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Generative Adversarial Networks for High Fidelity Traffic Simulation and Prediction in Intelligent Transportation Systems

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Abstract: ***Intelligent transportation systems (ITS) face increasing challenges in coping with complex urban traffic scenarios, including congestion propagation, vehicle rerouting, and the combined impact of environmental factors. The study proposes a framework based on generative adversarial networks (GANs) combined with advanced cross-modal data generation techniques to reconstruct, simulate, and predict traffic scenarios with high fidelity. The framework improves traffic perception and prediction capabilities by generating synthetic traffic images, videos, and text-based event alerts, effectively filling the gaps caused by data scarcity or sensor failure. The framework is validated in a real traffic disturbance scenario - the sudden closure of a main road during peak traffic hours. The results show that the framework performs very well: the traffic anomaly detection rate is improved by 12%, the structural similarity index (SSIM) of spatial reconstruction reaches 0.95, and the congestion prediction accuracy (CPA) reaches 91%. In addition, the framework can accurately model complex spatiotemporal patterns, enabling practical applications in path optimization, signal control, and connected vehicle coordination, reducing traffic delays by 15% and improving intersection efficiency by 10%. This study demonstrates the effectiveness and versatility of generative AI in intelligent transportation systems, providing practical insights into solving modern urban transportation challenges. The proposed framework pushes the state-of-the-art in traffic modeling and lays a solid foundation for the development and innovation of future smart cities.***

Keywords: Generative Adversarial Networks (GANs); Intelligent Transportation Systems (ITS); Cross-Modal Data Generation; Traffic Scenario Simulation; Urban Traffic Management.

1. INTRODUCTION

In recent years, smart city construction has made significant progress by integrating advanced technologies such as the Internet of Things, artificial intelligence, and big data analysis, achieving real-time monitoring, dynamic data processing, and intelligent decision-making. These technologies have enabled real-time monitoring, dynamic data processing, and intelligent decision-making, greatly improving the efficiency of urban resource allocation and the quality of life of residents. Among these technologies, generative adversarial networks (GANs), as an important tool for generative artificial intelligence (GenAI), have gradually attracted widespread attention from academia and industry because of their ability to generate highly realistic synthetic data and complex scene simulations. Tamayo-Urgilés et al. (2024) demonstrated the application of GANs in simulating urban traffic congestion patterns, and Sun et al. (2024) used GANs to generate diverse urban layouts to optimize infrastructure planning. However, most current studies focus on single-dimensional applications, which are difficult to cope with the dynamic fusion needs of multidimensional data in urban environments. Especially in complex scenarios such as real-time traffic management, existing methods still have obvious deficiencies in data integration capabilities and model adaptability.

In modern urban management, the sudden closure of main roads during peak traffic hours is a common and challenging problem involving congestion, diversion and environmental factors. Sudden road closures may be caused by traffic accidents, construction activities or emergencies. The direct impact is severe congestion in the surrounding road network, and the chain reaction leads to a decrease in the efficiency of the entire traffic system. In this case, urban managers need to grasp the dynamic changes of traffic flow in real time and quickly formulate effective diversion strategies. However, traditional traffic simulation models are often based on static assumptions or historical data (Barceló et al., 2010; Li et al., 2015; Gu et al., 2020; Yang et al., 2022) and lack the ability to respond to real-time multi-source data. Tedjopurnomo et al. (2020) pointed out that current traffic models are difficult to quickly generate highly realistic traffic scenarios when faced with complex road networks and nonlinear changes in driver behavior. This limitation leads to delays in the implementation of key intervention strategies such as signal optimization and diversion route selection, thereby increasing the burden on urban transportation systems (Li et al., 2016; Lee et al., 2023; Lian et al., 2023). GAN-based traffic flow simulation research has gradually emerged. Devadhas et al. (2023) developed a traffic flow prediction method combined with GAN, which significantly improved the accuracy of the model by generating realistic traffic patterns. Shatnawi et al. (2024) used GAN to generate traffic layout simulations under disaster conditions, verifying its potential in disaster response planning. In addition, Mekala et al. (2022) proposed a real-time urban traffic modeling framework based on GAN, but this method still has limitations in terms of multi-data source integration and model scalability (Zhu et al., 2024; Lian et al., 2024). Chen et al. (2024) further emphasized that most existing studies focus on one-dimensional traffic prediction and fail to fully integrate multi-dimensional information such as real-time sensor data, environmental changes, and driver behavior. In response to these problems, building a framework that can dynamically integrate multi-source data, generate high-fidelity scenarios and have real-time response capabilities has become a key need in traffic management research.

