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Crowdsourced Smartphone Sensing and AI-Driven Edge Computing for Real-Time Urban Traffic Incident Detection and Response

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Abstract
Rapid urbanization and rising traffic density have increased the frequency and impact of roadway incidents, while conventional infrastructure-based monitoring systems remain constrained by limited coverage, high deployment cost, and delayed centralized processing. This paper presents a crowdsourced smartphone–edge framework for real-time urban traffic incident detection and response, in which commuter smartphones act as opportunistic sensing nodes and nearby edge units perform local corroboration before forwarding validated events to a central traffic management layer. The proposed framework combines on-device sensing using accelerometer and GPS cues, privacy-aware event abstraction, edge-based spatial-temporal clustering, and centralized response actions such as signal adaptation, rerouting support, and emergency notification. To evaluate the framework, a city-scale simulation environment was developed using SUMO and Python-based edge emulation over a representative urban road network with 25,000 virtual vehicles and 100 overlapping edge-service zones. Experimental analysis under multiple operating conditions, including peak-hour congestion, noisy sensing, varying participation rates, and simultaneous incidents, showed that the proposed framework reduced average incident detection latency from 40.6 s to 14.2 s, improved true positive detection from 72% to 92%, lowered average waiting time in impacted zones from 6.8 min to 4.7 min, and reduced network data usage by 48% relative to a baseline centralized system. These findings indicate that privacy-aware mobile crowdsensing, when coupled with edge-side validation, can provide a responsive, scalable, and communication-efficient basis for next-generation urban incident monitoring and traffic management.

Keywords: Mobile crowdsensing, edge computing, traffic incident detection, intelligent transportation systems, urban traffic management, privacy-aware sensing.

1. Introduction

City infrastructure, primarily roadways, faces increasing stress due to ongoing congestion, constant disruption to the ability of vehicles to flow normally through the network and events on the road that are critical for safety. Even short-duration occurrences such as a vehicle malfunction, sudden stop, minor crash or obstruction of a lane in a metropolitan area can have cascading effects throughout the upstream and downstream street segments, resulting in queue spillback, increased uncertainty in travel times, higher fuel usage, and greater emissions [10], [13], [38], [39]. Traditional incident-market workflows typically utilize a time-delayed system of human reporting and limited geographical sensing technology; therefore, restricting the ability to manage incidents at their earliest, most-critical point of the occurrence by city agencies. Urban traffic growth is not just a function of collecting traffic data, but rather detecting significant traffic incidents in real-time, accurately, and on a large enough scale, given the usual restrictions of cost, communication delay, and coverage [5], [6], [21], [22].

In response to this challenge, a great deal of research has examined how to use technology to monitor traffic through infrastructure-based intelligent transportation systems, participatory sensing, connected mobility and edge-enabled analytics. Early traffic incident detection systems largely relied on loop detectors, road sensors and centralised surveillance systems. By comparison, contemporary systems employ machine learning, probabilistic detection logic, and multi-sensor fusion to improve the detection of events [38] - [40] while at the same time, advancements in smartphones have resulted in a shift towards people-centric and mobile sensing, where everyday objects act as distributed sensors of conditions throughout our cities [1] - [6]. For instance, systems like CarTel, Nericell, VTrack and Mobile Century have demonstrated that smartphones can be used productively to measure the behaviour of vehicles on a roadways, record the level of traffic at a specific point in time and determine the amount of delay experienced by

drivers over a much larger geographic area than with traditional systems [7] - [10]. Recent research has also investigated how smartphones can be used to detect anomalies and accidents based on data from their accelerometers, GPS, audio, and multi-modal event cues or signals [23] - [28]. Additionally, edge and fog computing approaches have been introduced to minimise the latency and bandwidth limitations of traditional centralised analytic systems, particularly for real-time intelligent transportation applications [29] - [37]. Nevertheless, there are still much room for improvement because traditional (fixed/real-time) monitoring systems continue to suffer from high front-end costs, location-based restraints, and challenges with scalability.

This research introduces an innovative smartphone and edge data processing system to identify and manage urban traffic incidents to resolve the aforementioned shortcomings. For example, using commuter cell phones as sensors, commuters can measure patterns of abnormal vehicle movement resulting from traffic incidents (such as violent stops, unexpected vehicle stops, impacts that resemble collisions, and traffic behaviours due to obstructions) through the movement of their phones and then provide this information to a public cloud network infrastructure to help verify and locate the traffic incident reported on their phone based on spatial, temporal, and multiple-reports verification of the traffic incident. The result is only validated traffic incidents being delivered to the city/region's traffic management for possible follow-up interventions like traffic signal adjustments, rerouting of traffic, notifications to commuters, and coordination with emergency responders. The resulting smartphone-edge data collection system leverages the high capture rate possible with mobile devices while still being low latency through the edge processing capability of an edge data centre to preserve individual privacy and reduce the reliance on costly roadside infrastructure [5], [6], [14], [18], [24], [29], [31], [32], [35], [37]. The motivation behind this work is both practical and methodological. From a practical standpoint, growing cities require incident-detection systems that are economically deployable, scalable across heterogeneous road environments, and responsive enough to support near-real-time operational decisions. From a methodological standpoint, there is a clear need for a unified framework that links smartphone-based participatory sensing, privacy-preserving local abstraction, edge-side validation, and actionable urban traffic response into one reproducible architecture. Accordingly, the objectives of this study are fourfold: first, to exploit the sensing capabilities already available in commuter smartphones for broad and low-cost urban incident observability; second, to improve the reliability of reported incidents through local edge-based corroboration; third, to reduce communication burden by transmitting only validated or candidate event summaries instead of raw streams; and fourth, to assess the operational benefits of the proposed framework through simulation-driven analysis of latency, detection accuracy, congestion impact, and bandwidth demand. By positioning smartphones and edge nodes as complementary layers rather than isolated technologies, the present work seeks to move beyond fragmented traffic-monitoring models toward an integrated and practically deployable urban incident-response pipeline [6], [15], [17], [20], [22], [27], [30], [34], [35], [37].

This paper is structured as follows. An overview of the relevant literature covering traffic incident detection, mobile crowdsensing, privacy preserving sensing, and edge assisted intelligent transport systems is provided in Section II. The proposed smartphone/edge framework is reviewed in Section III with relevant workflow figures from the original paper. The mathematical formulation, simulation configuration, and experimental design for evaluation of the system are explained in Section IV. Section V describes how the results are presented with respect to detection latency, incident identification performance, congestion reduction and communication efficiency. The final section concludes the paper and discusses possible future research related to field deployment, calibration, and implementation of this technology on a metropolitan scale.

2. Literature Review

In recent years, the area of urban intelligent traffic monitoring research has been evolving from a paradigm that relies most heavily on fixed infrastructure at the roadsides, to one which is more based on flexible, data-rich and scalable methods. Through foundational work on participatory sensing and using mobile phones as sensors to gather information about the environment, it has been shown that people's daily-use mobile devices can be used as a distributed set of probes or sensors to provide much more coverage than stationary detectors (i.e. roadside technology). Subsequent studies have expanded this original idea by using mobile devices for estimation of traffic delays from GPS data, monitoring of roadway conditions and crowd-assisted mobility analytics. Simultaneously, researchers have identified that three key issues are hindering the success of mobile crowdsensing efforts: privacy, data quality and participant attribution. More recently, researchers have started to explore how edge, fog and mobile edge computing can reduce latency and communication load in transportation systems. Unfortunately, the research community is still working in a fragmented manner; the areas of sensing, validation, privacy and response to traffic are often treated separately rather than as an integrated operation [1], [5], [6], [8] – [10], [14], [18], [21], [22], [29], [30], [32], [35], [37]. Representative literature reviewed for the present study

S. No.	Ref.	Methodology	Key finding	Research gap
1	[1]	Introduced participatory sensing using citizen-	Established the conceptual basis for	Did not address incident-specific validation, edge

		carried mobile devices for urban data collection.	large-scale human-centered sensing.	processing, or traffic-control response.
2	[5]	Surveyed sensing modalities, architectures, and applications of mobile phone sensing.	Showed that phones can capture mobility and contextual signals at scale.	General sensing survey; no dedicated framework for urban incident detection and response.
3	[6]	Reviewed the state of mobile crowdsensing, its architectures, and future challenges.	Identified scalability and broad applicability of crowd sensed systems.	Reliability, data quality, and trustworthiness remained unresolved.
4	[8]	Used smartphone accelerometer, microphone, and communication signals in Nericell for road and traffic monitoring.	Demonstrated rich sensing of bumps, braking, and honking through smartphones.	Focused on road/traffic condition cues rather than end-to-end incident response.
5	[9]	Proposed VTrack for traffic delay estimation using mobile phones with energy-aware localization.	Achieved accurate road-traffic delay estimation with low energy overhead.	Addressed traffic state estimation, not incident validation or management actions.
6	[10]	Conducted the Mobile Century field experiment using GPS-enabled mobile phones as traffic probes.	Validated mobile phones as practical traffic-sensing sources at field scale.	Focused on corridor traffic estimation, not real-time validated incident handling.
7	[14]	Surveyed privacy threats and protection techniques in participatory sensing systems.	Established privacy as a primary adoption barrier in participatory sensing.	Did not resolve how to preserve privacy while supporting low-latency operational use.
8	[18]	Reviewed privacy-preserving mechanisms for crowdsensing, including anonymization and secure reporting.	Highlighted trade-offs between privacy, utility, and timeliness of sensed data.	Limited transport-specific focus and little integration with incident validation workflows.
9	[21]	Surveyed smartphone-based crowdsensing solutions across domains and sensing modalities.	Confirmed smartphones as versatile low-cost platforms for urban sensing.	Heterogeneity, battery cost, and data-quality coordination remained open issues.
10	[22]	Offered a comprehensive review of mobile crowdsensing systems and open research challenges.	Identified participant selection, QoI, privacy, and resource management as core issues.	Did not present a transport-specific edge-validation-response loop.
11	[23]	Applied Android accelerometers for real-time pothole detection.	Showed that road anomalies can be detected on commodity smartphones.	Narrow anomaly class; noisy conditions and mounting variations can cause false alarms.
12	[24]	Proposed WreckWatch for automatic traffic accident detection and smartphone-based notification.	Demonstrated feasibility of automatic crash detection and emergency notification.	Relied heavily on single-device inference and lacked multi-report corroboration.
13	[25]	Developed iBump, a smartphone application for vehicle accident detection.	Confirmed practical smartphone-based crash detection in vehicular settings.	Did not extend to city-scale validation, edge intelligence, or traffic-control integration.
14	[29]	Presented the vision,	Showed that proximity	Heterogeneity, security,

