Machine Learning and 5G Edge Computing for Intelligent Traffic Management

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***Abstract*—The integration of fifth-generation (5G) communication technology and Artificial Intelligence (AI) is reshaping urban mobility by enabling intelligent transportation systems and smarter cities. This synergy allows real-time traffic management, predictive maintenance, and enhanced autonomous driving, supported by high-speed, low-latency networks and advanced data analytics. By leveraging 5G's strong connectivity, AI systems can process massive datasets to address urban challenges such as traffic congestion, environmental sustainability, and public safety. This study presents a framework that combines 5G and AI to optimize traffic management through dynamic congestion prediction and real-time routing, supported by edge computing. It highlights the benefits of improving traffic flow, reducing emissions, and enhancing overall urban mobility efficiency. In addition, it discusses key challenges including data privacy concerns, cybersecurity risks, and the high cost of infrastructure deployment. By analyzing existing technologies and proposing an AI-driven, 5G-enabled system model, this study aims to bridge the gap between theoretical advancements and practical urban implementations. The findings provide insights into scalable, efficient solutions for the future of smart transportation networks and offer directions for further research in this dynamic and evolving field.**

Keywords*—5G Edge computing; traffic management; dynamic routing; smart cities; machine learning

I. Introduction

Urban mobility is evolving rapidly due to the deployment of advanced technologies such as 5G and Artificial Intelligence (AI). These innovations enable smarter, more adaptive traffic management systems capable of responding to real-time changes in urban environments. The ultra-low latency and massive connectivity provided by 5G networks form a robust foundation for deploying AI-powered solutions at scale. In combination, these technologies promise to reduce congestion, improve traffic flow, and support more sustainable and efficient cities.

Recent studies illustrate this potential. Gheorghe et al. [1] demonstrated how AI and IoT, supported by predictive analytics, improve adaptive traffic control systems by enabling real-time decisions. Sharma et al. [2] showed that AI-driven route optimization in vehicular networks contributes to reduced fuel consumption and travel times. These findings confirm that integrating AI and 5G can significantly improve the operational efficiency of urban transportation.

However, existing traffic management systems face persistent limitations. Most rely on centralized architectures, which struggle to process the growing volume of sensor data in real time. They also lack the ability to dynamically adapt to evolving traffic patterns. As a result, cities continue to experience congestion peaks, inefficient route utilization, and increased emissions. There remains a gap between the potential offered by emerging technologies and their actual deployment in urban traffic systems.

This study addresses the challenge of building a scalable and responsive traffic management framework that overcomes these limitations. It proposes a system that combines machine learning models for congestion prediction with dynamic route optimization, all deployed through decentralized 5G-enabled edge computing. The objective is to ensure low-latency decision-making, minimize energy consumption, and improve overall traffic efficiency without relying on centralized processing.

Designing such a system introduces several challenges, including handling heterogeneous and noisy traffic data, maintaining real-time responsiveness at the network edge, and ensuring scalability across diverse urban environments. By integrating AI models with edge nodes capable of local processing and communication through 5G, the proposed framework responds directly to these issues.

The remainder of this study is structured as follows: Section II provides a review of related work. Section III presents the proposed methodology and system architecture. Section IV outlines the experimental results. Section V discusses limitations and future directions. Finally, Section VI concludes the study.

II. Related Work

Numerous studies have explored the intersection of 5G and AI in urban mobility, focusing on specific applications and challenges. Real-time traffic optimization has been a significant area of research, with Gheorghe et al. [1] demonstrating the efficacy of 5G-enabled AI systems in predicting and managing congestion through real-time data analysis and adaptive signal control, supported by edge computing to avoid centralized overload. Su and Xu [3] enhanced this approach with secure cluster-based authentication mechanisms, while Chuan et al. [4] emphasized the importance of robust algorithms to manage rainfall impacts on 5G millimeter-wave channels. Louvros et al.

[5] further highlighted QoS-aware resource management for traffic flow stability.

Autonomous vehicles (AVs), another critical focus, rely on 5G's high-speed connectivity for seamless data exchange. Moubayed et al. [6] demonstrated improved sensor fusion and navigation reliability, while Sharma et al. [2] optimized AV routes to reduce emissions. Khalid et al. [7] introduced hybrid V2X systems for enhanced coordination. Ge et al. (2024) validated 5G mmWave efficiency for single base stations, and Coll-Perales et al. [8] modeled end-to-end V2X latency in dense environments.

In the context of intelligent transportation systems (ITS), Chen and Song [9] explored the use of V2X communication for traffic pattern analysis and public transport enhancement. Their work is complemented by Barzegar et al. [10], who proposed predictive maintenance frameworks, and Amend and Rakocevic [11], who optimized video streaming in 5G-based ITS using multipath scheduling.

Security, data reliability, and resource allocation remain core challenges. Mongay Batalla et al. [12] proposed multi-layer security assurance models, while Rico et al. [13] examined multi-connection protocols for ITS reliability. Meanwhile, An et al. [14] and Vohra et al. [15] introduced distributed resource allocation strategies to process large traffic datasets efficiently. Mukherjee et al. [16] addressed anomaly detection in IoT-based monitoring, and Bonato et al. [17] evaluated exposure variability in 5G-V2X scenarios using deep learning.

