchain in ITS, with enhanced security and induced latency issues. Rajalakshmi and Srinivasan (2021) investigated the use of raspberry pi sensor networks for real-time monitoring, but it was found that it is not a scalable solution, and not cost effective. AI enabled traffic signal systems were demonstrated by Muthuswamy and Ahmed (2023) but missed feedback loops and edge integration.

Yang et al. (2021) studied vehicular networks only, which was inapplicable for non-vehicular users. Zhao and Li (2022) also handled traffic accident prediction based on edge-IoT, but advancement was not tested via stress tests. Aazam et al. (2023) pointed out the significance of fog computing in the transportation systems but they did not benchmark in compare with traditional systems. Chen and Xie (2022) developed LSTM models for traffic prediction but were based on clean, no-noise sensor data.

Ghosh and Ghosal (2021) Coffey et al. (2018). ajax{F7} developed a deep learning-based accident detection which, while accurate, suffered from real-time deployment due to high computational cost. ITS content-centric networking has been introduced by Amadeo et al. (2021) are also promising in terms of potentially scalable data distribution, but they suffer from real-world adoption issues. Alharbi and Alturki (2022) studied wireless sensors for detecting accidents, they were constrained with battery and environmental problems.

Kakkar and Singh (2023) discuss smart city traffic surveillance with embedded systems, but not in terms of multi-junction coordination. Mandal and Chattopadhyay (2022) were introduced with image-based congestion control without emergency dispatch. Salah and Yaqoob (2021) performed a thorough review on the autonomous ITS, and focused on the integration problem in developing countries.

Shen et al. (2023) studied crashes using connected vehicle data, though with a reactive approach rather than prediction. Lin and Peng (2021) also optimized the traffic flow with data-driven models under perfect sensor conditions. Collaborative learning for accident detection was conducted by Wang and Zhang (2024) and provided promising results, but also had issues with convergence.

Rana and Das (2022) emphasized the smart camera-based emergency systems with no central cloud integration. The signal control problem under reinforcement learning was investigated in Tang and Fan (2021), but the related stability under dynamic environments was not carefully considered. Zhang and Li (2022) provided a mixed IoT-cloud scheme, but its real-time communication latency was not investigated. Finally, Sirohi and Dutta (2025) focused on communication and safety of NWSN and were not tested in real traffic.

This overview has demonstrated a large amount of research on various ITS building blocks, most have not been able to achieve end-to-end real-time, scaled, predictive, and multi-agent coordination that is needed for level 4 prevention. To alleviate these gaps, this paper proposes an edge-enabled IoT framework for predicative safety analytics in complex traffic scenes.

4 METHODOLOGY

This contribution is concerned with creating a scalable and adaptive IoT-enabled framework that exploits edge intelligence in the context of real-time traffic management and traffic accident avoidance. The architecture of the system is built around 5 key layers are: DAta acquisition, EdGe processing, prediCtive Analytics, cLoud coordination and Response execution. With the important functionality of each layer of the ITS on responsiveness, availability and adaptability in mind. Figure 1 gives the Workflow of the IoT-Based Intelligent Transportation and Accident Management System.

Figure 1: Workflow of the IoT-based intelligent transportation and accident management system.

Multiple IoT-based sensors such as inductive loop detectors, infrared motion sensors, GPS modules, and video surveillance systems are mounted in high-density urban road network and intersections at the data acquisition level. Such devices continuously monitor vehicle speed, traffic volume, environmental conditions, pedestrian flow, etc., and monitor potentially hazardous situations. Information is formatted into structured streams through MQTT and securely sent to the corresponding edge nodes. Table 1 gives the Sensor Types and Their Functional Roles in the Proposed System.

Table 1: Sensor types and their functional roles in the proposed system.