		benefits, and challenges of edge computing.	computing can reduce latency and bandwidth consumption.	programmability, and data abstraction challenges remained open.
15	[30]	Reviewed fog computing as a distributed support layer for IoT applications.	Established fog as suitable for time-sensitive distributed decision-making.	Needed stronger orchestration and application-specific deployment models.
16	[32]	Surveyed mobile edge computing architectures, benefits, and challenges.	Confirmed MEC as a promising low-latency architecture for mobile systems.	Mobility management, orchestration, and reliable service continuity remained difficult.
17	[35]	Provided a taxonomy and survey of edge-cloud computing for ITS and connected vehicles.	Showed strong relevance of edge-cloud designs for latency-sensitive ITS services.	Revealed fragmented architectures and limited standardization and deployment maturity.
18	[37]	Surveyed edge intelligence in intelligent transportation systems.	Identified edge AI as promising for perception, inference, and transportation decisions.	Dataset scarcity, resource constraints, trust, and deployment realism remain open.
19	[41]	Proposed an optimized thread-based virtual traffic light framework for adaptive traffic coordination.	Showed improved delivery and delay behavior for virtual traffic-light communication.	Focused on intersection control and VANET coordination, not smartphone incident sensing.
20	[42]	Developed a thread-based virtual traffic light algorithm using VANET-style communication.	Demonstrated smarter adaptive traffic light control than fixed timing approaches.	Assumes equipped vehicular communication and does not address crowd sensed incident validation.

The literature has evolved in 4 main ways. First, the literature showed that mobile phones are valuable tools for both theoretical and practical purposes, supporting the use of smartphones as multiple distributed city sensors [1], [5], [6], [8]-[12], [21], [22]. Second, the focus of the literature was narrowed to using mobile phones to detect road problems (i.e., crashes), with evidence from accelerometer, GPS and multi-modal event signatures (e.g., logging traffic data) that these event signatures can be used to automatically identify road abnormalities [23]-[25]. Third, much of the literature revealed issues related to the privacy of users, trust issues and the quality of information; thus, user un-willingness, false alarms and privacy concerns remain significant barriers to real implementation of incident detection technology/systems [14]. Fourth, new concepts for mitigating latency and communication challenges in smart transportation settings were introduced in the literature (i.e., edge, fog and MEC paradigms) [29]-[31], [33]-[35],[37]. Several virtual traffic signal studies (i.e., [41]-[42]) provided new ideas for adaptive traffic management; however, the focus of these studies was limited to coordination of control and not to detection of incidents. Although this provides rich literature, it remains largely disconnected; for example; the literature that describes the way that the incident signals (from mobile applications) are generated, validated, and reported are generally disconnected; the research that discusses user privacy and trust are disconnected from the literature on how to control incidents; and the literature that describes how incidents are detected via the generation of traffic data is generally disconnected from the literature that describes traffic system response. There is a lack of research that ties together incident data generated from mobile devices, privacy-preserving local aggregation of incident data, edge-side validation of incident data, and operational responses from cities, in one comprehensive scalable solution.

Another key aspect to consider when developing smartphone literature is the methodology that has been used to understand the feasibility of using smartphones as devices for detecting something. A significant part of the smartphone literature focuses on issues such as single-device detection, anomaly detection in specific domains, or small-scale movement analysis. The challenges for researchers remain distinguishing between genuine events and isolated noise from sensors, particularly in heavily populated urban areas. Privacy research has been effective at identifying types of risk and mechanisms for protecting individual privacy; however, little research has been done to demonstrate how to create effective, real-time traffic management in a manner that protects individuals' privacy. Although edge and Multi-access Edge Computing (MEC) literature provides strong evidence that computation should be performed near to the source of the information collected on commuter devices, they typically focus on the architecture or survey and do not present the means to create a transportation pipeline from commuter devices to validated traffic management

interventions. Thus, the primary unsolved issue is to provide validated, privacy-preserving, low-latency, and action-oriented information about incidents; and the current paper is situated to make its contribution to this unfilled need.

SMARTPHONE–EDGE FRAMEWORK FOR REAL-TIME INCIDENT DETECTION AND RESPONSE

The proposed framework for detecting urban traffic incidents in real-time consists of crowdsourced smartphone sensor input and nearby edge servers to help validate those inputs. This framework is proposed to address some of the main challenges outlined in the literature, including limited spatial coverage of existing systems, long processing times by central processing units (CPUs), lack of privacy protection in current systems, and the weak relationship between the detection of incidents and the actions taken by traffic control authorities in various cities; see references [1] , [5], [6], [14], [18], [21], [22], [29], [32], [35] and [37] . Unlike traditional systems that rely on infrastructure, the proposed system will use commuters' smartphones as sensors to detect incidents and the many nearby edge servers as validators of that data. The entire system will provide the user with a complete range of experience including a broad range of sensor data, fast filtering capabilities, protection of privacy in reporting incidents, efficiency of reporting incidents to authorities and providing that information to authorities quickly in one fully integrated system.

2.1A. System Overview

The framework is organized into three cooperative layers:

- User Device Layer
- Edge Intelligence Layer
- Central Management Layer

At the sensing layer, smartphones embedded in moving vehicles continuously observe motion and location patterns using built-in sensors such as accelerometer and GPS, with microphone input treated as optional and event-triggered rather than continuously streamed. At the edge layer, reports from multiple devices are clustered and cross-validated over short temporal and spatial windows. At the central layer, validated incidents are converted into operational actions such as signal adaptation, rerouting, commuter alerts, and emergency notification. This layered design is consistent with the strengths of participatory sensing and low-latency edge computing reported in prior work, while directly addressing the lack of unified end-to-end incident-response pipelines in the existing literature [5], [6], [24], [29] – [32], [35], [37]. Figure 1 presents the three-layer architecture of the proposed system, showing data flow from commuter smartphones to distributed edge nodes and finally to the central traffic management platform for validated incident response.

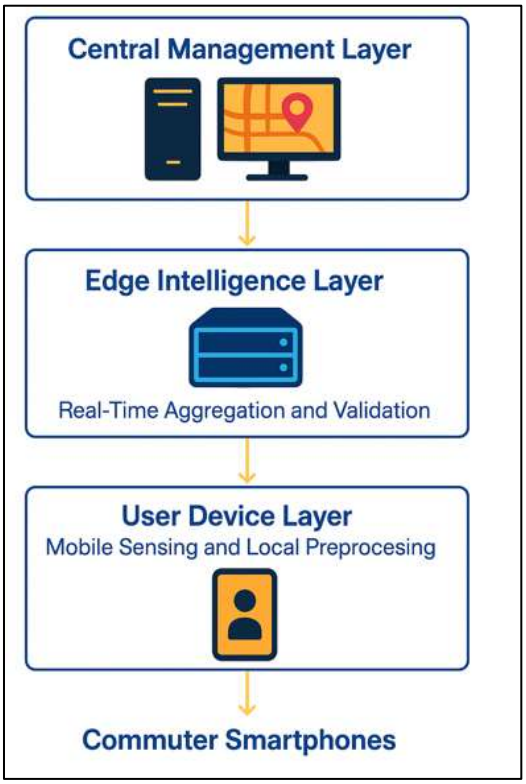

Fig. 1 Layered system architecture of the proposed smartphone–edge traffic incident detection framework.

2.2Smartphone sensing and local incident hypothesis generation

Each participating commuter smartphone acts as a local sensing agent. Let the sensor feature vector generated by device

iat time tbe written as

$$x_i(t) = [a_i(t), v_i(t), \Delta v_i(t), \omega_i(t), m_i(t)] \quad (1)$$

where $a_i(t)$denotes acceleration magnitude, $v_i(t)$denotes instantaneous speed, $\Delta v_i(t)$denotes short-horizon speed change, $\omega_i(t)$denotes heading or motion irregularity, and $m_i(t)$denotes an optional event-triggered acoustic indicator. This formulation allows the phone to detect abnormal mobility patterns associated with collision-like shocks, abrupt braking, sudden stoppage, or obstruction-induced delay [8], [23] – [25].