A structured summary of these contributions is presented in Table I, highlighting the main technologies used and challenges addressed across representative works.

TABLE I. RELATED WORKS

Authors	Main Contribution	Technologies Used	Challenges Addressed
Gheorghe and Soica (2025)	Systematic review of AI, IoT, predictive analytics for traffic control	AI, IoT, Predictive Analytics	Real-time traffic management, scalability
Sharma et al. (2023)	Privacy-aware post-quantum routing in 5G IoV	5G, IoV, Privacy Algorithms	Security, Privacy
Su and Xu (2025)	Mutual authentication in 5G sensor networks for vehicles	5G, Sensor Networks	Authentication, Key Update
Coll-Perales et al. (2023)	V2X latency modeling over 5G networks	V2X Communication, 5G	Latency, QoS
Moubayed et al. (2023)	OTN-over-WDM optimization for 5G	Optical Transport Networks, WDM, 5G	Network optimization challenges

III. Methodology and System Model

The proposed system integrates data collection, AI-powered congestion prediction, graph-based route optimization, edge computing, and cloud analytics to deliver real-time, scalable, and efficient urban mobility solutions.

The first step involves data collection and integration, where the system aggregates information from diverse sources, including IoT sensors, connected vehicles, and public transportation systems. Smart traffic lights, road sensors, and surveillance cameras provide real-time updates on traffic density, vehicle speeds, and incidents, forming the foundational dataset. Additionally, Vehicle-to-Everything (V2X) communication, enabled by the low-latency capabilities of 5G, ensures seamless data exchange between vehicles and infrastructure, fostering a holistic view of the traffic ecosystem.

At the core of the system lies AI-powered congestion prediction, which utilizes advanced machine learning models to forecast traffic conditions. Historical data, such as traffic volume, weather patterns, and temporal trends, is combined with live sensor inputs and fed into models like Long Short-Term Memory (LSTM) networks. These models are adept at handling time-series data and capturing both temporal dependencies and nonlinear patterns. The process begins with preprocessing, where noisy data is cleaned, and missing values are filled. Subsequently, LSTM models are trained on historical datasets to identify traffic patterns. During real-time operations, live data streams are processed at edge computing nodes, enabling immediate predictions without relying on centralized servers.

Based on the predictions, the system executes graph-based route optimization to dynamically adjust traffic flows. The urban road network is represented as a weighted graph, where nodes signify intersections and edges represent road segments, with weights corresponding to travel times or congestion levels. Real-time congestion predictions trigger dynamic weight adjustments to reflect current conditions. Algorithms such as Dijkstra or A* compute the shortest and most efficient routes for vehicles. A continuous feedback loop updates the graph with live traffic data, ensuring that routing decisions remain adaptive and responsive to evolving conditions.

To address latency and scalability challenges, the system employs edge computing for decentralized processing. Strategically placed edge nodes near data sources aggregate and analyze data locally, reducing the computational load on central servers. These nodes host lightweight AI models capable of making congestion predictions and suggesting optimized routes. They also communicate directly with vehicles via 5G, disseminating real-time traffic updates and route recommendations. This decentralized approach significantly reduces response times and enhances the system's scalability.

Complementing the edge computing layer, cloud integration for long-term analytics ensures continuous improvement and scalability of the system. While edge nodes handle real-time tasks, cloud servers store historical data and retrain AI models periodically to adapt to new traffic patterns. This hybrid architecture balances the need for immediate responsiveness with the benefits of long-term optimization and model refinement, paving the way for an adaptive and sustainable traffic management system.

By combining these elements, the proposed framework addresses the multifaceted challenges of urban traffic management, delivering a robust solution that enhances mobility, reduces congestion, and promotes sustainability.

A. Objectives

The study aims to develop and evaluate a real-time dynamic traffic management system focusing on: Real-time Congestion Prediction, Dynamic Route Optimization.

1) Real-time congestion prediction. The ability to predict traffic congestion in real-time is a cornerstone of efficient traffic management. This involves training AI models, such as Long Short-Term Memory (LSTM) networks or Gradient Boosted Decision Trees, on both historical traffic patterns and live sensor data. Historical data includes traffic volumes, weather conditions, special events, and temporal variations, while live data comes from IoT devices, V2X communication, and GPS-enabled vehicles. These models are designed to:

a) Identify traffic bottlenecks with high precision.

b) Predict congestion levels minutes or hours into the future.

c) Provide actionable insights to traffic management systems for preemptive actions. This prediction process is carried out locally at edge nodes to minimize latency and ensure timely decision-making.