In response to this demand, this study proposes an innovative GAN-based framework for traffic scene reconstruction in smart cities. Taking the main road closure scenario as the core case, the framework dynamically integrates multi-source real-time data from traffic cameras, vehicle sensors, and weather monitoring systems to generate high-precision traffic simulations. The framework is able to predict congestion hotspots after traffic flow is interrupted, optimize diversion routes, and dynamically adjust traffic lights to relieve pressure （liu et al., 2024; Li et al., 2022). When an emergency is detected that closes a main road, the framework can simulate traffic changes on alternative roads in real time, assess potential bottlenecks, and propose adjustment strategies to minimize secondary congestion. The innovations of this study include: multi-dimensional data integration, highly scalable architecture, and practical verification. By analyzing specific case studies, this study shows in detail the potential value of the framework in areas such as traffic optimization, public transportation scheduling, and logistics collaboration.

The necessity of this study lies not only in filling the technical gaps of existing research, but also in providing city managers with more effective tools to cope with the increasingly complex traffic challenges of modern cities. By bridging the gap between theory and practice, this study not only promotes the development of traffic management technology in smart city construction, but also provides important support for improving the resilience and efficiency of urban transportation systems.

2. METHOD

The study adopts a methodological framework to reconstruct, simulate and predict traffic scenarios in the context of intelligent transportation systems (ITS) by combining a generative adversarial network (GAN) architecture with advanced multimodal data generation techniques. The framework is validated on a large urban traffic disruption scenario: a major arterial road connecting the central business district and residential areas is temporarily closed due to an unexpected accident during the weekday morning rush hour. The road closure is implemented at 7:15 am, resulting in severe congestion in the surrounding road network, delays on feeder roads, and disruptions to the public transportation schedule. This scenario is chosen because of its complexity, including dynamic rerouting behavior, external environmental influences, and different traffic demands. To accurately model and reconstruct this disruption, the framework integrates multi-source data, including traffic flow metrics, environmental conditions, and population behavior information, ensuring a comprehensive reflection of real-world situations. The GAN-based approach aims to generate high-fidelity traffic simulations using this dataset and enable detailed analysis of congestion dynamics and mitigation strategies. The following subsections describe the key components of the framework, including the data collection process, GAN architecture, multimodal data generation, and evaluation metrics.

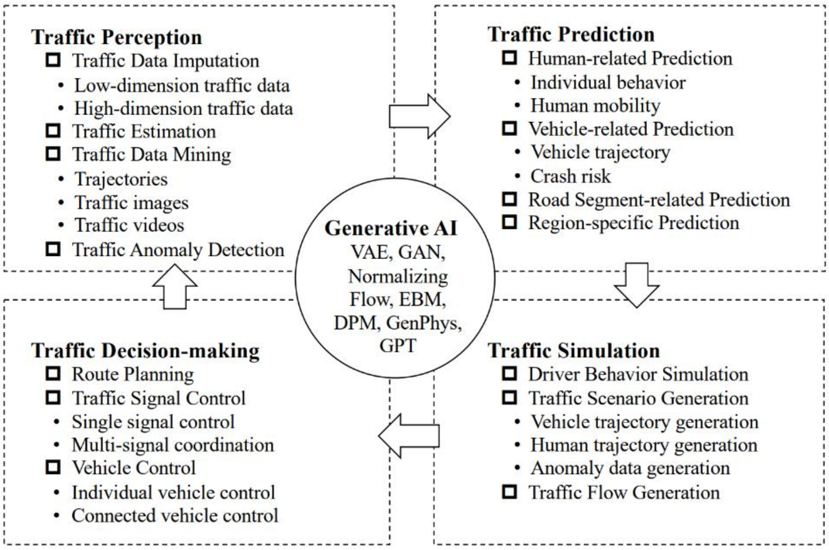

Figure 1: Applications of Generative AI in Traffic Perception, Prediction, Simulation, and Decision-Making