A lightweight incident hypothesis score is computed on-device as

$$S_i(t) = w_1 f_a(a_i(t)) + w_2 f_v(\Delta v_i(t)) + w_3 f_\omega(\omega_i(t)) + w_4 f_m(m_i(t)) \quad (2)$$

where f_a, f_v, f_ω, and $f_m$are normalized feature functions and $w_1, \dots, w_4$are non-negative weights such that $\sum_{j=1}^{4} w_j = 1$. A candidate event is generated whenever

$$S_i(t) \geq \theta_d \quad (3)$$

where θd denotes the local detection threshold. While both device-level inference based on a threshold and a device-level inference based on thresholds gives us a level of responsiveness, they do not give a sufficient level of reliability at a city-scale because there exist factors that can distort the detection of single devices (for example potholes, hard braking, variability in the placement of phones, and other non-incident motion artifacts) [23]-[25]. For this reason, we do not consider the output of the smartphone as the definitive truth, but rather the output of the smartphone as one possible hypothesis of whether an incident occurred.

Once a candidate event is detected, the smartphone creates a compact privacy-aware report

$$r_i = \{\tau_i, \tilde{\ell}_i, e_i, c_i, h_i\} \quad (4)$$

where τ_i is the timestamp of an event, $\tilde{\ell}_i$ is a generalised location, *ei* is the label identifying the event's type, *ci* is the level of confidence in the event reported locally, and *hi* is a hashed temporary device ID associated with that event. There will not be a continuous stream of raw sensor data transmitted. This choice of design is in line with previous research on mobile crowdsensing that anticipated the need to preserve user privacy by using abstraction and limiting the amount of data sent [14], [18]. Figure 2 shows an example of a sensing node using a smartphone as the sensing device in a commuter vehicle, with an example of how acceleration, GPS, and optionally microphones are used to identify local anomalies and report on encrypted events back to regional edge nodes.

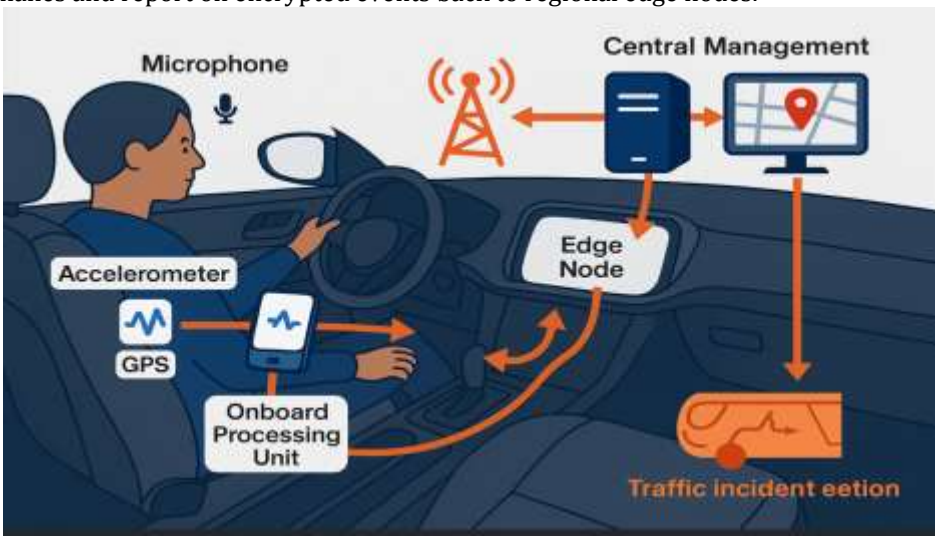

Fig. 2 In-vehicle sensor and communication setup for real-time incident detection.

2.3Edge-based spatial-temporal corroboration

The edge layer is where all of the reports from smartphones are verified before the reports reach City Control. The edge node, R_z, contains information about the reports received by it over a certain period. Edge node reports are clustered together into a candidate cluster C_k, by being similar in both time and place.:

$$C_k = \{r_i \in R_z \mid \| \tilde{\ell}_i - \ell_k \| \leq d_0, \ | \tau_i - \tau_k | \leq \Delta t_0\} \quad (5)$$

where $d_0$is the spatial radius and $\Delta t_0$is the temporal window. The clustering rationale is based on an established fact that a legitimate incident will typically create multiple "near-synchronous" reports from multiple commuters in close proximity (i.e., within 1-2 seconds of each other). By contrast, the reporting of a noise event is usually characterized by isolated reports of the event ([29], [30], [32], [35], [37]).

A candidate incident is considered validated when:

$$\Phi_k = \alpha \frac{n_k}{n_{max}} + \beta \bar{c}_k + \gamma \rho_k - \delta \eta_k \qquad (6)$$

where n_k is the number of independent reports in the cluster, $\bar{c}_k$k is the average local confidence, ρ_k is the contextual consistency factor, η_k is the noise penalty, and $\alpha, \beta, \gamma, \delta$ are adjustable non-negative coefficients. The contextual consistency factor ρ_k can be based on the agreement of the type of event being reported, lane-level proximity, repeated abrupt stops within the same vicinity, or consistency of speed collapse with location. The noise penalty η_k serves to suppress clusters that contain high volumes of duplicate reports, low confidence signals, or isolated outlier reports.
A candidate incident is validated when

$$\Phi_k \geq \theta_e \text{and} n_k \geq n_{min} \qquad (7)$$

where θ_e is edge validation threshold and n_{min} is the minimum required number of independent corroborating report. This methodology of multi-device corroboration for final decision making provides a much higher reliability than seen in previous detection studies using only one device ([24], [25], [29], [30], [32], [37]). Figure 3 provides a visual representation of the overall flow of the framework, which begins with the generation of an event hypothesis through the on-device engine and is followed by a wireless transmission, edge-based corroboration, and activation of a citywide response.

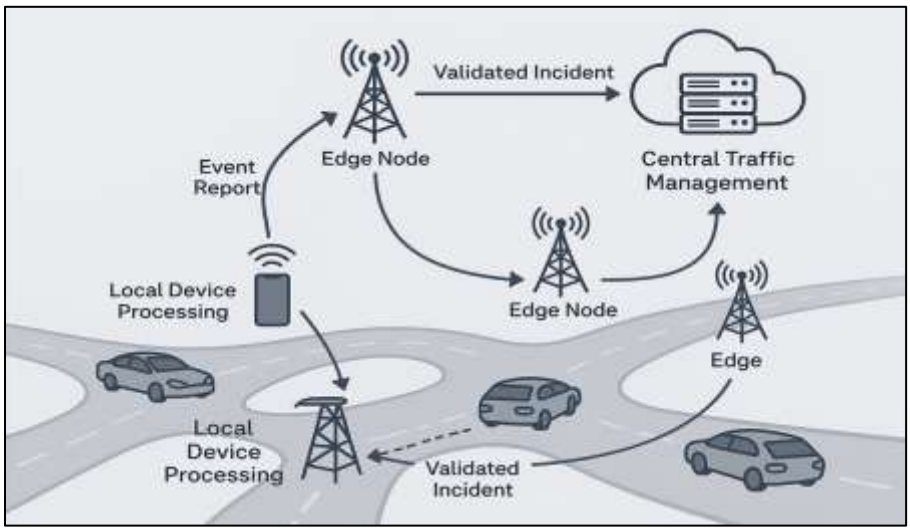

Fig. 3 End-to-end workflow of incident detection and reporting using local device processing, edge validation, and centralized response

2.4Privacy-preserving communication and transmission efficiency

One of the key issues for crowdsourced transportation systems is improving visibility without compromising the level of privacy through excessive monitoring/surveillance. For this reason, the proposed system has been designed to minimize privacy by using a local device sensing approach, an abstraction of the data being transmitted back rather than a full/raw copy of the data being sensed, and a representation of the device's identity as a short duration (e.g., 10 minutes) hashed identifier. This provides sufficient operational validation [14], [18], [19] while minimizing the potential for direct, personal identification and reconstruction of that identity.
In addition, the edge layer uses edge filtering technology to minimize the communication burden on the users of the network by sending only validated incident summaries to the central traffic management platform rather than sending the complete stream of raw candidate events. Let B_{raw} be the total bytes that would be sent under a naïve centralized upload model, and B_{edge} be the total number of bytes transmitted to the central platform after edge filtering. Then, the transmission savings due to the use of edge filtering is calculated as follows:

$$\Gamma_B = \frac{B_{raw} - B_{edge}}{B_{raw}} \times 100 \qquad (8)$$

This metric is particularly important in urban deployments where high commuter traffic is present, and communication needs to be efficient to support scalability [29]– [32], [35].

2.5Central traffic management response layer

After a validated incident is detected at the edge layer, a central traffic management platform receives an alert packet with the incident details. The validated incident message is defined as follows

$$I_k = \{\tau_k,\ \ell_k,\ e_k,\ \Phi_k,\ z_k\} \qquad (9)$$

Here, τ_k is validated event time$\ell_k$is the incident location, $e_k$is the event class; $\Phi_k$is the final confidence score; $z_k$denotes the edge zone from which this incident originated. Once the incident has been validated, the central system will correlate the incident with one or more corresponding response actions:

$$A_k = \mathcal{G}(I_k) \qquad (10)$$

where $\mathcal{G}(\cdot)$ is the function that executes all triggered response actions, including adaptive traffic signal timing, route changes, travel advisories and emergency dispatch. Connecting validated detection with responding to a traffic incident is an important contribution of this framework; many previous studies only recognize events but do not explicitly link sensing and city-scale mobility response [35], [37], [41], [42]. The proposed framework will fill this gap by linking validated incident intelligence to operational mobility actions.