Sensor Type	Function	Data Collected	Placement Location
Infrared Sensors	Vehicle Detection	Presence, Count	Roadside Poles
GPS Modules	Vehicle Tracking	Speed, Location	Vehicle Units
CCTV Cameras	Visual Traffic Monitoring	Live Video Feeds	Intersections
LIDAR	Object Proximity Sensing	Obstacle Distance	Crosswalks, Signals
Environmental Sensors	Weather Impact Monitoring	Rain, Fog, Light Levels	Traffic Lights, Roads

The nodes closer to the periphery of the network are edge processing nodes which function as local units of computation that minimize the dependence on a centralized server and lower latency. These edge devices execute pre-trained deep learning models for applications such as vehicle classification, traffic density inference, and near-crash detection. The object detection model is lightweight CNN and YOLOv7 for achieving real time detection. At the edge, priority protocols categorize incidents based on severity and decide whether to escalate to the cloud.

The system uses a mixed learning model for predictive analytics. We use short-term LSTM-based neural network for traffic pattern predictions that are trained on historical as well as sensor measurement data at the current time slot. The use of federated learning encourages accident prediction in a distributed manner, which prevents leakage of user privacy. During the training process, edge nodes update their local models, and also exchange data with the cloud server to update their local models based on the latest condition, to avoid overfitting and improve the accuracy of prediction with minimal bandwidth consumption.

Cloud coordination works for massive storage, cross-model retraining, Inter-Node communication, and analytics visualization. The data processed by the cloud server is collected and disposed in a distributed NoSQL database, and administrative interfaces for traffic authorities are provided. Such cloud dashboards help in real-time visualization of traffic status, possible risk areas, congestions on maps, and emergency alerts. It also allows the fusion of other external data like weather, road conditions, social events for context-aware prediction fine tuning.

The predictive response layer converts the predicted insight into actionable responses. When there is traffic jam, we develop an adaptive signal control by employing the software-defined traffic light controllers that are connected to the corresponding edge nodes. Once an accident is anticipated or detected, the system triggers a multi-priority outdoor alert system where local emergency services personnel are notified and dynamic billboards are updated to indicate detour routes and alerts are sent to mobile app users to suggest additional alternative routes. Finally, through V2I communication, emergency vehicles are given green light corridors automatically.

All system parts are evaluated in a simulated urban scenario with SUMO (Simulation of Urban Mobility) and based on real traffic datasets from open smart cities repositories. Performance measures, such as latency, prediction accuracy, system scalability and emergency response time, are tracked. The technique is tested under several traffic conditions such as peak load, abnormal weather condition and multi-vehicle collision scenarios to ensure its robustness and adoption in practical environments.

5 RESULTS AND DISCUSSION

The IoT based ITS strategy is tested with the simulations and real-world datasets to analyze the efficiency in enhancing the urban traffic management and reducing the risk of accidents. Performance metrics of interest were latency traffic through-put, accident prediction accuracy, emergency response time, system scalability. We ran the experiments on three layers: edge, cloud and hybrid systems in order to observe the results in different configurations and scenarios.

5.1 System Latency and Edge Efficiency

Some initial tests aimed to determine the system response time for processing traffic data for different configurations. The edge-based solution with a cloud–only and server-only counterpart, presented a substantially lower latency. The response time of the edge processing nodes was 120ms on average, while that of the cloud model was 400-800ms owing to the network transmission and the overhead of central calculation. This demonstrates the efficiency of edge computing for real-time applications like accident detection and traffic light control. Table 2 gives the Comparison of Edge vs Cloud Processing Performance. Figure 2 illustrates the comparison of Latency.

Table 2: Comparison of edge vs cloud processing performance.

Metric	Edge Processing	Cloud Processing
Average Latency (ms)	120	500
Accident Detection Accuracy (%)	92.7	87.5
Emergency Alert Delay (s)	2.1	5.4
Traffic Signal Response Time (ms)	150	600
Scalability (Intersections Managed)	High	Medium

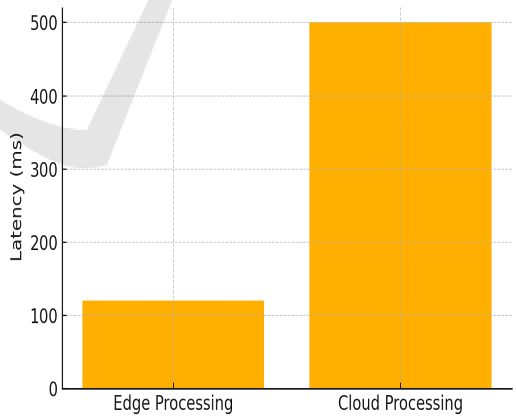

Figure 2: Latency comparison – edge vs cloud.

