Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 96 (2026) 156–163

Transportation Research Procedia

www.elsevier.com/locate/procedia

The 2nd International Conference on Smart Mobility and Logistics Ecosystems (SMILE 2026)

Adaptive multi-agent learning for infrastructure-aware ITS: the IMER data-processing approach

Mayssa Hamdani[a,*], Nafaa Jabeur[b], Ansar Yasar[a], Fatma Outay[c], Li Li[d]

a. Uhasselt - Hasselt university, Instituut voor Mobiliteit (IMOB), Maastrichterstraat 100, 3500 Hasselt, Belgium
b. Computer Science Department, German University of technology in Oman, Muscat, Oman
c. College of Technological Innovation, Zayed University, Dubai, UAE
d. Tongji University, Shanghai, China

Abstract

The performance of Intelligent Transportation Systems (ITS) critically depends on accurate and efficient road-condition monitoring. This paper presents IMER (Inspect–Map–Eliminate–Reduce), a novel AI-driven data-processing framework that extends the traditional Map-Reduce paradigm for infrastructure maintenance. IMER integrates confidence-based validation, redundancy elimination, and severity prioritization to enhance data quality and decision efficiency. Implemented within a multi-agent architecture, IMER enables autonomous agents to inspect, classify, and fuse multi-source road data in real time, supporting predictive and adaptive maintenance planning. Simulation results using augmented pothole datasets demonstrate a 39.9 % reduction in redundant reports and 39.8 % fewer false positives. These findings highlight IMER's potential to advance data-driven, resilient, and sustainable road-infrastructure management for next-generation ITS.

Keywords: Road Infrastructure Monitoring; Intelligent Transportation Systems (ITS); Inspect-Map-Eliminate-Reduce, Multi-Agent Systems

1. Introduction

Efficient and safe road networks are essential to modern Intelligent Transportation Systems (ITS). Yet, aging infrastructure, increasing traffic, and unexpected incidents continue to degrade mobility, elevate crash risk, and inflate maintenance costs. Although ITS aims to enhance efficiency and sustainability, its performance ultimately depends on timely awareness of road conditions and adaptive decision-making. Traditional reactive maintenance programs cannot match dynamic and evolving network demands (Almeida, et al., 2023). Consequently, many ITS deployments struggle with delayed responses and sub-optimal control strategies(Alqasi, Alkelanie, & Alnagrat, 2024).

---

* Corresponding author. Tel.: +96879016132.
E-mail address: Mayssa.hamdani@uhasselt.be

10.1016/j.trpro.2026.03.021

Recent advances in Artificial Intelligence (AI), Internet of Things (IoT), and Multi-Agent Systems (MAS) have transformed infrastructure monitoring and traffic optimization (Jayakody, et al., 2024). Multi-source data acquisition from vehicles, pedestrians, and roadside sensors now enables continuous visibility into network health (Pallavi, Pavani, Jayalakshmi, & Sravani, 2025). However, inconsistent, redundant, or inaccurate data still impede efficient processing and hinder maintenance scheduling at both local and network scales.

To address these limitations, this study introduces IMER (Inspect–Map–Eliminate–Reduce), a structured data-processing framework that enhances road-condition monitoring and ITS optimization. IMER extends Map–Reduce with additional stages that ensure data quality, relevance, and efficiency, and is deployed within a multi-agent ITS architecture composed of RSCEA, CA, ITSOA, and RIPA agents. These agents process and exchange information autonomously to maintain adaptive, infrastructure-aware decision-making. The main contributions are: a novel IMER-based method integrating multi-source filtering and optimization for improved ITS reliability; a MAS framework enabling adaptive coordination among agents; and a proof-of-concept simulation showing reduced redundancy, prioritized maintenance, and enhanced real-time traffic response. Section 2 reviews related work, Section 3 details IMER, Section 4 presents the architecture, and Section 5 reports the simulation results.