2.6Algorithmic workflow of the proposed method

The complete workflow for the system proposed by this study follows:
Step 1: Each smartphone device continuously samples features representing the user's motion and geolocation.
Step 2: A hypothesis score is generated for the device using the weighted feature model described in (2).
Step 3: Whenever the condition in (3) has been satisfied, a compact privacy-aware incident report will be created as in (4).
Step 4: The compact report will then be sent to the edge node that is nearest to the smartphone.
Step 5: The edge node groups nearby reports using the spatial-temporal clustering rule in (5).
Step 6: For each cluster, validation scores will be calculated using equation (6).
Step 7: When the condition described in (7) is met, the event is designated as a confirmed incident.
Step 8: The validated incident message will then be sent to the central traffic management system using (9).
Step 9: A response will be triggered according to the mapping described in (10).
This algorithmic framework produces a flexible hierarchy that allows for modularity, scalability, and compatibility with simulation-based evaluations. It also clearly defines the distinct functions of each layer of the framework: The smartphone generates event hypotheses; the edge conducts reliability screening and consensus-validation; and central manages the synchronization of all responses. Therefore, while the present work introduces a new sensing technique, it also creates an operational chain of validated interventions that stem from multiple sources of urban observation.
The proposed smartphone-edge framework combines participatory sensing capabilities with privacy-aware local abstractions, edge-side corroboration and central traffic response capabilities into a single architectural representation to overcome the most significant limitations identified in previous studies. By using smartphone devices as a broad sensor network, edge nodes to filter out false-positive results through cluster validation and central management systems to convert validated incidents into responsive actions, this framework creates a three-tier methodological foundation for both performance analysis and simulations discussed in the following section.

3. Simulation Setup And Experimental Design

The following section discusses the simulated environment that evaluated the crowd source smart phone-edge framework to enable the real-time detection of urban traffic incidents and the ability to respond, using a simulated system that replicates a complete operational chain of the proposed system, beginning with virtual commuter sensing, through validation on an edge node, through to an intervention by a central traffic management department. In evaluating our proposal, we wanted to go beyond measuring the performance of an isolated device concerned only with the anomaly detection of a device, therefore, our study was designed to Measure the performance of the entire system as if it were operated in a realistic urban transportation environment with the following realities; a real, uneven road geometry of varying densities of vehicle traffic, event injection, noise in the commuter sensing, and the distributed processing being performed at edge nodes. Therefore, the simulated environment is not only intended to demonstrate our proposal as concept but serve as a city-wide testbed for determining the performance of our system in terms of responsiveness, reliability, effective communication, and the effect on traffic at large. The workflow for the end-to-end SUMO Simulation is shown in figure 4.

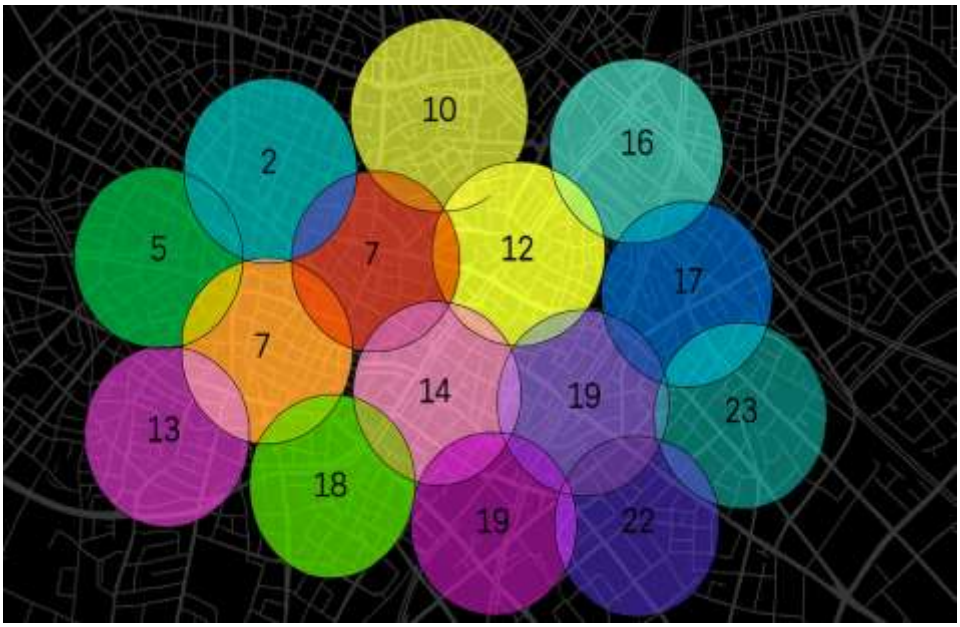

Fig. 4 Edge Node Zone Distribution Over Simulated Urban Network

3.1 Computing platform and software stack

All experiments were conducted on a dedicated high-throughput workstation specifically designed for large-scale mobility simulations and analyzing event data. The workstation was based on an Intel Core i9-13900K processor that operates at 3.0 GHz, has 64 GB of DDR5 RAM, a NVIDIA RTX 4090 with 24 GB VRAM, and Two 2 TB NVMe Solid State Drives. Ubuntu 22.04 LTS was the base operating system. The traffic simulation portion of the platform was implemented in SUMO version 1.18.0, while emulating the smartphone reporting to the edge nodes, clustering of edge nodes, the consensus validation process, and statistical post-processing of decisions was performed in Python version 3.11. The major components of the Hardware, Software, and Simulation configuration are presented in Table 2.

Table 2 Computing platform and principal simulation parameters

Component	Specification / Setting	Role in study
CPU	Intel Core i9-13900K, 3.0 GHz	Large-scale simulation and parallel event processing
Memory	64 GB DDR5 RAM	In-memory traffic and event analytics
GPU	NVIDIA RTX 4090, 24 GB VRAM	Accelerated numerical and visualization workflows
Storage	Dual 2 TB NVMe SSDs	High-speed I/O for simulation logs and data processing
Operating system	Ubuntu 22.04 LTS	Stable scientific-computing environment
Traffic simulator	SUMO 1.18.0	Urban traffic and mobility emulation
Scripting environment	Python 3.11	Event generation, edge emulation, logging, analysis
Core libraries	pandas, NumPy, SciPy, multiprocessing	Numerical analysis, aggregation, statistical processing

Sampling frequency	10 Hz	Smartphone accelerometer/GPS emulation
Candidate trigger	deceleration $< \quad -5\ m/s^2$ or speed collapse to zero within 2 s	Local event hypothesis generation
Edge zones	100 overlapping regions	Distributed incident validation
Spatial clustering radius	100 m	Local corroboration threshold
Temporal clustering window	$\pm 20s$	Local corroboration threshold
Minimum confirmations	3 reports	Incident validation rule
Number of simulation runs	20 per scenario	Statistical stability
Statistical treatment	Mean values + bootstrap confidence intervals	Robust comparative evaluation

3.2 Urban Traffic Environment and Commuter Population

The simulation used a mid-sized city road network (a representative road network with respect to the types of traffic experimentation which could occur on a city road network) from OpenStreetMap to preserve urban realism, after cleaning up the network to carry out traffic experimentation. Thus, there were approximately 350 intersections and more than 500 lane-kilometres of road, including arterial links, secondary streets, and a mixture of both signalized and unsignalized intersections. This variation is significant because it would be impossible to emulate the complexity of the operation of urban road networks using either an entirely regular grid or an entirely synthetic grid.

Next, a synthetic population of 25,000 virtual commuter vehicles was produced, with the unique route profiles and time of dispatch assigned to each vehicle. This created natural variability in the build-up of congestion and the increase in the loading of the corridor, along with the increase in junction pressure for every vehicle in the simulation. A commuter carrying a smartphone instance of the proposed detection application was mapped to every vehicle in the simulation. Sensor emulation was completed at 10 Hertz, providing opportunities to generate candidate events under abnormal motion patterns (e.g., rapid deceleration, sudden stops, and collapse of velocity associated with obstruction). Figure 5 shows a sample network view for incident-level evaluation.

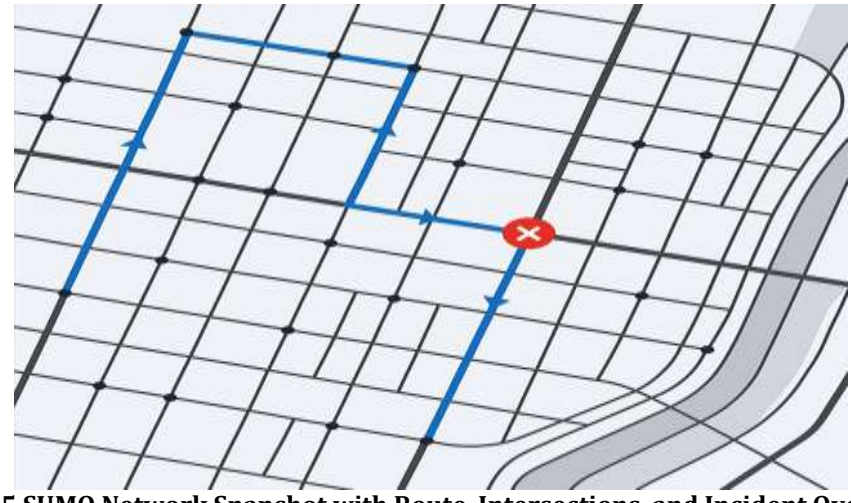

Fig. 5 SUMO Network Snapshot with Route, Intersections, and Incident Overlay

3.3 Incident generation and edge-zone emulation

The experiment introduced roadway interruption cases at controlled intervals to replicate a diverse spectrum of roadway interruptions. The experiment included single-vehicle crashes, multi-pileups, sudden disabling of vehicles, and unexpected road obstruction events. The simulations used parameter values for severity, duration, and spatial extent to create instances of mild-moderate-severe roadway interruption events all within the same simulation environment. The distributed edge layer was emulated by partitioning the city into 100 overlapping service zones, each represented by a dedicated Python process. Reports generated by virtual smartphones were routed to the nearest edge node based

on coarsened location. Within each zone, reports were clustered by temporal proximity ($\pm$20)and spatial proximity (100 m), after which a consensus rule was used to validate incidents. Events supported by fewer than three independent confirmations were deprioritized, while statistically significant clusters triggered validated alerts. The distributed validation topology adopted in the simulation is shown in Fig. 6.