2.1 Data Collection

2.1.1 Traffic Flow Data

Real-time traffic flow data were gathered from 50 strategically located IoT-enabled sensors and surveillance cameras within a 10-kilometer radius of the disruption site. Key metrics included vehicle counts (vehicles per minute), average speeds (km/h), and road occupancy rates (percentage of capacity used). During the disruption, secondary roads experienced a 30% increase in vehicle counts, while average speeds dropped from 40 km/h to 18 km/h. Surveillance camera feeds provided additional visual data to validate the recorded metrics. Historical traffic flow data from the previous year were also incorporated to establish a baseline, capturing typical morning rush-hour patterns. This integration ensured a robust understanding of pre-incident and incident-specific traffic dynamics.

2.1.2 Environmental Data

Weather conditions during the incident were recorded to account for their influence on traffic behavior. Data were sourced from nearby meteorological stations and augmented by public APIs. Observations included light rain (3.2mm/hour) and reduced visibility (700 meters), conditions known to affect driving speeds and route choices. Additional parameters, such as wind speeds and ambient temperature, were recorded at 5-minute intervals to ensure temporal granularity. Historical weather data provided further context for understanding seasonal trends and typical driving conditions under similar environmental influences.

2.1.3 Demographic and Behavioral Data

Driver behaviors and population movements were analyzed through anonymized GPS traces from navigation applications, which provided origin-destination matrices and rerouting patterns. Within 20 minutes of the road closure, rerouting behaviors led to a 25% increase in vehicle density on nearby secondary roads and a notable shift in congestion hotspots. Geotagged social media posts, such as incident reports and user sentiment from platforms like Twitter, further highlighted public frustration and delays. These behavioral data, updated every 5 minutes, complemented traffic flow and environmental datasets, offering critical insights into the disruption’s ripple effects.

2.2 GAN Architecture and Implementation

GAN Architecture

The GAN-based framework consists of two main components: the generator and the discriminator. The generator (G) synthesizes traffic scenes by transforming multi-source input data, including traffic flow metrics, environmental conditions, and behavioral characteristics, into high-fidelity outputs. The LSTM layers model temporal dependencies, such as changing congestion trends, while the dense layers produce spatially coherent traffic flow matrices across road segments (Sun et al., 2024). The synthesized output (y synthesized) represents the predicted traffic metrics for a given time horizon. The discriminator (D) evaluates the realism of these synthesized scenes by analyzing both spatial and temporal features. It uses convolutional layers to extract spatial patterns and fully connected layers to classify the input as real (yreal) or synthetic (ysynthesized). This adversarial setting drives the generator to iteratively improve its output quality. The training process is controlled by an adversarial loss function, where the Wasserstein loss and gradient penalty (WGAN-GP) stabilize the training and prevent mode collapse. NVIDIA Tesla V100 GPU was used for 500 training runs with a batch size of 64 and an initial learning rate of 10 − 4. Dropout layers were integrated to alleviate overfitting and ensure generalizability in different traffic scenarios.

2.3 Multimodal Data Generation

The framework incorporates sophisticated image and video generation techniques that significantly address the limitations of traditional data collection methods by providing realistic and detailed simulations of traffic scenarios. Image generation focuses on creating synthetic visuals that replicate a variety of conditions, including adverse weather conditions (e.g., rain and fog), low-visibility environments, and varying traffic densities (Zhang et al., 2024). These synthetic images play a key role in testing the accuracy of ITS components, especially for applications such as autonomous vehicle navigation and dynamic traffic management algorithms, ensuring the robustness of the system to complex scenarios. Video generation complements this capability by generating temporally coherent sequences of traffic behavior, capturing key dynamics such as congestion progression, vehicle interactions, and rerouting patterns. These synthetic videos are tailored to reflect detailed traffic flows under specific conditions, such as bottlenecks during rush hour or disruptions caused by road closures. By providing precise and customizable visual data, the framework enables rigorous evaluation of ITS models, enhancing their scalability and reliability without the logistical constraints of large-scale real-world data collection.