2) Dynamic Route Optimization. Once congestion is detected or predicted, the next step is to dynamically redistribute traffic to alternative routes to prevent or alleviate congestion. The urban road network is modeled as a weighted graph, where nodes represent intersections, and edges represent road segments. The weights of edges correspond to travel times, which are adjusted dynamically based on:

a) Real-time congestion levels predicted by the AI models.

b) Road closures, construction work, or accidents reported through live feeds. Using algorithms like Dijkstra, A*, or even reinforcement learning-based methods, optimal routes are calculated and suggested to vehicles in real-time. A feedback loop is maintained where updated traffic data continuously refines the routing decisions, ensuring adaptability to changing conditions.

3) Energy-efficient transportation. Optimizing traffic flow not only improves travel times but also significantly reduces energy consumption and emissions. Idle times at congested intersections and prolonged travel distances contribute heavily to urban pollution. By dynamically managing traffic:

a) Fuel consumption is reduced by avoiding stop-and-go traffic conditions.

b) Electric vehicles (EVs) benefit from extended range due to smoother traffic flows.

c) Emissions are minimized, contributing to greener and more sustainable urban environments. To further enhance energy efficiency, the system integrates vehicle-specific data (e.g., fuel efficiency or EV battery levels) into the optimization process, tailoring route recommendations for maximum energy savings.

4) Scalable and decentralized architecture. The implementation of 5G and edge computing is critical for ensuring the scalability and responsiveness of the proposed system. The architecture involves:

a) Edge nodes are placed strategically throughout the urban area, these nodes handle real-time data processing, congestion predictions, and route optimization locally. This reduces the computational load on centralized servers and minimizes data transmission delays.

b) 5G Connectivity enables high-speed and low-latency communication between vehicles, edge nodes, and centralized systems. It also supports massive IoT device connectivity, essential for collecting data from diverse sources.

c) Cloud integration: While edge nodes manage real-time tasks, cloud servers are used for long-term analytics, retraining AI models, and storing historical traffic data. This hybrid approach ensures both scalability and the continuous improvement of prediction and optimization algorithms. By decentralizing computational workloads, the system can scale efficiently across cities of varying sizes and complexities while maintaining low-latency decision-making capabilities.

B. Implementation Plan

The implementation of the proposed dynamic traffic management system follows a comprehensive plan designed to ensure scalability and real-world applicability. The initial phase begins with the creation of a simulated urban traffic network using platforms like SUMO (Simulation of Urban Mobility) or OpenStreetMap. These tools enable the generation of realistic traffic scenarios, simulating vehicle behaviors, road layouts, and dynamic traffic signals. The simulation environment provides a controlled setting to test the framework under various conditions, including peak traffic hours, accidents, and road closures, generating a robust dataset for validation.

The second phase focuses on algorithm development, starting with congestion prediction through advanced AI models. Long Short-Term Memory (LSTM) networks, implemented using TensorFlow or PyTorch, are trained on historical traffic data such as vehicle counts, speeds, weather conditions, and time-of-day patterns. These models process live sensor data streams in real time to predict traffic congestion, leveraging their ability to handle sequential data and temporal dependencies. Concurrently, route optimization is performed using graph-based algorithms. The urban road network is represented as a weighted graph, where nodes are intersections, and edges are road segments. Algorithms like Dijkstra or A* calculate optimal routes dynamically, adjusting edge weights based on real-time congestion predictions. A feedback loop ensures that traffic conditions continuously refine routing decisions, maintaining adaptability.

The third phase involves the deployment of edge computing nodes, which are critical for decentralized processing and low-latency operations. Lightweight computational devices, such as Raspberry Pi or NVIDIA Jetson Nano, equipped with 5G connectivity, are strategically placed at high-traffic areas and key intersections. These nodes host containerized AI models managed through Docker and orchestrated with Kubernetes for scalability and fault tolerance. The edge nodes process data locally, execute congestion predictions, and disseminate route recommendations to connected vehicles in real time, reducing the load on centralized servers.

Finally, the system undergoes real-world testing in collaboration with municipalities or urban traffic authorities. A representative urban area with varying traffic densities is selected for the pilot implementation, where the system integrates with existing traffic management infrastructure. Performance metrics such as average travel time, congestion levels, fuel consumption, and system latency are monitored to evaluate the framework's effectiveness. The collected feedback is used to iteratively refine the system, ensuring robustness and adaptability.

By combining simulation, advanced AI algorithms, edge computing, and real-world testing, the proposed implementation plan offers a scalable and efficient solution for real-time traffic management, paving the way for smarter and more sustainable urban transportation systems.

C. Expected Contributions

This study aims to address the pressing challenges of urban traffic management by introducing a scalable and efficient framework tailored for real-time applications. At its core, the framework leverages a decentralized approach powered by 5G-enabled edge computing, enabling rapid data processing and decision-making directly at strategic points within the urban landscape. By integrating AI-driven congestion prediction with graph-based routing algorithms, the system offers a hybrid optimization model capable of dynamically redistributing traffic to mitigate bottlenecks. Beyond improving traffic flow, the framework emphasizes sustainability by reducing emissions and energy consumption through the elimination of idling and inefficient routes. Furthermore, the study provides a comprehensive blueprint for integrating advanced technologies—such as 5G, AI, and edge computing—into existing urban transportation infrastructures, paving the way for smarter, more adaptive, and environmentally conscious cities.