2. Related Work

Road-infrastructure monitoring and Intelligent Transportation Systems (ITS) have evolved rapidly through the IoT, advanced sensing, AI integrartion, improving efficiency, safety, and sustainability while reducing maintenance costs. Recent studies achieved high accuracy in pavement-distress detection using deep-learning models such as U-Net and YOLO (Almeida, et al., 2023). AI-based predictive maintenance models analyze real-time sensor data to avoid infrastructure failures, cutting maintenance costs by up to 30% (Alqasi, Alkelanie, & Alnagrat, 2024). Crowdsourced approaches using smartphone sensors and convolutional networks have also been developed to estimate pavement roughness (Jeong & Jo, 2023). IoT technology has reformed road infrastructure monitoring by allowing real-time data gathering via distributed sensor networks. In this regard, (Ye, et al., 2024) proposed a self-powered pavement-monitoring system combining IoT sensors and cloud analytics to track vibrations and temperature. Similarly, (Kubra, et al., 2025) integrated fuzzy logic and V2X communication for real-time speed monitoring and driver-fitness assessment. In addition, (Arce-Saenz, Izquierdo-Reyes, & Bustamante-Bello, 2023) introduced low-resource machine learning models using accelerometer and gyroscope data for accurate detection of pavement defects. Advanced sensing using Fiber Bragg Grating (FBG) sensors supports real-time structural-change monitoring (Golmohammadi, Hasheminejad, bergh, & Hernando, 2024), and the Transportation RF-Based Monitoring (TRAM) system employs battery-less RF sensors to track displacement and moisture (Eng, et al., 2024).

Despite these advances, ITS data streams remain massive, heterogeneous, and noisy, demanding effective filtering and aggregation. In this regard, (Kuftinova, Ostroukh, Maksimychev, Pronin, & Ostroukh, 2024) proposed a clustering-based filtering method to remove outliers in real-time traffic systems. Similarly, (Pallavi, Pavani, Jayalakshmi, & Sravani, 2025) refined predictive maintenance through sensor-data filtering that minimizes false alerts. (Rangaiah, et al., 2024) applied feature-selection techniques to reduce data dimensionality and optimize congestion control. (Jalooli & Murcia, 2023) introduced adaptive Huffman coding to compress ITS data with minimal information loss. Meanwhile, (Yu, Qiao, Wang, & Xu, 2002) used wavelet decomposition to filter irrelevant traffic signals while preserving critical congestion patterns, (Mishra & Murthy, 2024) leveraged distributed-computing frameworks such as Apache Spark to accelerate real-time analysis. (Lin, 2024) explored deep-learning models including LSTM and Temporal Fusion Transformers to improve route optimization.

AI-based maintenance continues to expand, enabling proactive anomaly detection and cost optimization. (Rezgui, Rachala, & Ayyash, 2024) introduced RoadProbe, which combines LSTM and crowdsourcing to predict potholes and cracks. On the same page, (Alqasi, Alkelanie, & Alnagrat, 2024) demonstrated AI-driven urban-infrastructure models that lower maintenance costs by 30 % and prevent 92 % of unexpected failures. (Jayakody, et al., 2024) proposed a probabilistic pavement-degradation framework using 15 years of monitoring data to show that evenly distributed maintenance is more cost-effective than reactive strategies.

Multi-Agent Systems (MAS) further strengthen ITS scalability and adaptability. (Wang, Shen, Lei, & Zhang, 2024) (Song, Zhou, & Ma, 2024) demonstrated that multi-agent reinforcement-learning approaches can coordinate signal control and enhance throughput. (Fu, Chen, Liang, & Li, 2023) showed that decentralized MAS architectures improve responsiveness in dynamic ITS environments. MAS thus provides flexibility to process heterogeneous data sources and coordinate diverse stakeholders (road-infrastructure evaluators, traffic-management systems, and decision-makers) toward safer and more sustainable transportation networks.