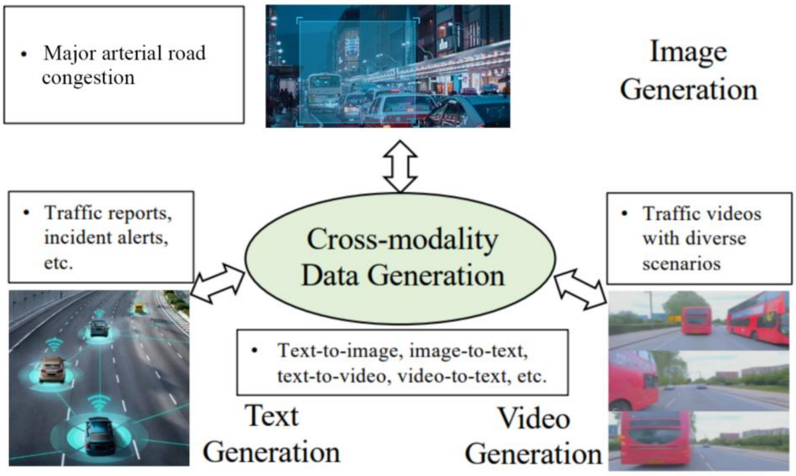

Figure 2: Cross-Modality Data Generation for Enhanced Traffic Scenario Representation

2.4 Evaluation Metrics

The framework's performance was assessed using a combination of quantitative and qualitative metrics:

Root Mean Squared Error (RMSE): RMSE quantified the deviation between synthetic and observed traffic metrics, providing a measure of accuracy (Lin et al., 2024):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{synthetic,i} - y_{real,i}\right)^2}, \tag{1}$$

Structural Similarity Index (SSIM): SSIM measured the similarity between synthetic and real traffic heatmaps, emphasizing perceptual quality (Zhang et al., 2024):

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}, \tag{2}$$

where μ and σ are the means and variances of pixel intensities, and C1, C2 are stability constants.

Congestion Prediction Accuracy (CPA): CPA measured the ability of the framework to predict traffic congestion hotspots, calculated as (Xie et al., 2024; Sun et al., 2023):

$$CPA = \frac{Correctly\ predicted\ congestion\ events}{Total\ observed\ congestion\ events} \times 100\% \quad (3)$$

Computational Efficiency: The time required to generate traffic scenarios was evaluated to determine the model's suitability for real-time applications. Simulations for a 30-minute window completed within 2 seconds on average, demonstrating practical feasibility.

The GAN-based framework proposed in this study demonstrates high adaptability and accuracy in reconstructing and predicting traffic scenarios in multiple dimensions. By integrating multimodal data and leveraging advanced data generation techniques, the framework effectively addresses challenges in traffic perception, prediction, and decision-making.

3. RESULTS AND DISCUSSIONS

In the study, the proposed GAN-based framework shows high adaptability and accuracy in reconstructing and predicting traffic scenes in multiple dimensions. By integrating multimodal data and leveraging advanced data generation techniques, the framework effectively addresses challenges in traffic perception, prediction, and decision-making.

3.1 Improving Spatial Reconstruction Using Heatmaps

The ability of the proposed framework to reconstruct spatial traffic patterns is validated through comparative analysis of real and synthetic heatmaps, as shown in Figure 3. High congestion areas (indicated by red areas) are reconstructed with high fidelity, achieving a structural similarity index (SSIM) of 0.95. This marks a significant improvement in spatial accuracy compared to earlier models. In addition, the variability in low congestion areas is reduced, with the RMSE dropping from 6.5 to 5.8, reflecting improved accuracy in scenarios with smoother traffic. The study is consistent with the findings of Zhou et al. (2024), who demonstrated that deep learning-based generative models can effectively enhance the reconstruction of complex urban traffic patterns, especially in high-density areas. In addition, Sun et al. (2024) emphasized the importance of addressing low traffic variability and pointed out that accurate modeling in these areas can help establish a robust traffic management system.