D. Practical Implementation

As part of this study, we proposed an innovative solution for dynamic urban traffic management, leveraging the integration of 5G, Artificial Intelligence (AI), and edge computing. To validate the presented concepts and illustrate their implementation, an algorithm has been developed to predict traffic congestion and optimize routes in real-time. This implementation relies on machine learning models and graph algorithms, two fundamental pillars for intelligent traffic management.

IV. Results

A. Algorithm – Traffic Simulation and Routing

In this study, we designed and implemented a traffic management algorithm aimed at optimizing urban mobility by dynamically predicting congestion and adjusting routing decisions in real time. The core of the solution combines graph-based optimization methods and machine learning techniques. Initially, congestion levels were estimated using a heuristic congestion scoring formula derived from three traffic features: Traffic Density, Estimated Speed, and Weather Conditions. Based on these scores, the system dynamically adjusted road network weights and calculated optimal routes using Dijkstra's algorithm.

To further enhance prediction reliability and address the complexity of urban traffic patterns, we trained a supervised machine learning model to predict congestion. We selected the Random Forest Classifier for its robustness, ability to capture non-linear relationships, and strong performance on structured traffic data.

a) Input and output: To clarify the data structure used during the simulation phase, the main parameters involved in the proposed traffic management algorithm are summarized in Table II. This table details the inputs required to simulate and evaluate routing scenarios, along with the expected outputs generated by the system.

The inputs include the number of simulated samples, the set of features characterizing each sample (such as estimated speed, traffic density, or incident reports), and the source and destination nodes within the road network. These parameters allow the algorithm to simulate traffic conditions and compute the most efficient path.

The outputs correspond to the resulting optimal route, represented as an ordered list of nodes, and the total cost of that route under the influence of congestion. The cost reflects the dynamic weights applied to the road network based on real-time traffic conditions.

TABLE II. SUMMARY OF INPUTS AND OUTPUTS FOR THE PROPOSED TRAFFIC MANAGEMENT ALGORITHM

INPUT	OUTPUT
num_samples: number of simulated data samples	• List of nodes representing the best route. • Total cost considering simulated congestion
num_features: number of features per sample (e.g., speed, density, incidents)	
source: starting node	
target: destination node	

b) Process: A real-world dataset comprising 627 samples was utilized in this study, with each sample initially described by several traffic-related parameters. The primary objective was to simulate traffic conditions and evaluate the impact of congestion on route optimization. To prepare the data for the model, specific features were derived through additional computations, resulting in three key attributes: Traffic Density, Estimated Speed, and Weather Conditions. Missing values were calculated where necessary, and all extracted features were normalized to ensure consistent scaling and comparability.

The original dataset included the following fields:

- TMJA (Average Annual Daily Traffic): Used as an indicator of traffic density, representing the average number of vehicles passing through a segment daily.
- ratio_PL: Denoting the proportion of heavy vehicles, influencing the overall estimated speed on the segment.

- longueur: Length of the road segment, employed to estimate travel speed when time data is available.
- route: Road identifier, enabling cross-referencing with external geographic datasets.
- dateReferentiel: Date of traffic measurement, used for aligning with historical weather information.
- xD, yD, xF, yF: GPS coordinates marking the start and end points of the road segment, facilitating the retrieval of location-specific weather conditions.

The proposed traffic management algorithm was applied across all data points. It involved computing a congestion score, determining a congestion factor when necessary, adjusting the weights of the corresponding road network, and ultimatelycalculating the optimal route under the updated traffic conditions. Below, we detail the normalization process applied to each extracted parameter to ensure consistency and comparability across the dataset.

The extracted features were normalized to ensure consistent scaling. Traffic density was standardized using the min-max formula described in Eq. (1). Estimated speed was calculated from the road segment length and travel time as shown in Eq. (2). Weather conditions were normalized in two steps: first by converting temperature from Kelvin to Celsius using Eq. (3), and then applying min-max normalization as shown in Eq. (4).

Traffic Density:

$$Standardised\ density = \frac{TMJA - \min(TMJA)}{\max(TMJA) - \min(TMJA)} \quad (1)$$

Estimated Speed:

$$Average\ speed = \frac{length}{travel\ time} \quad (2)$$

Weather Conditions:

$$T_{Celsius} = T_{Kelvin} - 273{,}15 \quad (3)$$

$$\text{Weather\_conditions} = \frac{Temperature_C - \min(Temperature_c)}{\max(Temperature_c) - \min(Temperature_c)} \quad (4)$$

When the computed congestion score exceeded a threshold of 1, a congestion factor of 0.2 was systematically applied to adjust the network parameters; otherwise, the original weights remained unchanged. Based on this approach, a directed graph representing the road network was constructed, with predefined base weights assigned to each edge. Upon congestion detection, all edge weights were proportionally increased using the congestion factor to reflect the associated traffic delays. Subsequently, Dijkstra's algorithm was employed to determine the shortest path between the defined source and destination nodes within the updated network structure. The final step involved visualizing the adjusted road network to highlight the effects of congestion on optimal routing strategies.