3. The Inspect-Map-Eliminate-Reduce Framework Architecture

To optimize ITS decision-making, we propose the Inspect–Map–Eliminate–Reduce (IMER) framework, an enhanced version of Map–Reduce that adds Inspect and Eliminate stages to ensure data quality and efficiency. These steps address the heterogeneity and inconsistency of multi-source road data by validating, categorizing, de-duplicating, and aggregating information into actionable insights. IMER is implemented within a Multi-Agent System (MAS) comprising four autonomous agents: the Road Section Condition Evaluator (RSCEA), which analyses local infrastructure data; the Collaboration Agent (CA), which integrates regional inputs; the ITS Optimizer Agent (ITSOA), which coordinates network-level control; and the Road Infrastructure Planner Agent (RIPA), which supports predictive maintenance. By combining structured data processing with adaptive agent collaboration, the system enhances accuracy, reduces redundancy, and enables resilient, congestion aware ITS operations.

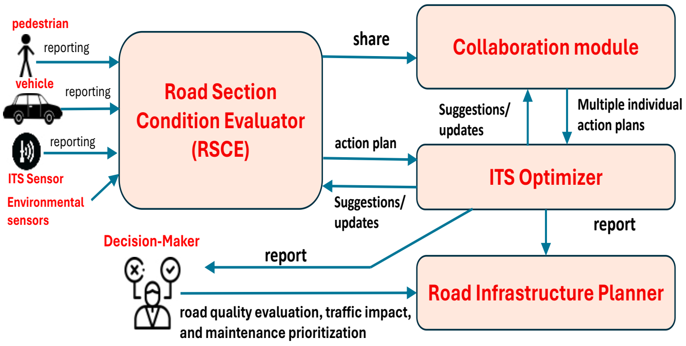

Fig. 1. Proposed Architecture

3.1 Road Section Condition Agent (RSCEA)

The RSCEA manages an assigned road segment and continuously processes heterogeneous inputs from vehicles, pedestrians, and environmental sensors.

- Inspect: Verifies authenticity, consistency, and completeness of each report r_i; producing a filtered set R'. To this end, each report r_i is characterized with the following attributes: (1) Reliability score $C(r_i)$ (confidence level from the source, such as sensor accuracy, vehicle reputation, etc.); (2) Consistency factor $\Gamma(r_i)$ (agreement with other reports on the same road section); and (3) Completeness factor $\Omega(r_i)$ (whether all required data fields are provided). A report r_i is considered valid if:

$$C(r_i) \times \Gamma(r_i) \times \Omega(r_i) \geq \theta_I \tag{1}$$

where θ_I is a predefined threshold. Reports that do not meet this condition are discarded.

- Map: Organizes validated reports into structural categories such as cracks or obstructions. Each filtered report $r_i \in R'$ contributes to a specific condition category:

$$M(c_k) = \sum_{r_i \in R'} W_k(r_i) \times f_k(r_i) \tag{2}$$

where c_k is a road condition category (e.g., potholes, cracks), $W_k(r_i)$ is the weight of report r_i for category c_k (importance based on confidence), and $f_k(r_i)$ is a feature extraction function that maps report attributes to the condition category.

- Eliminate: The goal is to remove duplicate/conflicting data and ensure consistency in the structured dataset. The agent receives as input a structured map representation M. It will then output a refined dataset R' with only relevant and unique road condition data. To this end, we define a redundancy function $R_d(c_k)$ to measure data duplication:
  $$R_d(c_k) = \frac{\sum_{r_i, r_j \in M} \Pi(r_i, r_j)}{|M|} \tag{3}$$
  where $\Pi(r_i, r_j) = 1$ if two reports are near-duplicates (same road section, similar attributes) and $\Pi(r_i, r_j) = 0$ otherwise. If redundancy $R_d(c_k)$ exceeds a threshold θ_E, we apply data fusion techniques (e.g., weighted averaging) to ensure high-confidence values dominate while eliminating redundancy:
  $$M'(c_k) = \frac{\sum_{r_i \in M} W_k(r_i) \times M(c_k)}{\sum_{r_i \in M} W_k(r_i)} \tag{4}$$