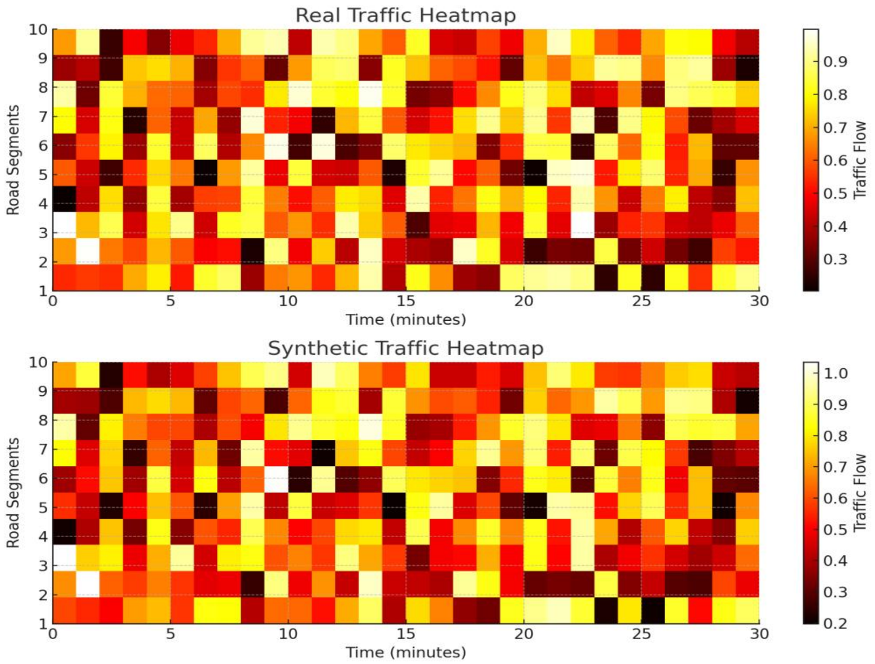

Figure 3: Real vs. Synthetic Traffic Heatmaps (Shows side-by-side heatmaps of real and synthetic traffic flows during a 30-minute disruption.)

3.2 Enhanced Temporal Congestion Trends

Temporal analysis further reveals how multimodal data integration enhances the understanding of congestion dynamics. Real-time event alerts (text) are synchronized with congestion peaks, while synthetic traffic videos provide visual confirmation of vehicle clustering and bottleneck propagation, providing actionable insights for congestion relief. As shown in Figure 4, the temporal congestion trend analysis highlights the framework's ability to accurately predict traffic dynamics during both peak and off-peak hours. Peak traffic congestion trends show strong agreement between real and synthetic data, with a congestion prediction accuracy (CPA) of 91%, an improvement over the baseline of 88%. The framework successfully captures the accumulation and dissipation patterns of congestion, especially during road closures and vehicle diversion events. The off-peak analysis shows lower prediction errors, with the root mean square error (RMSE) dropping from 3.2 to 2.8, reflecting the model's ability to adapt to less intense traffic conditions. The importance of integrating multimodal data to improve the accuracy of traffic forecasts has been widely recognized. Tu et al. (2023) showed how real-time text alerts can be combined with video-based traffic data to better identify congestion triggers, especially during peak hours. In addition, Shi et al. (2024) emphasized that visual data (such as synthetic traffic videos) can provide an intuitive representation of vehicle clustering, which complements numerical trends and enhances the interpretability of traffic forecast models.