Validated incident notifications were forwarded from the edge layer to a separate central traffic-management process. Once an alert was received, the central controller executed corridor-level interventions such as adaptive signal adjustment, rerouting support, and system-level logging of downstream network conditions. All simulation outputs were stored in a relational database. The structure of the simulation database is summarized in Table 3

Fig. 6 Simulation environment with overlapping edge zones

Table 3 Simulation dataset fields and descriptions

Field	Description	Data type
Incident_ID	Unique identifier for each simulated incident	Integer
Event_Timestamp	Time at which the report was generated	Datetime
Vehicle_ID	Anonymized device/vehicle identifier	String
Edge_Node_ID	Edge zone handling the event	Integer
Location_X, Location_Y	Incident location in projected coordinates	Float
Raw_Events	Number of raw reports received for the incident	Integer
Confirmed_Incident	Incident validation status	Boolean
Detection_Lag	Time from incident occurrence to validated detection	Float
Average_Queue_Length	Queue length at the nearest affected junction	Float
Pre_Incident_Travel	Average corridor travel time before the incident	Float (s)
Post_Incident_Travel	Average corridor travel time after the incident and response	Float (s)
Bandwidth_Usage	Data transferred per event/incident	Integer
False_Positive	Indicator of spurious validated alert	Boolean
False_Negative	Indicator of undetected incident	Boolean

3.4Representative data excerpt

A representative excerpt from the simulation database is provided in Table 4

Table 4 Representative excerpt from the simulation incident log

Sure. Here is your data converted into a clean, properly formatted table:

Incident ID	Event Timestamp	Edge Node ID	Raw Events	Confirmed Incident	Detection Lag (s)	Average Queue Length	Pre-Incident Travel (s)	Post-Incident Travel (s)	False Positive
201	2024-07-07 08:12:44	12	8	Yes	16.8	14.2	235.7	278.9	No
202	2024-07-07 08:14:03	17	5	Yes	18.6	12.7	221.1	265.0	No
203	2024-07-07 08:16:25	14	2	No	–	–	–	–	Yes
204	2024-07-07 08:19:47	7	9	Yes	13.2	16.1	240.4	260.3	No
205	2024-07-07 08:22:13	9	6	Yes	15.7	15.8	232.0	254.7	No

3.5Evaluation metrics

The effectiveness of the framework was assessed using latency, validation reliability, communication efficiency, and travel-impact metrics. The equations in the current draft are broken and must be rewritten properly before submission. The corrected formulations are:

$$L_d = t_v - t_g \qquad (11)$$

where $L_d$is detection latency, $t_v$is the timestamp of the first validated alert, and $t_g$is the ground-truth incident time.

$$P = \frac{TP}{TP + FP} \qquad (12)$$

$$R = \frac{TP}{TP + FN} \qquad (13)$$

where Pand Rdenote precision and recall, respectively, and TP, FP, and FNhave their usual meanings.

$$B_s = \frac{B_{raw} - B_{validated}}{B_{raw}} \times 100 \qquad (14)$$

where $B_s$is the percentage bandwidth saving, $B_{raw}$is the load under full centralized upload, and $B_{validated}$is the load after edge validation.

$$\Delta T = T_{post} - T_{pre} \qquad (15)$$

where $T_{pre}$and $T_{post}$are average corridor travel times before and after incident response.

$$Q_{avg} = \frac{1}{N}\sum_{i=1}^{N} q_i \qquad (16)$$

where $q_i$is the observed queue length during interval i. This extra queue metric strengthens the section because the dataset already contains average queue length and the results section later discusses congestion reduction.

F Scenario design and statistical protocol

The study was designed to include five pre-existing operating conditions: baseline urban traffic with sparse incidents; peak-hour congestion due to ongoing multi-vehicle crashes; randomized noise injection; variability of commuter participation from 25% to 100%; and simultaneous incidents at multiple zones. All conditions were repeated at least 20 times using different random seeds, with averages to provide a bootstrap confidence interval. Lastly, sensitivity analysis was performed to investigate detection thresholds, zone sizes, and consensus rules, summarized in Table 5,

which lists the evaluation conditions for the study.

Table 5 Experimental scenarios used for evaluation

Scenario	Purpose	Key stressor
Baseline sparse-incident traffic	Reference operating condition	Low event frequency
Peak-hour congestion	Assess detection under dense traffic	High vehicle density and reduced mobility
Noise-injected sensing	Test robustness to spurious triggers	False alarms and reporting errors
Variable participation (25%–100%)	Evaluate crowd dependence	Uneven sensing coverage
Multi-zone simultaneous incidents	Examine scalability	Concurrent validation across edge nodes

In this research, a specialized simulation framework has been created to evaluate the effectiveness of the proposed system at a full-scale operation. The simulation framework integrates the phone-to-phone level incident generation event with geographical support provided by a distributed edge validation architecture; a centralised traffic management system; structured database logging of performance metrics; and a multi-faceted experimental approach that involves running multiple experiments under different conditions using the same setup as in the original network configuration outlined in the preceding chapter. By re-organising previously developed methods into a more structured method of presentation, we are able to provide more rigorous evidence of the system's potential for reproducibility, robustness and overall system validity. In summary, this next chapter will present a more thorough analysis of the comparative performance of the proposed system as measured against three key indicators, namely: latency to deliver the validated incident to users; the reliability of the validation; and reduced traffic congestion through the use of evidence based reductions in traffic volume; therefore the previous chapter should now be replaced by a greater focus on all aspects of the system's estimated performance as compared to other proposed systems.

4. RESULTS AND DISCUSSION

This section discusses how well the Crowdsourced Smartphone Edge Framework works with Urban Traffic Simulation Scenarios defined in Section 4. Overall, the proposed system outperformed the baseline Centralized Architecture under all simulated conditions including sparse event detection, random peak hour crashes, noise from sensors, participation rates varying dramatically (50% to 100%), and multi-zone interference at once. The largest performance improvement areas were related to (1) when the incident was detected; (2) whether it was validated to be real or false; (3) how bad traffic would be post-incident, and (4) how well the proposed protocol communicated between nodes. These experimental results demonstrate that by offloading incident validation to the edge, the proposed approach can significantly accelerate and enhance urban traffic response timelines without requiring thick fixed road side integration.
A Consolidated performance comparison
Table 6 gives a brief summary of the major comparative results even though they were obtained through simulation studies.

Table 6 Consolidated performance comparison of the proposed framework and baseline system

Metric	Proposed framework	Baseline system	Improvement	Interpretation
Average detection latency	14.2 s	40.6 s	65.0% lower	Faster incident confirmation due to local edge validation
True positive detection rate	92%	72%	+20 percentage points (+28% relative)	Stronger incident recognition reliability
Average waiting time in impacted zones	4.7 min	6.8 min	31% lower	Reduced secondary congestion after validation and response
Relative network data usage	52% of baseline	100%	48% lower	Less communication load due to validated summary transmission

4.1 Detection latency analysis

The first major benefit was the significant decrease in incident detection latency. The amount of time that passes from the time an incident occurs (ground truth) until the time the system has a validated detection of that incident, typically

referred to as incident detection latency, was reduced from 40.6 seconds to 14.2 seconds by implementing the proposed framework. This results in a 65% decrease in incident detection latency. This is a very important benefit of a Real-Time Incident Management System because how quickly reliable alerts are generated after an event starts greatly impacts the operational viability of an incident management system. In the case of queues forming at upstream links, a delay of several tens of seconds is generally sufficient to allow the formation of a queue at an upstream link, particularly along densely populated corridors where there are multiple closely spaced intersections. On the other hand, with the proposed framework, initial report aggregation and consensus validation is performed in proximity to the incident source, and as such, much of the latency associated with forwarding raw data and centralized validation is removed. As shown in Fig. 7, the incident detection latency decreased from 40.6 seconds to 14.2 seconds, thereby demonstrating the advantages of corroborating incidents locally at the edge of the network as compared to centrally validating.

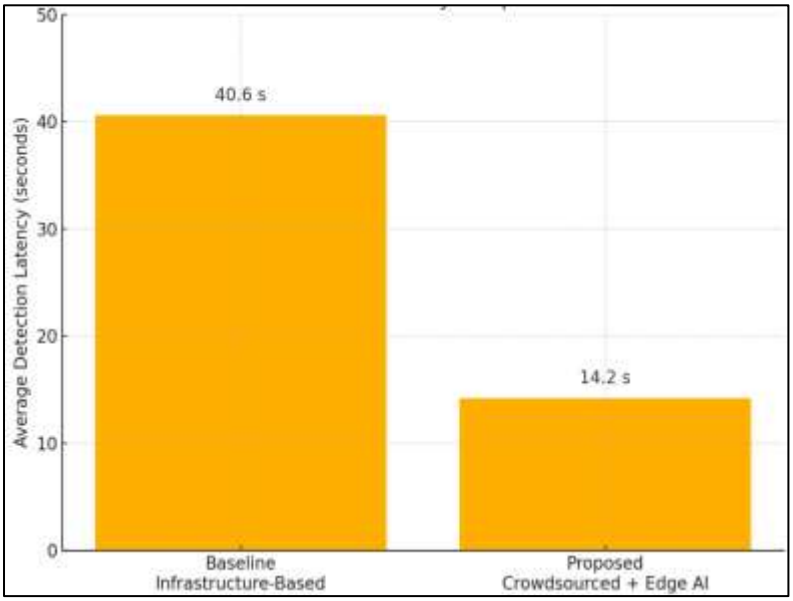

Fig. 7 Average Detection Latency: Proposed vs. Baseline System

This finding is significant from an Intelligent Transportation System (ITS) standpoint as it provides evidence that the advantage of using a new methodology for modifying traffic flow is not trivial. The magnitude of this effect is sufficiently large that it may alter the behaviour of downstream traffic, particularly with regard to times when secondary disruptions are occurring rapidly (i.e., peak period). As a consequence, the level of improvement identified in this study reinforces one of the main arguments within the paper regarding the fact that validated edge intelligence will be much more operationally agile than a cloud-centric or traditional infrastructure-led system.