The entire simulation workflow is summarized in Table III, outlining each stage from data generation to route computation.

TABLE III. PROCESS OVERVIEW FOR TRAFFIC SIMULATION AND NETWORK ADJUSTMENT

Step	Action
1. Generate Data	Create num_samples of random data with num_features
2. Estimate Congestion	For each sample: if (f1 + 2*f2 - f3 > 1) → label = high congestion
3. Set Congestion Factor	If congestion is high → congestion_factor = 0.2 else → 0.0
4. Build Road Graph	Create a graph with nodes and standard edge weights
5. Adjust Weights	Multiply all edge weights by (1 + congestion_factor)
6. Compute Route	Use shortest path algorithm (e.g., Dijkstra) from source to target
7. Output Result	Display optimal route and total adjusted cost

c) Algorithm: Following the execution of the steps outlined in Algorithm 1, the adjusted road network was generated. Fig. 1 illustrates the updated graph structure, highlighting how congestion factors impact the routing through modified edge weights.

Algorithm 1: Visualization of the Adjusted Road Network

```
Initialize:
    Define manual positions for each node.
Compute:
    Create edge labels based on adjusted edge weights.
While (graph is being prepared) do
    Draw network nodes at specified positions.
    Draw directed edges between nodes with arrows.
    Label each node with its identifier.
    Annotate edges with their corresponding weights.
    Update:
        Set title of the graph to "Adjusted Road Network (With
Congestion Penalty)".
        Hide axes to enhance visualization.
        Adjust layout for better spacing.
    End
End
Display:
    Render and show the final visualized graph.
End
```

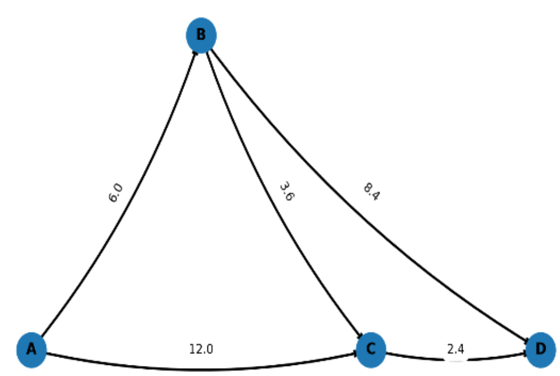

Fig. 1. Adjusted road network visualization considering congestion penalties.

Following the application of a 20% congestion penalty to the edge weights, the network structure was updated to reflect the increased travel costs. Notably, the path A → B → C → D continues to represent the optimal route under the adjusted conditions.

d) Machine learning congestion prediction: To improve traffic congestion prediction and support adaptive routing decisions, we implemented a supervised machine learning approach. The objective was to train a classification model capable of predicting congestion based on real traffic-related variables.

As a starting point, we constructed an initial congestion label (Congestion_Predite) using a heuristic scoring function based on three key features extracted or derived from the dataset [Eq. (5)]:

$$\mathrm{Congestion}_{\mathrm{Score}} = (0.60 \times \text{Traffic Density}) + (0.23 \times \text{Estimated Speed}) + (0.17 \times \text{Weather Conditions}) \quad (5)$$

The binary target variable was then defined using a threshold as in Eq. (6):

$$Congestion_{Predite} = \begin{cases} 1 & \text{if Score} > 1 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

This labeled dataset served as the foundation for training a Random Forest classifier, which learned more complex and non-linear relationships between the variables and congestion states. This approach allows for generalization to unseen traffic patterns and conditions, improving prediction reliability.

The performance of both the routing and prediction components is influenced by key algorithmic parameters. In the case of the Random Forest classifier, the number of trees (estimators), maximum depth, and minimum samples per split directly affect the model's ability to generalize. A higher number of trees tends to improve robustness, while excessively deep trees may lead to overfitting. For Dijkstra's algorithm, the accuracy of route computation depends on the dynamic edge weights, which are adjusted based on the congestion factor. The choice of base weights and how they scale with congestion (e.g., a 20% increase as used here) influences routing outcomes. These parameters were empirically chosen to balance performance and computational efficiency in real-time settings.

The model's predictive performance was evaluated using standard classification metrics. The results are summarized in Table IV.

TABLE IV. MODEL RESULTS

Metric	Value
Overall Accuracy	99%
Precision (Not Congested)	100%
Precision (Congested)	98%
Dominant Factor	Traffic Density (highest importance)

To assess the effectiveness of the proposed prediction model, we conducted a basic comparison with other standard classification algorithms on the same dataset. Support Vector Machines (SVM), Gradient Boosted Decision Trees (GBDT), and K-Nearest Neighbors (KNN) were evaluated using identical input features and a consistent data split. Among all tested models, the Random Forest classifier achieved the highest accuracy (99%), with better balance between precision and recall. SVM and GBDT followed with slightly lower accuracy scores (95% and 96% respectively), while KNN showed more variance depending on the feature scale and neighborhood size. These results validate the choice of Random Forest for this application, given its robustness, interpretability, and suitability for edge deployment.