- Reduce: The goal is to aggregate the filtered road condition data obtained from the eliminate step into a final action plan for traffic management and maintenance. The plan includes prioritized actions for ITS interventions. We define an action impact score $I(a_j)$ for each possible intervention a_j as follows:
  $$I(a_j) = \sum_{c_k \in M'} W_a(c_k) \times S(c_k) \tag{5}$$
  where $W_a(c_k)$ is the weight of road condition c_k for action a_j and $S(c_k)$ is the severity score of condition c_k.
  An action a_j is selected for execution if its impact score exceeds a threshold θ_R:
  $$A = \{a_j \in A \mid I(a_j) \geq \theta_R\} \tag{6}$$
  where A is the set of possible interventions (e.g., rerouting traffic, scheduling maintenance).

3.2 Collaboration Agent (CA)

The Collaboration Agent (CA) coordinates data exchange among RSCEs, using the IMER approach to collectively validate, map, and refine road condition data.

- Inspect: Like the RSCEA agents, the CA verifies the authenticity, consistency, and completeness of reports before further processing. However, instead of working with raw road condition reports, the CA receives filtered action plans from multiple RSCEAs:
  $$R_{CA} = \{A_{RSCEA_1}, A_{RSCEA_2}, \dots, A_{RSCEA_n}\} \tag{7}$$
  where each action plan A_{RSCEA} contains multiple actions proposed for a road section. The CA assesses: (1) The inter-RSCE consistency $\Gamma(A_{RSCEA})$ – measures how much agreement exists between multiple RSCEA agents regarding a particular road condition. Since different RSCEAs manage different road sections, but may overlap in observations or receive reports from nearby areas, this metric helps determine whether an issue is widely confirmed or if there are conflicting assessments; (2) Collaboration factor $\Psi(A_{RSCEA})$ – whether an RSCEA needs input from neighbouring RSCEAs before executing actions; and (3) Feasibility score $\phi(A_{RSCEA})$ – whether the proposed actions are realistic given current road conditions and ITS capabilities.
  Given an RSCE action plan ((A_{RSCEA}), which contains multiple road condition reports, consistency cab ne defined as follows:
  $$\Gamma(A_{RSCEA}) = \frac{1}{|A_{RSCEA}|} \sum_{a_i \in A_{RSCEA}} \frac{\sum_{RSCEA_i \neq RSCEA_j} \Pi\left(a_i, A_{RSCEA_j}\right)}{|RSCEA_{neighbors}|} \tag{8}$$
  where A_{RSCEA} denote the set of actions proposed by the RSCEA based on its observations, a_i denote an individual action in the RSCEA's action plan, $RSCEA_{neighbors}$ denote the set of neighboring RSCEA agents that could also report on the same road section, and $\Pi\left(a_i, A_{RSCEA_j}\right)$ denote a binary function that checks if a neighboring $RSCEA_j$ has proposed a similar action a_i for the same location ($\Pi\left(a_i, A_{RSCEA_j}\right) = 1$ if $RSCEA_j$ has a matching or similar action in its action plan and $\Pi\left(a_i, A_{RSCEA_j}\right) = 0$ otherwise). The normalization in the formula above is used to average the agreement across all actions in A_{RSCEA} and across all neighboring RSCEAs.
  An RSCEA action plan is accepted if:
  $$\Gamma(A_{RSCEA}) \times \Psi(A_{RSCEA}) \times \phi(A_{RSCEA}) \geq \theta_C \tag{9}$$
  where θ_C is the predefined collaboration threshold.

- Map: Unlike RSCEA agents that map road conditions into predefined categories, the CA maps action plans into regional collaboration clusters:
  $$M_{CA}(C_m) = \sum_{A_{RSCE} \in R_{CA}} W_m(A_{RSCEA}) \times f_m(A_{RSCEA}) \quad (10)$$
  where C_m represents a collaboration category (e.g., joint traffic rerouting, shared maintenance scheduling), $W_m(A_{RSCEA})$ represents the confidence weight of an RSCEA's action plan, and $f_m(A_{RSCEA})$ maps action plan attributes to a collaborative response category.