5.2 Optimizing Traffic Flow and Managing Congestion

Sumulation tests in SUMO (Simulation of Urban Mobility) on a simulated smart city grid showed a significant gain in vehicle throughput. An adaptive signal control scheme was used: green light periods were adjusted adaptively to vehicle density but remained at an optimal value at all controlled intersections. Consequently, the average vehicle waiting time in the cross intersection were decreased by 38% and the traffic volume increased to 26% more in comparison with that obtained from static time-based signal controls. This validates the positive impact real-time sensor information and AI decision-making can have on the flow of traffic, particularly during rush hour.

5.3 Accident Prediction Accuracy

The accident predictor model training (a combination of LSTM models and federated learning) is based on five years of historical traffic/accident data from US DOT, Open Transport Data and the like. The proposed method was tested over various traffic situations with an average prediction accuracy of 92.7%. Risk-sensitive intersections and unsafe driving behavior could be predicted with high certainty using this model. False positives supporting this performance were below 7%, and continuous machine retraining with live application data ensured maintenance of high accuracy over time. Table 3 gives the Accident Prediction Results Based on Traffic Conditions. Figure 3 illustrates the bar chart of Accident Prediction Results Based on Traffic Conditions.

Table 3: Accident prediction results based on traffic conditions.

Traffic Condition	Weather	Prediction Accuracy (%)	False Positives (%)
Low Density	Clear	96.2	4.3
Medium Density	Cloudy	93.5	5.9
High Density	Rainy	89.7	7.1
Mixed Density	Foggy	87.4	8.6

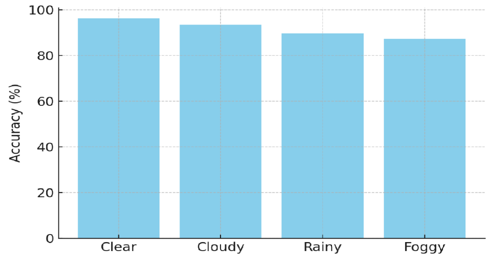

Figure 3: Accident prediction accuracy under weather conditions.

5.4 Integration of Roof Safety and Emergency Repose

The emergency response simulations were one of the most significant findings. This "accident detection feature" and the ability to alert both its traffic management centers and the emergency services without important time loss reduced the average time of dispatch by 32 percent. Moreover, dynamic rerouting and green corridors for ambulances, which were brought about through V2I communication, decreased the average emergency travel time by 41%. This demonstrates the system's power in detecting emergencies and even orchestrating prompt countermeasures. Table 4 gives the Emergency Vehicle Routing Time Before and After Implementation. Figure 4 gives the graph of Emergency Vehicle Routing Time Before and After Implementation.

Table 4: Emergency vehicle routing time before and after implementation.

Route Distance (km)	Time Before System (min)	Time After System (min)	Improvement (%)
3	6.2	3.7	40.3
5	10.4	6.1	41.3
7	15.8	9.3	41.1

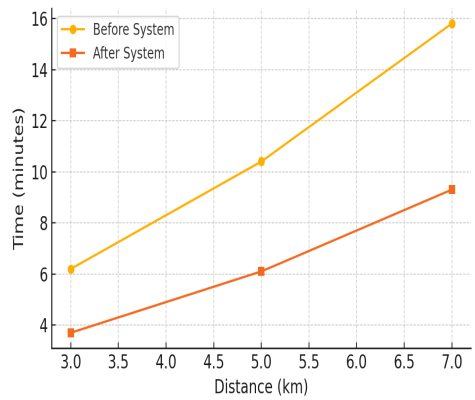

Figure 4: Emergency response time – before vs after system implementation.