These metrics confirm the model's high precision, particularly in identifying congested cases with minimal false positives. Traffic density emerged as the most influential variable, followed by speed and weather conditions. This ranking aligns with known determinants of urban traffic congestion.

Additional evaluation tools, including the confusion matrix, the ROC curve, and feature importance analysis, are presented in the next section to provide further insight into the classifier's behavior and reliability.

The performance of the developed machine learning model was evaluated through several key visualization tools, each offering complementary insights into classification reliability. Among these, the confusion matrix provides a direct view of the model's effectiveness in distinguishing between congested and non-congested traffic segments.

As shown in Fig. 2, the confusion matrix displays the number of correct and incorrect predictions across both classes. The model correctly identified nearly all instances, with minimal misclassification. This confirms its ability to separate the two categories with high precision, reinforcing the metrics reported in Table IV.

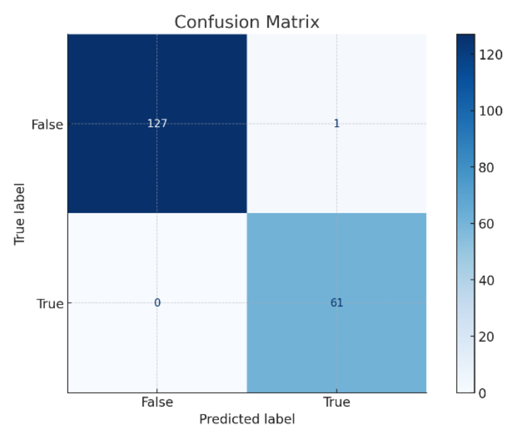

Fig. 2. Confusion matrix.

The confusion matrix summarizes the model's prediction outcomes by displaying the number of correct and incorrect classifications for both congested and non-congested traffic conditions. It provides a clear view of how well the model distinguishes between the two classes, highlighting both true positives and true negatives.

As presented in Fig. 3, the ROC curve plots the true positive rate against the false positive rate. The model achieved an Area Under the Curve (AUC) of 0.99, indicating a near-perfect capacity to discriminate between congested and non-congested traffic conditions.

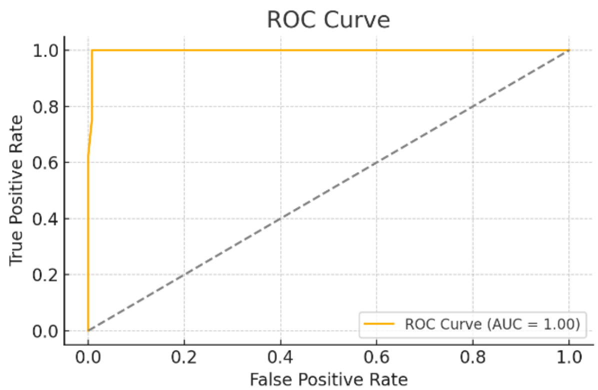

Fig. 3. Receiver Operating Characteristic (ROC) curve.

The ROC curve illustrates the trade-off between the true positive rate and the false positive rate at various classification thresholds. The Area Under the Curve (AUC) achieved a value of 0.99, demonstrating that the model possesses excellent discrimination capability between congested and non-congested states. A near-perfect AUC score reflects the model's robustness and high predictive accuracy.

To further interpret the internal behavior of the model, we examined feature importance, which ranks the contribution of each input variable to the prediction outcomes. This analysis helps identify which factors most strongly influence the classifier's decision.

As illustrated in Fig. 4, traffic density emerges as the dominant variable, followed by estimated speed and weather conditions. The important ranking aligns with domain knowledge, where density is often the primary driver of congestion.

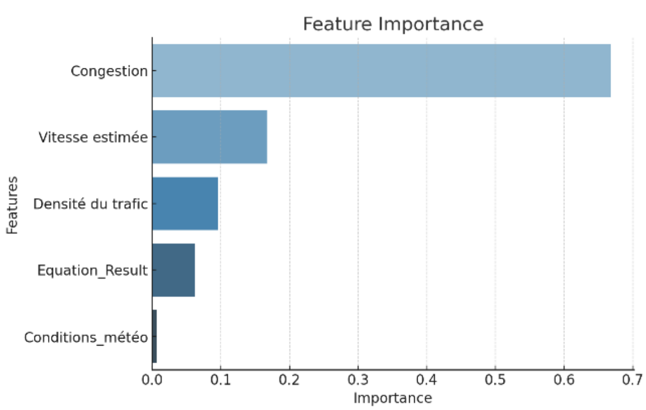

Fig. 4. Feature importance plot.

The feature importance analysis identifies and ranks the contribution of each input variable to the model's predictions. The results show that traffic density is the most influential feature, exerting the greatest impact on the model's ability to predict congestion. Other variables, such as estimated speed and weather conditions, also contribute, but to a lesser extent.