- Eliminate: Since multiple RSCEAs may propose overlapping or contradictory actions, the CA eliminates redundant or conflicting interventions using the following formula:
  $$R_d(C_m) = \frac{\sum_{A_{RSCEA_i}, A_{RSCEA_j} \in M_{CA}} \Pi\left(A_{RSCEA_i}, A_{RSCEA_j}\right)}{|M_{CA}|} \quad (11)$$
  Where $\Pi\left(A_{RSCEA_i}, A_{RSCEA_j}\right) = 1$ if two RSCEAs propose conflicting actions and $\Pi\left(A_{RSCEA_i}, A_{RSCEA_j}\right) = 0$ otherwise. If redundancy $R_d(C_m)$ exceeds θ_E, the CA applies a conflict resolution mechanism, such as weighted voting or merging similar actions.

- Reduce: The CA produces an optimized regional action plan that ensures ITS efficiency across multiple road sections:
  $$A_{CA} = \sum_{C_m \in M'_{CA}} W_c(C_m) \times S(C_m) \quad (12)$$
  where $W_c(C_m)$ represents the weight of a collaboration category and $S(C_m)$ represents the regional severity score. The CA submits the plan A_{CA} to the ITS Optimizer Agent (ITSOA).

3.3 ITS Optimizer Agent (ITSOA)

The ITSOA agent is responsible for aggregating regional action plans to optimize traffic management decisions.

- Inspect: The ITSOA agent receives aggregated action plans from one or more Collaboration Agents (CAs):
  $$R_{ITSOA} = \{A_{CA_1}, A_{CA_2}, \dots, A_{CA_n}\} \quad (13)$$
  The agent can inspect each action plan using several approaches. We are using in this paper the following approaches: (1) The network-wide impact score $\Lambda(A_{CA})$ that predicts the overall impact of an action plan on the ITS network; (2) The historical success rate $\mathrm{H}(A_{CA})$ that measures how effective similar actions were in the past; and (3) The traffic flow disruption factor $\mathrm{T}(A_{CA})$ that estimates whether an action plan disrupts traffic in other road sections. Based on these approaches, an action plan passes the Inspect step if:
  $$\Lambda(A_{CA}) \times \mathrm{H}(A_{CA}) \times \mathrm{T}(A_{CA}) \geq \theta_I \quad (14)$$

- Map: The ITSOA agent maps regional action plans into ITS strategy categories:
  $$M_{ITSOA}(C_s) = \sum_{A_{CA} \in R_{ITSOA}} W_s(A_{CA}) \times f_s(A_{CA}) \quad (15)$$
  where C_s is an ITS strategy category (e.g., emergency rerouting, congestion mitigation, predictive maintenance scheduling), $W_s(A_{CA})$ represents the importance weight of an action plan, and $f_s(A_{CA})$ maps action plan features to ITS strategies.

- Eliminate: The ITSOA agent eliminates low-impact or redundant interventions as follows:
  $$R_d(C_s) = \frac{\sum_{A_{CA_i}, A_{CA_j} \in M_{ITSOA}} \Pi\left(A_{CA_i}, A_{CA_j}\right)}{|M_{ITSOA}|} \quad (16)$$
  where $\Pi\left(A_{CA_i}, A_{CA_j}\right) = 1$ if two action plans overlap without added benefit.

- Reduce: The final ITS action plan is refined, where the ITSOA agent selects actions based on long-term impact:
  $$A_{ITSOA} = \arg\max_{a_j \in A} Q(a_j, s) \quad (17)$$
  where: $Q(a_j, s)$ is the Q-value (expected reward) of action a_j given the system state s. The ITSOA selects actions

that maximize long-term network efficiency.

3.4 Road Infrastructure Planner Agent (RIPA)

The RIPA agent focuses on long-term maintenance planning and road quality forecasting.