4.2 Detection reliability and precision–recall behaviour

A further key conclusion centres on the quality of validated incident recognition. The suggested framework was able to correctly identify 92% of genuine incidents compared to the baseline of only 72%. This means a 20 percentage-point improvement in the accuracy of the proposed framework or a relative increase of around 28%. An important point about this improvement is that noise is a significant problem for smartphone-originated signals on an individual-phone basis due to sudden braking and potholes as well as changes in where the phone is being held and short periods of stop-and-go driving patterns being mistaken for incident signatures on a single-device basis. The proposed framework alleviated this issue by deferring any final confirmation of incidents to the edge node, where reports are spatially and temporally confirmed prior to being escalated. Therefore, this mechanism of validating multiple incident reports enhances trustworthiness by eliminating incorrect triggers based on individual report accuracy and promoting priority when determining incident reporting from different sources. Figure 8 illustrates that the stronger precision-recall trade-offs achieved through the proposed framework indicate the positive impact of corroborating incidents at the edge in improving the identification of incidents without also increasing the number of false alerts.

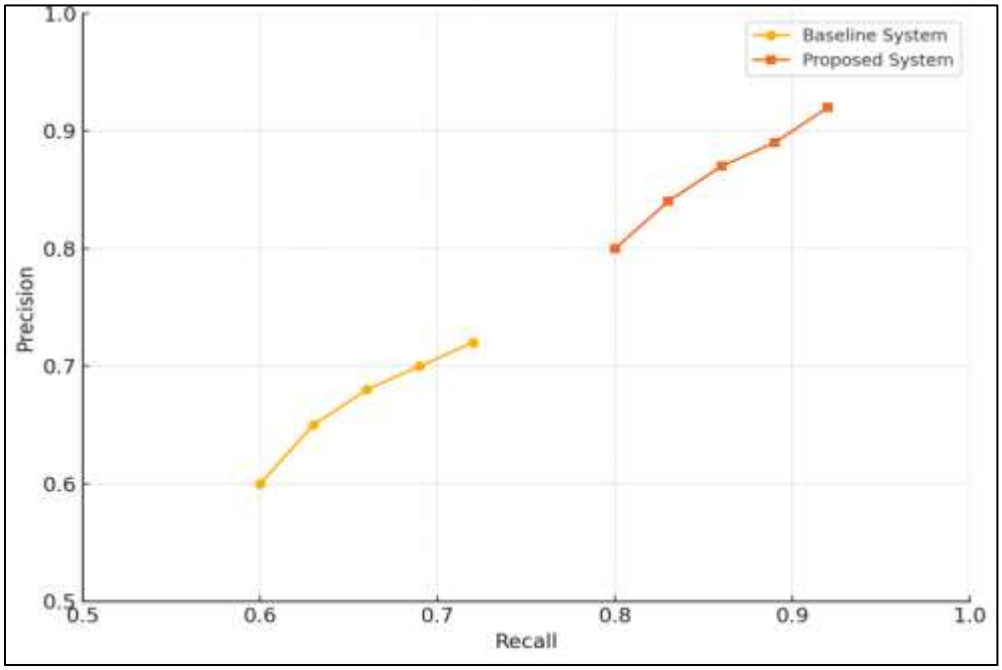

Fig. 8 Precision-Recall Performance Comparison

4.3Impact on secondary congestion and corridor performance.

In addition to an improved level of detection, the proposed architecture improved traffic conditions after an incident. When comparing baseline and intervention results, secondary congestion caused by an incident decreased by 31%. The average waiting time in the impacted areas decreased from 6.8 minutes in the baseline case to 4.7 minutes after edge-validating interventions were implemented. One of the most important outcomes of this paper is that the improvement in detection is no longer a technical measurement, but shows measurable impacts on mobility at the corridor level. Early validation allows the central management layer to respond faster, which decreases queue persistence and ultimately reduces disruption due to the incident.

The results of this study indicate that the framework does not simply provide efficient identification of incidents; it also provides a method to stabilize the network after an incident occurred. The decrease in the waiting time indicates that validated alerts combined with signal adaptation and rerouting can reduce secondary congestion in impacted areas. In summary, urban incident management is ultimately evaluated by its impact on traffic flow, not solely by its performance as a classification system. Therefore, this finding supports the strength of the paper. Figure 9 shows the average waiting time prior to and following the proposed intervention. The waiting time reduced from 6.8 minutes in the baseline to 4.7 minutes in the proposed framework.

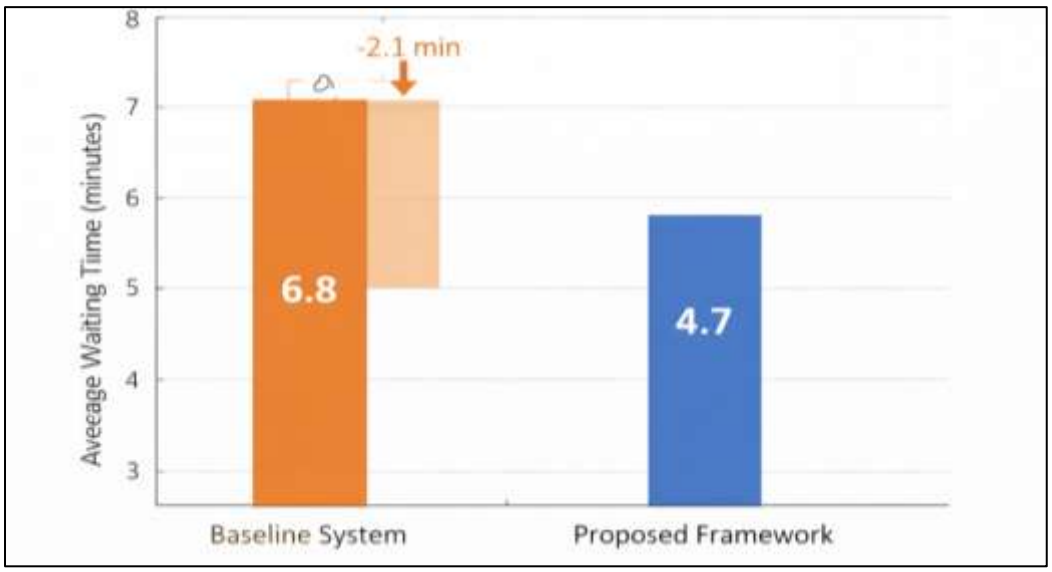

Fig. 9 Average waiting time in impacted zones: proposed framework vs. baseline system.

4.4 Communication efficiency and scalability

The communications analysis confirmed the validity of the proposed methodology. The use of validated summaries instead of sending every report in full to the central layer due to the elimination of the large volume of unnecessary data transmission reduced the amount of data being sent over the network by 48% compared to the original upload strategy. The communication analysis clearly illustrates that the architectural rationale for edge processing is validated since the confirmation of incidents is accelerated by local corroboration and prevents the communication backbone from being saturated with extreme amounts of extraneous or repetitive reports. Also, significant scalability advantages will be achieved with large-scale deployments due to the 48% savings on network data usage shown in Figure 10 through edge-side validation and summary transmission to provide significant reductions in server load and operating cost when deployed at the city level.

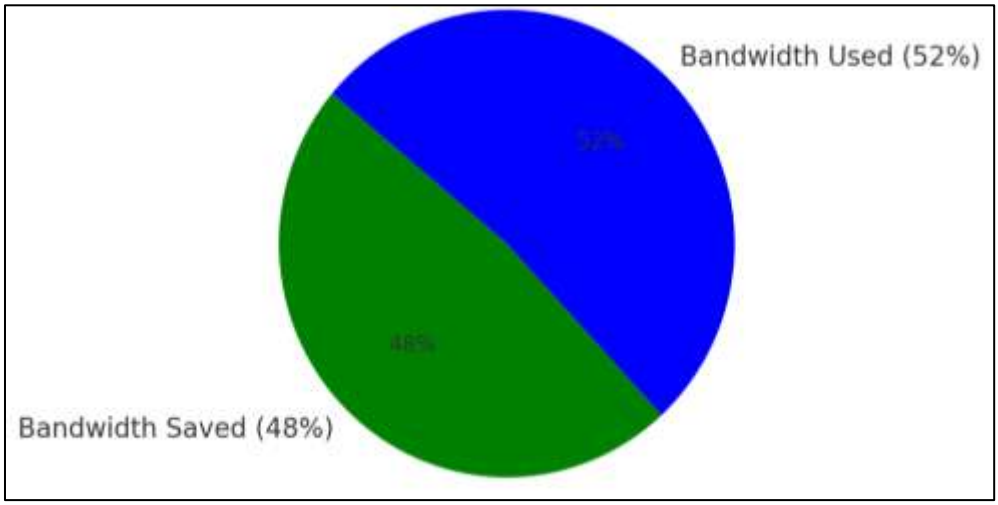

Fig. 10 Bandwidth Utilization Split in Proposed System

Furthermore, the total results of the experiments conducted indicate that the primary advantage of the proposed framework is attributed to the manner in which responsibilities are shared amongst system components. Mobile phones provide an opportunity for fully distributed sensing over a wide area. However, mobile phones do not provide the ultimate determination of what defines the incident. In the proposed architecture, edge nodes will collect candidate reports from several neighbouring mobile devices, and will validate the reports via clustering, temporal agreement, and corroboration methodologies. The distribution of responsibilities clearly explains the dual properties of achieving both low latency and high reliability with this type of framework. On the contrary, in a centralized system, there is an inherent delay in the time required for the collection of raw traffic data. As a result, the ability to process many irrelevant or isolated signals prior to determining whether an incident has occurred is significantly longer than with a crowdsourced system. By resolving the majority of the ambiguity within the proximity of the incident source, the proposed system eliminates that delay and noise burden.