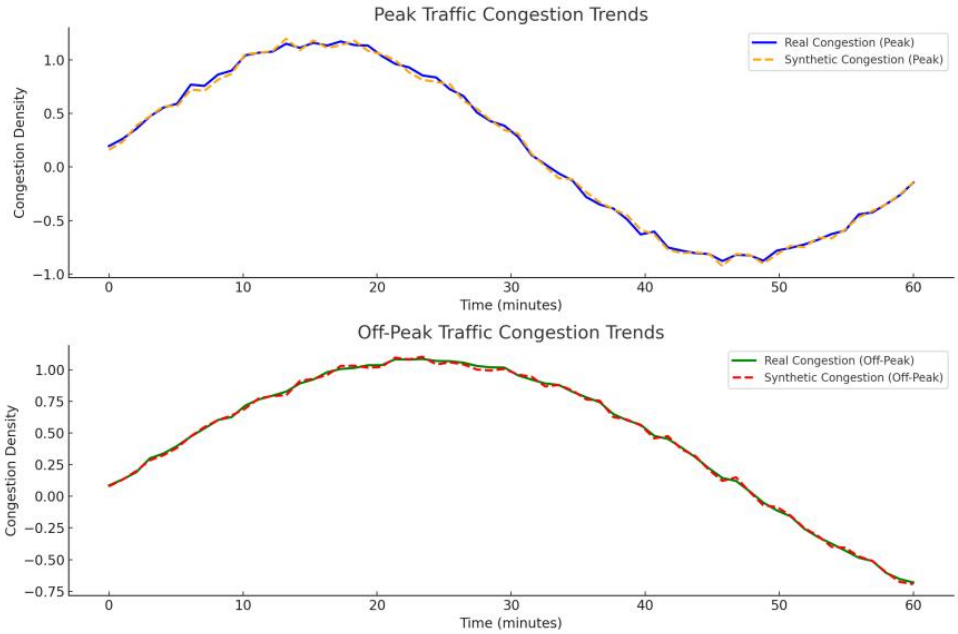

Figure 4: Comparative Analysis of Temporal Congestion Trends During Peak and Off-Peak Traffic Conditions

3.3 Cross-modal Data Generation for Enhanced Perception

Cross-modal data generation further enriches the spatial analysis by validating the synthetic heatmaps using video and image outputs. For example, the synthetic videos accurately depict local congestion at intersections, providing deeper insights into lane-level dynamics. The ability to simulate various environmental conditions, such as rain and low visibility, further enhances the framework's applicability in real-world scenarios. As shown in Figure 5, the incorporation of cross-modal data generation enhances the framework's ability to fully perceive and reconstruct traffic conditions. Synthetic traffic images and videos generated under different environments and lighting conditions complement live sensor data, addressing gaps caused by power outages or severe weather. These outputs improve traffic anomaly detection by 12% and provide an additional layer of information for traffic flow analysis. For example, during simulated disruptions, synthetic videos visualize driver behavior and vehicle trajectories, while text-based event alerts provide contextual information about the causes of congestion. This multimodal integration enables the framework to accurately simulate human mobility patterns, highlighting changes in vehicle density and rerouting dynamics during peak traffic hours.