- Inspect: The RIPA agent receives road condition trends:
  $$R_{RIPA} = \{M'_{ITSOA_1}, M'_{ITSOA_2}, \dots, M'_{ITSOA_n}\} \tag{18}$$
  The agent can inspect reports based on several criteria, such as the historical degradation rate (predicts how fast a road section deteriorates) and the maintenance impact factor (measures how effective past maintenance was).

- Map: The RIPA agent categorizes road conditions into maintenance strategies:
  $$M_{RIPA}(C_m) = \sum_{M'_{ITSOA} \in R_{RIPA}} W_m(M'_{ITSOA}) \times f_m(M'_{ITSOA}) \tag{19}$$

- Eliminate: The RIPA agent filters out the low-priority maintenance requests using the following formula:
  $$R_d(C_m) = \frac{\sum_{M'_{ITSOA_i}, M'_{ITSOA_j} \in M_{RIPA}} \Pi\left(M'_{ITSOA_i}, M'_{ITSOA_j}\right)}{|M_{RIPA}|} \tag{20}$$

- Reduce: To generate maintenance schedules, the RIPA agent outputs the following final maintenance action plan, prioritizing roads that need intervention before severe degradation occurs.
  $$A_{RIPA} = \sum_{C_m \in M'_{RIPA}} W_m(C_m) \times S(C_m) \tag{21}$$

4. Simulation and Results

A publicly available Kaggle dataset of over 30,000 annotated pothole images with metadata on count, severity, and environmental context was used. To better simulate real-world ITS monitoring, the dataset was augmented with confidence scores (to represent data-source reliability), geolocation data (for spatial analysis), redundant entries (to mimic conflicting reports), and action plans (reflecting maintenance priorities). Simulations were conducted in a controlled environment using parameters fine-tuned for data completeness and accuracy. The evaluation metrics included total reports before and after IMER, redundancy and false-positive reduction, and precision and recall for high-severity detection—summarized in Table 1.

Table 1. Simulation parameters and performance metrics

Category	Parameter/Metric	Description	Value/Result
Simulation Parameters	Dataset Size	Number of pothole records	30000
	Confidence threshold	Minimum reliability accepted	0.7 (≤ discarded)
	Redundancy threshold	Similarity cutoff for elimination	30%
	Impact weighting	Computed as number × severity level	-
	Geolocation range	Latitude 405-40.9; Longitude -74.2—73.7	-
Simulation Results	Total reports (before IMER)	Raw Collected data	30000
	Total reports (after IMER)	Filtered valid data	18026
	Redundancy reduction	Duplicate and conflict removal	39.91%
	False-positive reduction (%)	Decrease in invalid detections	39.87%
	Precision (%)	High-severity detection accuracy	100%
	Recall (%)	True positive detection rate	60.13%

IMER prioritized high-risk potholes (Levels B–S) over low-severity ones (Level A), directing maintenance toward urgent interventions and improving overall road safety and efficiency (Fig. 2).

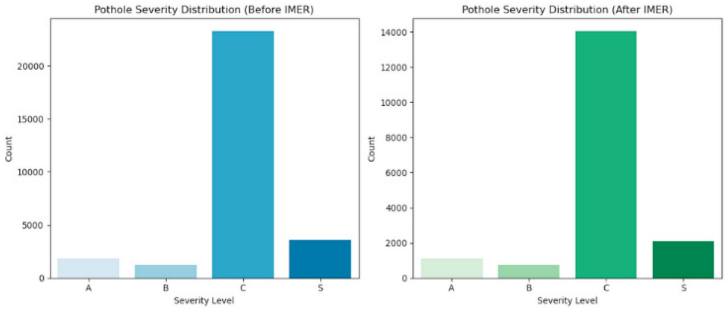

Fig. 2. Pothole severity distribution (left) before and (right) after IMER

Furthermore, IMER also improves the detection of high-impact potholes through confidence-based filtering and weighted severity assessment, enhancing the reliability of retained reports (Fig. 3).