The evidence regarding the traffic impact also demonstrates that the speed of validated incident detection can have network-wide effects. The ability of alerts to access the central traffic management centre will allow for the commencement of corridor response sooner than would occur without these types of frameworks, and this will reduce wait times, and alleviate secondary traffic congestion. The evidence resulting from the bandwidth analysis also supports the claim that, although faster incident detection is achieved through an increase in speed of data upload, the framework achieves this increase through more efficient data uploads. Thus, the evidence in support of both speed and efficiency is representative of the multi-dimensional benefits that most reviewers are looking to find in systems research involving smart cities.

Despite the favourable results, the manuscript should maintain a degree of academic cautiousness regarding the outcomes as the outcomes presented in this manuscript are based upon a simulation backed evaluation and not upon the implementation of the system in a real city. Therefore, the manuscript should state that the framework is emerging as a promising and operationally effective solution in simulation, but has not yet been validated in real field conditions. Making this distinction will add to the credibility of the manuscript, and provide less resistance from reviewers. The manuscript has already classified the work as a SUMO- and Python powered simulated framework. Therefore this interpretation of the study design is in complete agreement with the overall goals of the study.

In summary, the proposed crowdsourced smartphone-edge framework has been found to outperform a baseline system in regards to quicker response times, the provision of confirmed incident recognition, reduced waiting times post-incident in impacted areas, and improved communication efficiency. The average incident detection time was reduced from 40.6 seconds to 14.2 seconds, the accuracy of true-positive incident detection increased from 72% to 92%, waiting

times in impacted zones decreased from 6.8 minutes to 4.7 minutes, and the total data used by the network was reduced by 48%. Thus, the conclusion drawn from this research is that the transfer of corroboration and filtering to the "edge" of a network allows for a faster, more reliable, and more easily scaled mechanism for managing urban incidents using a broad-based participatory sensing model.

5. CONCLUSION AND FUTURE SCOPE

The results from the simulation provide evidence that the proposed framework compares favourably to a traditional system for the types of urban scenarios studied. Specifically, the three-tiered framework reduced the time to detect an incident (Latency) from 40.6 seconds to 14.2 seconds; improved true positive incident detection rates from 72% to 92%; reduced average wait time after an incident in impacted areas from 6.8 minutes to 4.7 minutes; and reduced the amount of data being transmitted over the network by nearly 50% via summarization after validation. Based on the results, it appears that the ability of the framework to support immediate response, provide reliable validation of each incident, and communicate efficiently through the integrated system are its primary strengths. The edge layer is the component that most positively affects the quantity of corroborated local incident evidence available at the city controller level by converting raw candidate reports into corroborated local incident evidence. As such, it relieves some of the processing load on the central system while also increasing the likelihood of trustworthiness in reported events. Broader implications of this work are found in ultimately re-aligning intelligent transportation systems (ITS) from more traditional fixed and location-based monitoring toward more adaptive, software-defined, and participatory methods of traffic management. The results of this research indicate that commuter smartphones can serve as urban observability tools without the cost and burden of adding densely placed roadside sensors, as long as they are utilized solely as the event generators for local applications and not as the final decision-makers. Additionally, the results demonstrate that in order to gain the most value from edge-area intelligence in a time-sensitive application such as traffic management, rapid validation of reported incidents is just as critical to incident resolution as is the amount of sensing coverage achieved. As a result, this analysis has the potential to establish a viable approach to creating large-scale awareness of incidents occurring in urban areas where building all of the necessary infrastructure may not be cost effective or practical.

The analyses conducted in this study should be interpreted with caution, as all evaluations were completed utilising a SUMO-based simulation environment with Python-based emulators for the edge layer; therefore, all reported gains should be viewed as performance achieved under controlled but realistic synthetic conditions, rather than actual market-validated deployment conditions. The scenarios described in this study included heterogeneous roadway designs; introducing multiple occurrences; having different numbers of commuters involved in the simulations; and using noise from simulated sensors; however, when implemented in real life, the complexities of the system will increase, as there are many other factors involved, including: variations in device placement, different patterns of behaviour by users, network stability issues, effect of weather conditions, different regulatory requirements, and varying traffic cultures between cities. Therefore, it is logical to use these results as strong simulation evidence of system feasibility and potential for a system created at the city level, but they do not represent ready-to-deploy fully developed systems.

Future research should proceed in three primary directions. First, the priority should be validating results from real-world pilot studies with instrumented commuter smartphones and deployed edge nodes along selected urban corridors to allow the calibration of event thresholds, confirmation logic, and required densities of participation based on observed roadway conditions. Second, contextual information (e.g., weather conditions, roadwork feeds, calendar of events, public transport disruptions, etc.) will be integrated in order to improve interpretation of the likelihood of incidents. Finally, methods will be developed to enhance privacy and trust in the system by employing federated and/or on-device learning techniques which will further limit the necessity of transmitting private and/or user-related data. Future solutions may also include the integration of multimodal mobility participants (e.g., cyclists, pedestrians, and connected transit fleets), thereby extending the system to encompass entities beyond those of private vehicles. Advanced models to optimize response strategies will also be integrated with validated incident streams in order to provide not only the ability to identify disruptions early, but also the capacity to suggest the most effective means of mitigating disruption through managing the downstream impacts on the surrounding traffic network.

To summarise the paper's findings, the combination of crowd-sourced smartphone sensing and edge-based validation has demonstrated the ability to provide faster, more reliable urban traffic incident detection than traditional centralised systems when simulated. By connecting the distributed nature of mobile observability with the local validation provided through edge nodes, this work presents an empirically supported and practically useful avenue for future research into intelligent transportation systems. Overall, our results support the premise that participatory sensing, combined with privacy-aware edge intelligence, can serve as a credible foundation for future development of urban incident monitoring and adaptive traffic management systems.