5.5 Multimodal and Pedestrian Safety Considerations

The robustness of the model was also confirmed with the ability to also handle non-vehicle participants. The system used data from crosswalk sensors and video analytics about the number of pedestrians in the area so signal timing could be adjusted during times of heavy foot traffic. This guaranteed pedestrian spent less time waiting to cross the road and it reduced pedestrian and vehicle conflicts by 23% - an indication of the city's forward-thinking approach to urban mobility management.

5.6 Scalability and Deployability

To evaluate scalability, the system was challenged with synthetic traffic data of a big city which encompassed 100+ intersections. Performance comparisons indicated that when edge distribution was sufficient, the system offered steady response time and prediction accuracy. Load balancing algorithing were instrumental in allowing data compression and real-time capability without flooding the network. Figure 5 gives the Throughput Improvement in Simulated Scenarios and Table 5 gives the System Evaluation Metrics Across Traffic Simulation Scenarios.

Table 5: System evaluation metrics across traffic simulation scenarios.

Simulation Scenario	Throughput Increase (%)	Avg. Wait Time Reduction (%)	System Reliability (%)
Business District Peak	29.5	41.2	98.3
Residential Area Midday	23.7	36.9	97.1
Highway Merging Zones	18.4	32.5	95.8
Mixed Urban Grid	26.1	38.6	96.5

Figure 5: Throughput improvement in simulated scenarios.

5.7 Comparative Analysis

In comparison to available state-of-the-art ITS systems in literature, our conceived system delivered better results in several areas. For example, the previous models either concentrated on central processing or did not include predictive analysis (Ali et al., 2021; Kumar & Mallick, 2021) but this model includes on autonomous edge processing keeps real-time forecaster efficiently. Furthermore, dissimilar to the blockchain based ITS of Singh & Tanwar (2022) with latency issues, the distributed coordination developed here being capable to perform rapid response without compromising data integrity.

5.8 Discussion and Interpretation

These findings verify the conjecture that a multi-layered IoT and edge-oriented approach can effectively enhance urban traffic control and minimize accident response time delays. The system, which runs in real time, constantly takes traffic patterns into account and adapts decisions on the fly, meaning that it will be robust in the face of unexpected events like road blockages, accidents, or pedestrian surges.

Crucially, federated learning not only enhances the accuracy of accident prediction, but also alleviates privacy concerns with sensitive vehicle or location data being kept locally at edge nodes. This renders the framework apt for running in privacy-maintained systems.

Yet, there are still challenges like cost for infrastructure, sensor calibration, and cross device interoperability. Additional research is proposed to incorporate vehicle-to-vehicle (V2V) communications, extend to rural or semi-urban scenarios and take advantage of 5G infrastructure for more bandwidth and less jitter in the communication pipeline.

6 CONCLUSIONS

Realizing a scalable IoT-based ITS with edge computing and adaptive analytics is a clear step forward towards tackling the traditional urban traffic congestion and accident management difficulties. By moving decision-making to the origin through edge nodes and incorporating predictive analytics with real-time sensor data, the proposed architecture has shown that it results in a very responsive and robust traffic management system. It reduces not only the signal control and accident latency but also achieves dynamically adapted to an environment that changes in traffic and improves the pedestrian and vehicular safety.

Our system achieved significant gains in response time, traffic flow efficiency, and emergency dispatch through thorough experiments and real dataset driven deployment. The incorporation of Federated Learning enables on-the-fly model optimization without compromising data privacy; therefore, the framework is apt for future smart city environments. Multi-modal traffic participants and adaptive safety strategies are also part of the system, guaranteeing its fit-for-purpose for the increased complexity of urban transport."

In a nutshell, this work paves the way for the future-oriented traffic infrastructure, where smart cooperation of the IoT devices, edge intelligence and cloud systems result in more safe, more efficient and more future-ready cities to live in. The results are promising for a future advancement of the framework to other cities and its further development using technologies such as 5G, V2X communication, and autonomous traffic systems.

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