These evaluation tools provide complementary evidence of the model's effectiveness. The confusion matrix, ROC curve, and feature importance collectively validate both its predictive accuracy and its alignment with real-world traffic behavior.

Despite its strong performance, the model presents several limitations. First, the training was based on simulated data, which does not fully reflect real-time traffic irregularities. Second, the system depends on the reliability of sensor inputs, which may be affected by latency, noise, or missing data. Third, the tested road network was simplified, and external factors such as road incidents or construction zones were not included. These constraints may limit the immediate deployment of the system in uncontrolled real-world conditions and require further calibration.

V. Discussion

This study proposed and validated an integrated traffic management framework that combines AI-driven congestion prediction, graph-based dynamic routing, and 5G-enabled edge computing to support real-time decision-making. The methodology was built around two key components: a graph-based traffic simulation and routing algorithm that dynamically adjusted road network weights based on a computed congestion score, and a supervised machine learning model designed to predict congestion states using traffic-related features. Initially, congestion levels were estimated heuristically based on Traffic Density, Estimated Speed, and Weather Conditions, and road weights were adjusted accordingly to guide routing using Dijkstra's algorithm. To enhance prediction reliability beyond heuristic methods, a Random Forest Classifier was developed, chosen for its robustness against overfitting, its ability to capture non-linear feature interactions without extensive preprocessing, its interpretability through feature importance analysis, and its computational efficiency suitable for edge deployment. The model achieved outstanding performance, with an overall accuracy of 99%, a precision of 100% for non-congested cases, and 98% for congested cases, identifying Traffic Density as the dominant predictive factor. These results were reinforced by a confusion matrix analysis and a ROC curve yielding an AUC of 0.99. Compared to other machine learning models, such as SVMs, GBDTs, Neural Networks, and KNN, Random Forests provided the best trade-off between predictive power, scalability, and interpretability, making them particularly suitable for real-time, decentralized urban mobility systems. By combining accurate congestion prediction, adaptive routing, and efficient edge computing, the proposed framework delivers a scalable and effective solution to the evolving challenges of traffic management in smart cities, as illustrated in Fig. 5.

Future work will aim to extend the system's capabilities in several directions. First, the integration with connected vehicle platforms will enable the framework to receive and act upon live feedback from on-road users. Second, deploying the model in a real-world urban environment, in collaboration with traffic authorities, will allow validation under operational conditions. Third, additional traffic dynamics—such as incident detection, weather disruptions, and multi-agent coordination—will be incorporated to improve adaptability. Lastly, the framework will be tested on data from other cities to evaluate generalizability across different urban structures.

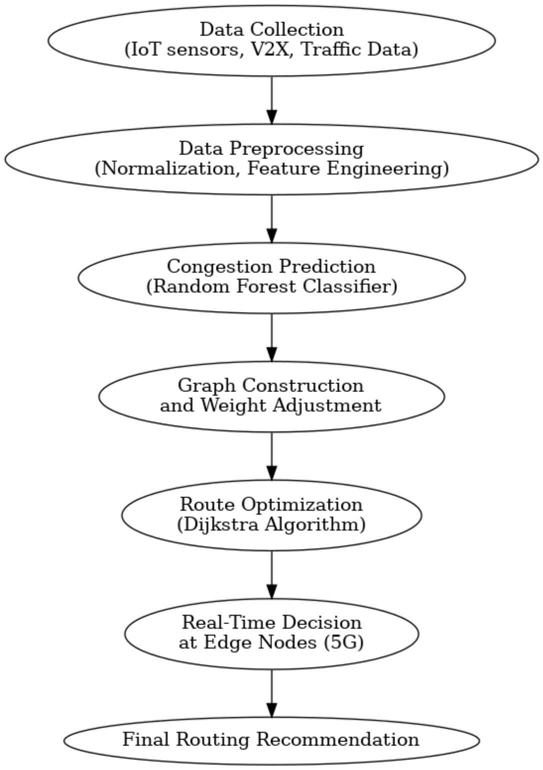

Fig. 5. Traffic management system workflow integrating machine learning and 5G edge computing.

VI. Conclusion

This study presented an integrated framework that combines AI-based congestion prediction, dynamic graph-based routing, and 5G-enabled edge computing to support real-time urban traffic management. The main contribution lies in the design and validation of a decentralized system capable of adapting to evolving traffic conditions using machine learning and network optimization in a scalable architecture.

The proposed solution leverages a Random Forest classifier for congestion detection and Dijkstra's algorithm for dynamic routing, applied to a simulated urban environment. The model achieved an overall accuracy of 99%, with strong precision across both congested and non-congested cases. Feature analysis confirmed traffic density as the most influential variable, validating the model's alignment with known traffic behaviors. Additional evaluation tools, such as the confusion matrix and ROC curve (AUC = 0.99), demonstrated the system's robustness and predictive reliability.

By processing data locally at the edge and reacting in near real-time, the system achieves both performance and scalability, meeting key requirements for smart city deployment. Future work will focus on integrating connected vehicle feedback, incorporating real-time disruptions such as incidents or construction, and testing the system across different urban contexts to assess transferability and operational impact.