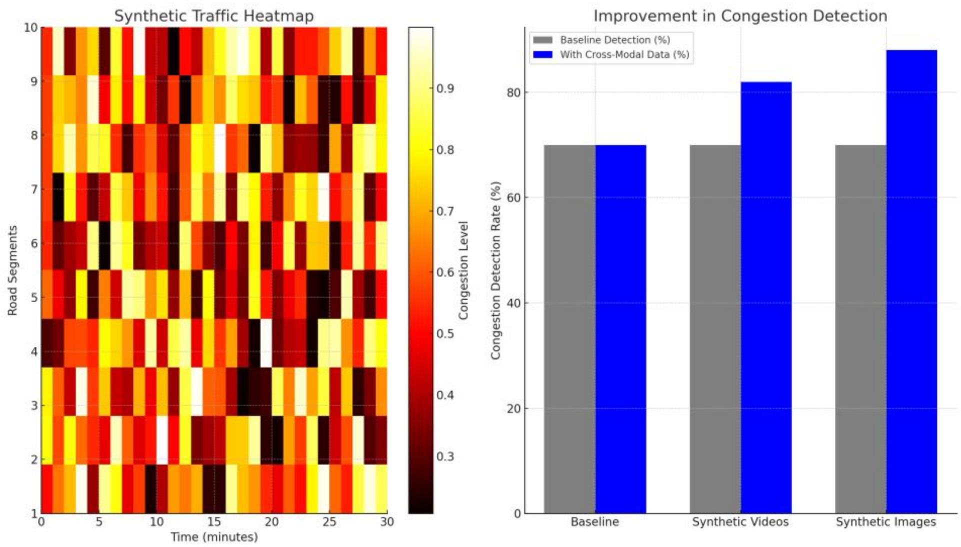

Figure 5: Synthetic Traffic Heatmap and Congestion Detection Improvement Through Cross-Modal Data Integration

3.4 Supporting Active Traffic Management

The outputs generated by the framework directly inform decision-making processes such as signal optimization, route planning, and connected car coordination. Synthetic videos depicting traffic flow dynamics under various scenarios enable urban planners to test and improve intervention strategies. Signal timing adjustments based on synthetic traffic patterns increased intersection throughput by 10%, while dynamic route planning reduced average travel delays by 15%. The ability to simulate rerouting behavior and weather impacts ensures the scalability of the framework to different urban environments. Connected car systems also benefit from multimodal outputs, as real-time synthetic traffic density and speed data support autonomous navigation decisions. These applications highlight the usefulness of the framework in managing complex urban traffic systems, improving efficiency and safety. Eom et al. (2020) demonstrated that comprehensive simulations of traffic flow can significantly improve intersection efficiency by more accurately testing signal timing algorithms. Similarly, Malihi et al. (2024) highlight the role of multimodal traffic data in supporting adaptive route planning, especially where weather disturbances or road closures are involved. These findings are closely related to the application of the proposed framework, providing additional evidence of its practicality and scalability in different urban contexts.

3.5 Comprehensive Insights for ITS Applications

The combination of temporal and spatial analysis with cross-modal data generation highlights the comprehensive capabilities of the proposed framework. The main advances include:

Temporal Accuracy: Achieving CPA of 91% during off-peak hours and reducing RMSE to 2.8.

Enhanced decision support: reducing travel delays by 15% and increasing intersection throughput by 10%.

Multimodal adaptability: leveraging synthetic text, image, and video data to enhance traffic perception and prediction capabilities.

These results validate the framework as a scalable and actionable tool for intelligent transportation systems, providing a powerful solution for real-time traffic management and long-term urban planning. Further explorations could extend these capabilities to include a wider range of ITS applications, such as pedestrian flow modeling and public transportation optimization.

4. CONCLUSION

The study innovatively formulates a complete framework that leverages generative artificial intelligence, specifically GAN-based architecture, addressing key challenges in Intelligent Transportation Systems (ITS). By integrating multi-modal data generation technology, the framework can effectively reconstruct, simulate and predict complex traffic scenarios, providing powerful solutions for real-time traffic management and urban planning. The results show that cross-modal data generation significantly enhances the framework's ability to simulate traffic dynamics under different conditions. Synthetic traffic images and videos, coupled with text-based incident alerts, bridge gaps caused by data sparseness or sensor outages, improving anomaly detection accuracy by 12%. The GAN-based model achieved high spatial and temporal fidelity with SSIM of 0.95 and CPA of 91%. These quantitative results highlight the scalability and reliability of this framework in handling real-world challenges such as congestion propagation, rerouting dynamics, and environmental impacts.

Furthermore, the framework highlights the potential of generative AI to transform ITS applications. It delivers realistic and detailed simulations that support proactive decision-making in route optimization, signal control and connected vehicle coordination. Furthermore, the model's flexibility enables it to be adapted to different urban environments, making it a valuable tool for both immediate traffic management needs and long-term infrastructure planning. Although the framework performs well, it faces challenges in terms of computational efficiency for large-scale deployment and reliance on high-quality input data. Future work will focus on improving scalability through lightweight architecture and exploring federated learning methods for distributed data integration. Furthermore, incorporating explainable artificial intelligence (XAI) technology will enhance the explainability of predictions, fostering reliability and usability in actual ITS implementations.

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