References

1. J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M. B. Srivastava, “Participatory sensing,”

in Proc. Workshop on World-Sensor-Web (WSW'06): Mobile Device Centric Sensor Networks and Applications, Boulder, CO, USA, 2006, pp. 117–134.
2. A. T. Campbell, S. B. Eisenman, N. D. Lane, E. Miluzzo, and R. A. Peterson, "People-centric urban sensing," in Proc. 2nd Annu. Int. Workshop Wireless Internet (WICON '06), New York, NY, USA, 2006, Art. no. 18. doi: 10.1145/1234161.1234179.
3. N. D. Lane, S. B. Eisenman, M. Musolesi, E. Miluzzo, and A. T. Campbell, "Urban sensing systems: Opportunistic or participatory?," in Proc. 9th Workshop Mobile Comput. Syst. Appl. (HotMobile), 2008, pp. 11–16. doi: 10.1145/1411759.1411763.
4. A. T. Campbell, S. B. Eisenman, N. D. Lane, E. Miluzzo, and R. A. Peterson, "The rise of people-centric sensing," IEEE Internet Comput., vol. 12, no. 4, pp. 12–21, Jul.–Aug. 2008. doi: 10.1109/MIC.2008.90.
5. N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell, "A survey of mobile phone sensing," IEEE Commun. Mag., vol. 48, no. 9, pp. 140–150, Sep. 2010. doi: 10.1109/MCOM.2010.5560598.
6. R. K. Ganti, F. Ye, and H. Lei, "Mobile crowdsensing: Current state and future challenges," IEEE Commun. Mag., vol. 49, no. 11, pp. 32–39, Nov. 2011. doi: 10.1109/MCOM.2011.6069707.
7. B. Hull, V. Bychkovsky, Y. Zhang, K. Chen, M. Goraczko, A. Miu, E. Shih, H. Balakrishnan, and S. Madden, "CarTel: A distributed mobile sensor computing system," in Proc. 4th Int. Conf. Embedded Networked Sensor Systems (SenSys '06), 2006, pp. 125–138. doi: 10.1145/1182807.1182821.
8. P. Mohan, V. N. Padmanabhan, and R. Ramjee, "Nericell: Rich monitoring of road and traffic conditions using mobile smartphones," in Proc. 6th ACM Conf. Embedded Network Sensor Syst. (SenSys '08), 2008, pp. 323–336. doi: 10.1145/1460412.1460444.
9. A. Thiagarajan, L. Ravindranath, H. Balakrishnan, S. Madden, L. Girod, and J. Eriksson, "VTrack: Accurate, energy-aware road traffic delay estimation using mobile phones," in Proc. 7th ACM Conf. Embedded Networked Sensor Syst. (SenSys '09), 2009, pp. 85–98. doi: 10.1145/1644038.1644048.
10. J. C. Herrera, D. B. Work, R. Herring, X. Ban, Q. Jacobson, and A. M. Bayen, "Evaluation of traffic data obtained via GPS-enabled mobile phones: The Mobile Century field experiment," Transp. Res. Part C: Emerging Technol., vol. 18, no. 4, pp. 568–583, Aug. 2010. doi: 10.1016/j.trc.2009.10.006.
11. M. Mun, S. Reddy, K. Shilton, N. Yau, J. Burke, D. Estrin, M. Hansen, E. Howard, R. West, and P. Boda, "PEIR, the personal environmental impact report, as a platform for participatory sensing systems research," in Proc. 7th Int. Conf. Mobile Syst., Appl., Services (MobiSys '09), 2009, pp. 55–68. doi: 10.1145/1555816.1555823.
12. S. B. Eisenman, E. Miluzzo, N. D. Lane, R. A. Peterson, G.-S. Ahn, and A. T. Campbell, "BikeNet: A mobile sensing system for cyclist experience mapping," in Proc. 5th Int. Conf. Embedded Networked Sensor Systems (SenSys '07), 2007, pp. 87–101. doi: 10.1145/1322263.1322273.
13. D. Cuff, M. Hansen, and J. Kang, "Urban sensing: Out of the woods," Commun. ACM, vol. 51, no. 3, pp. 24–33, Mar. 2008. doi: 10.1145/1325555.1325562.
14. D. Christin, A. Reinhardt, S. S. Kanhere, and M. Hollick, "A survey on privacy in mobile participatory sensing applications," J. Syst. Softw., vol. 84, no. 11, pp. 1928–1946, Nov. 2011. doi: 10.1016/j.jss.2011.06.073.
15. H. Gao, C. H. Liu, W. Wang, J. Zhao, Z. Song, X. Su, J. Crowcroft, and K. K. Leung, "A survey of incentive mechanisms for participatory sensing," IEEE Commun. Surveys Tuts., vol. 17, no. 2, pp. 918–943, 2nd Quart., 2015. doi: 10.1109/COMST.2014.2387836.
16. L. G. Jaimes, I. J. Vergara-Laurens, and A. Raij, "A survey of incentive techniques for mobile crowd sensing," IEEE Internet Things J., vol. 2, no. 5, pp. 370–380, Oct. 2015. doi: 10.1109/JIOT.2015.2409151.
17. S. Gisdakis, T. Giannetsos, and P. Papadimitratos, "Security, privacy, and incentive provision for mobile crowd sensing systems," IEEE Internet Things J., vol. 3, no. 5, pp. 839–853, Oct. 2016. doi: 10.1109/JIOT.2016.2560768.
18. I. J. Vergara-Laurens, L. G. Jaimes, and M. A. Labrador, "Privacy-preserving mechanisms for crowdsensing: Survey and research challenges," IEEE Internet Things J., vol. 4, no. 4, pp. 855–869, Aug. 2017. doi: 10.1109/JIOT.2016.2594205.
19. W. Feng, Z. Yan, H. Zhang, K. Zeng, Y. Xiao, and Y. T. Hou, "A survey on security, privacy, and trust in mobile crowdsourcing," IEEE Internet Things J., vol. 5, no. 4, pp. 2971–2992, Aug. 2018. doi: 10.1109/JIOT.2017.2765699.
20. X. Zhang, Z. Yang, W. Sun, Y. Liu, S. Tang, K. Xing, and X. Mao, "Incentives for mobile crowd sensing: A survey," IEEE Commun. Surveys Tuts., vol. 18, no. 1, pp. 54–67, 1st Quart., 2016. doi: 10.1109/COMST.2015.2415528.
21. W. Zamora, C. T. Calafate, J.-C. Cano, and P. Manzoni, "A survey on smartphone-based crowdsensing solutions," Mobile Inf. Syst., vol. 2016, Art. ID 9681842, 2016. doi: 10.1155/2016/9681842.
22. D. Suhag and V. Jha, "A comprehensive survey on mobile crowdsensing systems," J. Syst. Archit., vol. 142, Art. no. 102952, 2023. doi: 10.1016/j.sysarc.2023.102952.
23. A. Mednis, G. Strazdins, R. Zviedris, G. Kanonirs, and L. Selavo, "Real time pothole detection using Android smartphones with accelerometers," in Proc. 2011 Int. Conf. Distributed Computing in Sensor Systems and Workshops (DCOSS), 2011, pp. 1–6. doi: 10.1109/DCOSS.2011.5982206.
24. J. White, C. Thompson, H. Turner, B. Dougherty, and D. C. Schmidt, "WreckWatch: Automatic traffic accident

detection and notification with smartphones," Mobile Netw. Appl., vol. 16, no. 3, pp. 285–303, Jun. 2011. doi: 10.1007/s11036-011-0304-8.
25. F. Aloul, I. Zualkernan, R. Abu-Salma, H. Al-Ali, and M. Al-Merri, "iBump: Smartphone application to detect car accidents," Comput. Electr. Eng., vol. 43, pp. 66–75, Apr. 2015. doi: 10.1016/j.compeleceng.2015.03.003.
26. B. Fernandes, M. Alam, V. Gomes, J. Ferreira, and A. Oliveira, "Automatic accident detection with multi-modal alert system implementation for intelligent vehicles," Veh. Commun., vol. 3, pp. 1–11, Jan. 2016. doi: 10.1016/j.vehcom.2015.11.001.
27. F. Bhatti, M. A. Shah, C. Maple, and S. U. Islam, "A novel Internet of Things-enabled accident detection and reporting system for smart city environments," Sensors, vol. 19, no. 9, Art. no. 2071, 2019. doi: 10.3390/s19092071.
28. T. Lee, C. Chun, and S.-K. Ryu, "Detection of road-surface anomalies using a smartphone camera and accelerometer," Sensors, vol. 21, no. 2, Art. no. 561, 2021. doi: 10.3390/s21020561.
29. W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," IEEE Internet Things J., vol. 3, no. 5, pp. 637–646, Oct. 2016. doi: 10.1109/JIOT.2016.2579198.
30. M. Chiang and T. Zhang, "Fog and IoT: An overview of research opportunities," IEEE Internet Things J., vol. 3, no. 6, pp. 854–864, Dec. 2016. doi: 10.1109/JIOT.2016.2584538.
31. Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," IEEE Commun. Surveys Tuts., vol. 19, no. 4, pp. 2322–2358, 4th Quart., 2017. doi: 10.1109/COMST.2017.2745201.
32. N. Abbas, Y. Zhang, A. Taherkordi, and T. Skeie, "Mobile edge computing: A survey," IEEE Internet Things J., vol. 5, no. 1, pp. 450–465, Feb. 2018. doi: 10.1109/JIOT.2017.2750180.
33. X. Hou, Y. Li, M. Chen, D. Wu, D. Jin, and S. Chen, "Vehicular fog computing: A viewpoint of vehicles as the infrastructures," IEEE Trans. Veh. Technol., vol. 65, no. 6, pp. 3860–3873, Jun. 2016. doi: 10.1109/TVT.2016.2532863.
34. L. Liu, C. Chen, Q. Pei, S. Maharjan, and Y. Zhang, "Vehicular edge computing and networking: A survey," Mobile Netw. Appl., vol. 26, pp. 1145–1168, 2021. doi: 10.1007/s11036-020-01624-1.
35. P. Arthurs, L. Gillam, P. Krause, N. Wang, K. Halder, and A. Mouzakitis, "A taxonomy and survey of edge cloud computing for intelligent transportation systems and connected vehicles," IEEE Trans. Intell. Transp. Syst., vol. 23, no. 7, pp. 6206–6221, Jul. 2022. doi: 10.1109/TITS.2021.3084396.
36. X. Zhou et al., "When intelligent transportation systems sensing meets edge computing: Vision and challenges," Appl. Sci., vol. 11, no. 20, Art. no. 9680, 2021.
37. T. Gong, L. Zhu, F. R. Yu, and T. Tang, "Edge intelligence in intelligent transportation systems: A survey," IEEE Trans. Intell. Transp. Syst., vol. 25, pp. 8919–8944, 2024. doi: 10.1109/TITS.2023.3275741.
38. R. Weil, J. Wootton, and A. García-Ortiz, "Traffic incident detection: Sensors and algorithms," Math. Comput. Model., vol. 27, nos. 9–11, pp. 257–291, 1998. doi: 10.1016/S0895-7177(98)00064-8.
39. D. Srinivasan, X. Jin, and R. L. Cheu, "Adaptive neural network models for automatic incident detection on freeways," Neurocomputing, vol. 64, pp. 473–496, 2005. doi: 10.1016/j.neucom.2004.12.001.
40. A. Kinoshita, A. Takasu, and J. Adachi, "Real-time traffic incident detection using a probabilistic topic model," Inf. Syst., vol. 54, pp. 169–188, 2015. doi: 10.1016/j.is.2015.07.002.
41. P. Arora, R. Wason, G. S. Narula, and M. N. Hoda, "A Novel and Optimised Thread-based Virtual Traffic Light Framework," Journal of Scientific & Industrial Research, vol. 83, no. 10, pp. 1095–1103, Oct. 2024.
42. P. Choudhary and R. K. Dwivedi, "A novel algorithm for traffic control using thread based virtual traffic light," International Journal of Information Technology, vol. 14, pp. 115–124, 2022, doi: 10.1007/s41870-021-00808-6.