References

[1] C. Gheorghe, A. Soica, "Revolutionizing Urban Mobility: A Systematic Review of AI, IoT, and Predictive Analytics in Adaptive Traffic Control Systems for Road Networks", Electronics, vol. 14, pp. 719, 2025.

[2] T. Sharma, M.R. Kumar, S. Kaushal, D. Chaudhary, K. Saleem, "Privacy Aware Post Quantum Secure Ant Colony Optimization Ad Hoc On-Demand Distance Vector Routing in Intent Based Internet of Vehicles for 5G Smart Cities", IEEE Access, vol. 11, pp. 110391-110399, 2023.

[3] X. Su, Y. Xu, "An Efficient Cluster-Based Mutual Authentication and Key Update Protocol for Secure Internet of Vehicles in 5G Sensor Networks", Sensors, vol. 25, pp. 212, 2025.

[4] L.L. Chuan, M. Roslee, C. Sudhamani, S.M.I. Mitani, A. Waseem, A.F. Osman, F.Z. Ali, Y. Ullah, "Impact of Rainfall on 5G Millimeter Wave Channels", Progress In Electromagnetics Research C, vol. 148, pp. 97-107, 2024.

[5] S. Louvros, M. Paraskevas, T. Chrysikos, "QoS-Aware Resource Management in 5G and 6G Cloud-Based Architectures with Priorities", Information (Switzerland), vol. 14, pp. 175, 2023.

[6] A. Moubayed, D.M. Manias, A. Javadtalab, M. Hemmati, Y. You, A. Shami, "OTN-over-WDM Optimization in 5G Networks: Key Challenges and Innovation Opportunities", Photonic Network Communications, vol. 45, pp. 49-66, 2023.

[7] I. Khalid, V. Maglogiannis, D. Naudts, A. Shahid, I. Moerman, "Optimizing Hybrid V2X Communication: An Intelligent Technology Selection Algorithm Using 5G, C-V2X PC5 and DSRC", Future Internet, vol. 16, pp. 107, 2024.

[8] B. Coll-Perales, M.C. Lucas-Estan, T. Shimizu, J. Gozalvez, T. Higuchi, S. Avedisov, O. Altintas, M. Sepulcre, "End-to-End V2X Latency Modeling and Analysis in 5G Networks", IEEE Transactions on Vehicular Technology, vol. 72, pp. 5094-5109, 2023.

[9] Y. Chen, X. Song, "Application of 5G Combined Wireless Interconnection Technology in the Reform of English Education in Colleges and Universities", Mobile Information Systems, vol. 2022, pp. 5774132, 2022.

[10] S. Barzegar, M. Ruiz, L. Velasco, "Autonomous Flow Routing for Near Real-Time Quality of Service Assurance", IEEE Transactions on Network and Service Management, vol. 21, pp. 2504-2514, 2024.

[11] M. Amend, V. Rakocevic, "Cost-Efficient Multipath Scheduling of Video-on-Demand Traffic for the 5G ATSSS Splitting Function", Computer Networks, vol. 242, pp. 110218, 2024.

[12] J. Mongay Batalla, L.J. De La Cruz Llopis, G.P. Gomez, E. Andrukiewicz, P. Krawiec, C.X. Mavromoustakis, H.H. Song, "Multi-Layer Security Assurance of the 5G Automotive System Based on Multi-Criteria Decision Making", IEEE Transactions on Intelligent Transportation Systems, vol. 25, pp. 3496-3512, 2024.

[13] D. Rico, K.-J. Grinemmo, A. Brunstrom, P. Merino, "Performance Analysis of the Multi-Connection Tactile Internet Protocol over 5G", Journal of Network and Systems Management, vol. 31, pp. 49, 2023.

[14] C. An, A. Zhou, J. Pei, X. Liu, D. Xu, L. Liu, H. Ma, "Octopus: Exploiting the Edge Intelligence for Accessible 5G Mobile Performance Enhancement", IEEE/ACM Transactions on Networking, vol. 31, pp. 2454-2469, 2023.

[15] S.K. Kumar, V.S. Kumar, R. Krishnamoorthy, P. Mahesh, B. Haravohra layya, N. Soni, S.K. Gupta, "The 5G Revolution: Tackling Challenges in Smart Cities and Intelligent Transportation Systems", Journal of Autonomous Intelligence, vol. 7, pp. 1342, 2024.

[16] A. Mukherjee, M. Sasidharan, M. Herrera, A.K. Parlikad, "Unsupervised Constrained Discord Detection in IoT-Based Online Crane Monitoring", Advanced Engineering Informatics, vol. 60, pp. 102444, 2024.

[17] M. Bonato, G. Tognola, M. Benini, S. Gallucci, E. Chiaramello, S. Fiocchi, M. Parazzini, "Stochastic Dosimetry Assessment of Human RF-EMF Spatial Exposure Variability in 5G-V2X Vehicular Communication Scenario", IEEE Access, vol. 11, pp. 94962-94973, 2023.