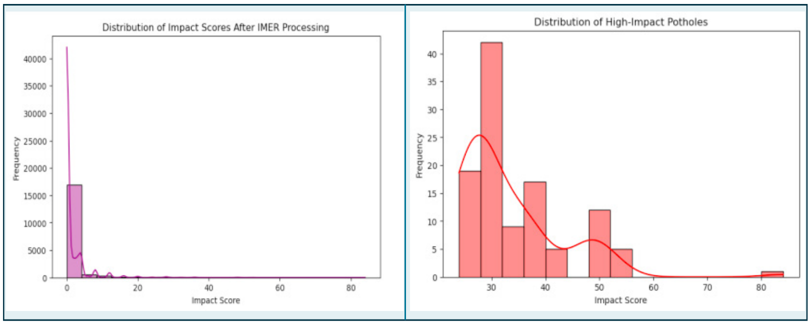

Fig. 3. Distributions of impact score (left) and high-impact potholes (right) after IMER

IMER streamlined maintenance planning by transforming fragmented, reactive recommendations into structured action plans focused on severely damaged road sections (Fig. 4).

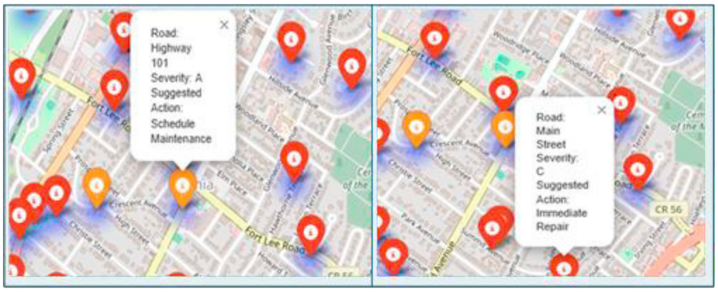

Fig. 4. Impact of IMER processing on pothole reports and recommended interventions

5. **Conclusion**

This paper introduced IMER (Inspect-Map-Eliminate-Reduce), a data-processing framework for improving road infrastructure monitoring in Intelligent Transportation Systems (ITS). IMER effectively reduces data redundancy (by 39.91%), enhances computational efficiency, and improves decision-making accuracy. The system prioritizes high-impact potholes, ensuring that critical defects receive immediate intervention. IMER also minimizes false positives and refines severity classification for better infrastructure planning. However, improvements are needed to improve recall rates and prevent under-reporting in some areas. Future work will focus on adaptive learning for dynamic filtering and machine learning integration for predictive maintenance.

References

Alagirisamy, M. (2024). Design and Development of a Real-Time Monitoring System for Highway Road Surface Anomalies. Journal of Ubiquitous Computing and Communication Technologies, 311-322.

Almeida, A., Fonseca, J., Rasinhas, P., Costa, C., Paiva, D., Silva, G., Sargento, S. (2023). Safe Roads: Traffic Management and Road Safety Platform for Smart Cities. IEEE 9th World Forum on Internet of Things . Aveiro,

Alqasi, M. A., Alkelanie, Y. A., & Alnagrat, A. J. (2024). Intelligent Infrastructure for Urban Transportation: The Role of Artificial Intelligence in Predictive Maintenance. Brilliance: Research of Artificial Intelligence, 625–637.

Arce-Saenz, L. A., Izquierdo-Reyes, J., & Bustamante-Bello, R. (2023). Road Surface Monitoring System Through Machine Learning Ensemble Models. 26th International Conference on Intelligent Transportation Systems Bilbao.

Eng, K. X., Xie, Y., Pereira, M., Haas, Z. J., Das, S. R., Djurić, P. M., . . . Stanaćević, M. (2024). A Vision and Proof of Concept for New Approach to Monitoring for Safer Future Smart Transportation Systems. Sensors.

Fu, X., Chen, S., Liang, Q., & Li, Y. (2023). Research on Multi-Agent Reinforcement Learning Traffic Control. IEEE International Conference on Control, Electronics and Computer Technology (ICCECT). Jilin, China: IEEE.

Gagliardi, V., Giammorcaro, B., Bella, F., & Sansonetti, G. (2023). Deep neural networks for asphalt pavement distress detection and condition assessment. Earth Resources and Environmental Remote Sensing/GIS Applications XIV. Amsterdam, Netherlands:

Golmohammadi, A., Hasheminejad, N., bergh, W. V., & Hernando, D. (2024). Enhancing Roads Infrastructure Monitoring with FBG Sensors and Multi-Threshold Signal Tracking. 10th European Workshop on Structural Health Monitoring. Potsdam.

Jalooli, A., & Murcia, F. (2023). Vehicular Edge Computing-Driven Optimized Multihop Clustering with Data Aggregation. 2023 IEEE 12th International Conference on Cloud Networking (CloudNet).

Jayakody, N., Robert, D., Navaratnarajah, S., Tran, H., Nasvi, M., Gunarathna, P., . Setunge, S. (2024). Road maintenance optimization using a probabilistic approach calibrated with 15-year monitoring data. Structure and Infrastructure Engineering.

Jeong, J.-H., & Jo, H. (2023). Toward Real-World Implementation of Deep Learning for Smartphone-Crowdsourced Pavement Condition Assessment. IEEE Internet of Things Journal, 6328 - 6337.

Kubra, K. T., Akhund, T. M., Al-Nuwaiser, W. M., Assaduzzaman, M., Ali, M. S., & Sarker, M. M. (2025). Integrated IoT-Driven System with Fuzzy Logic and V2X Communication for Real-Time Speed Monitoring and Accident Prevention in Urban Traffic. International Journal of Advanced Computer Science and Applications(ijacsa).

Kuftinova, N. G., Ostroukh, A. V., Maksimychev, O. I., Pronin, C. B., & Ostroukh, I. A. (2024). Efficient Machine Learning Methods for Real-Time Transport System Optimization and Predictive Maintenance. Intelligent Technologies and Electronic Devices in Vehicle and Road Transport Complex (TIRVED). Moscow, Russian Federation: IEEE.

Lin, Y. (2024). Data-Driven Urban Traffic Flow Prediction and Optimization of Intelligent Transportation Systems in Hong Kong. International Conference on Biotechnology, Energy Materials, and Intelligent Computing (BEMIC 2024) .

Mishra, S., & Murthy, T. S. (2024). A Predictive and Optimization Approach for Enhanced Urban Mobility.arXiv.

Pallavi, M., Pavani, P., Jayalakshmi, M., & Sravani, G. (2025). A Dynamic Model Integrating Machine Learning and IOT for Real-Time Traffic Management. International Journal for Research in Applied Science and Engineering Technology .

Rangaiah, Y. P., Revathi, V., Dutt, A., Sharma, S., Al-Rubaye, T. M., & Rani, K. P. (2024). Advanced Traffic Flow Prediction Using LSTM Networks and Big Data Integration for Urban Mobility Optimization. 7th International Conference on Contemporary Computing and Informatics (IC3I). Greater Noida, India: IEEE.

Rezgui, A., Rachala, Y. S., & Ayyash, M. (2024). RoadProbe: A Machine Learning-based System for Predictive Road Maintenance. 11th International Conference on Future Internet of Things and Cloud (FiCloud). Vienna, Austria: IEEE.

Song, X. (., Zhou, B., & Ma, D. (2024). Cooperative traffic signal control through a counterfactual multi-agent deep actor critic approach. Transportation Research Part C: Emerging Technologies.

Wang, K., Shen, Z., Lei, Z., & Zhang, T. (2024). Towards Multi-agent Reinforcement Learning based Traffic Signal Control through Spatio-temporal Hypergraphs. arXiv .

Ye, Z., Wei, Y., Yang, S., Li, P., Yang, F., Yang, B., & Wang, L. (2024). IoT-enhanced smart road infrastructure systems for comprehensive real-time monitoring. Internet of Things and Cyber-Physical Systems, 235-249