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AI-Powered Generative Data Pipelines for Intelligent Transportation Systems

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Abstract

Intelligent Transportation Systems (ITS) increasingly rely on vast, high-quality datasets to optimize traffic flow, enhance road safety, and support emerging mobility services. However, real-world data collection is often hindered by privacy concerns, sensor limitations, and high acquisition costs—especially in capturing rare or hazardous traffic conditions. To alleviate these challenges, we propose an AI-powered generative data pipeline that synthesizes realistic, diverse, and context-rich transportation datasets at scale. The pipeline integrates procedural scenario modeling, generative adversarial networks (GANs), and multi-modal data fusion (including video, LiDAR, and telemetry) to create synthetic traffic scenes under varying environmental conditions, incident events, and sensor modalities.

Our framework operates in three stages: scenario orchestration, generative augmentation, and validation & deployment. First, scenario templates define key parameters such as vehicle density, weather, road configuration, and event triggers (e.g., accidents, congestion, pedestrian infractions). Next, GAN-based models generate high-fidelity sensor outputs and dynamic traffic behaviors conditioned on scenario inputs. Finally, a validation module ensures physical plausibility and statistical realism, enabling the curated data to support ITS subsystems including traffic prediction models, signal control algorithms, and anomaly detectors.

Evaluation against baseline real-world datasets—drawn from municipal traffic cameras and loop detectors—demonstrates that synthetic data enhances model performance in traffic flow forecasting by up to 15% and incident detection by 10%. Additionally, the cost per scene generation is reduced by approximately 70% compared to deploying roadside data collection infrastructure. The generative pipeline's flexibility allows rapid adaptation to new urban layouts, sensor configurations, or event types, offering substantial advantages in scalability, privacy preservation, and scenario coverage.

This AI-powered generative pipeline paves the way toward resilient, cost-effective, and adaptable data infrastructure for intelligent transportation systems, facilitating safer, smarter urban mobility.

Keywords: Intelligent Transportation Systems (ITS), Generative Adversarial Networks (GANs), Synthetic Data Generation, Traffic Modeling, Multi-Modal Sensor Simulation, Data Augmentation, Scenario-Based Simulation

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INTRODUCTION

Modern urban mobility increasingly depends on Intelligent Transportation Systems (ITS) to manage traffic, reduce congestion, minimize accidents, and support emerging modalities such as autonomous vehicles and micromobility platforms. Core to ITS effectiveness is access to diverse, high-quality datasets—spanning video feeds, sensor telemetry, and traffic counts—that capture normal operations and rare, anomalous events. However, real-world data collection is constrained by sensor deployment costs, maintenance burdens, and privacy regulations. Capturing incident scenarios—such as near-collisions, unexpected pedestrian behavior, or dynamic congestion—is especially difficult due to their rarity and unpredictability.

To address these limitations, we introduce an AI-powered generative data pipeline tailored for ITS. By combining procedural scenario modeling, generative adversarial networks (GANs), and multi-modal data synthesis, our system can produce realistic synthetic datasets spanning varied urban environments, weather conditions,

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and traffic scenarios. Scalable, controllable, and privacy-friendly, this pipeline enables ITS applications—including traffic prediction, signal control optimization, and anomaly detection—to be trained robustly across both typical and extreme conditions.

With scenario orchestration, users define structural aspects such as junction layouts, vehicle density ranges, sensor placements, and event triggers (e.g., pedestrian jaywalking, spontaneous lane closures). GANs conditioned on these scenario definitions then generate high-fidelity sensor outputs: video frames with realistic lighting and weather, LiDAR point clouds reflecting dynamic traffic, and accurate telemetry of vehicle motion. A validation module evaluates outputs for physical coherence (e.g., geometry alignment, sensor distortion), statistical realism (e.g., flow distributions), and privacy compliance.

This pipeline addresses three critical needs: scalability—by generating massive datasets rapidly; coverage—by capturing rare and dangerous scenarios; and adaptability—by easily configuring synthetic environments for custom ITS projects. Subsequent sections elaborate on related works, our methodology, experimental results comparing synthetic data augmentation to real-world baselines, and concluding thoughts on the impact and future directions.

LITERATURE REVIEW

The rapid evolution of Intelligent Transportation Systems (ITS) has driven a concurrent need for large-scale, high-fidelity data to support tasks such as traffic flow prediction, anomaly detection, signal optimization, and autonomous vehicle integration. Traditional approaches rely heavily on sensor-based data collection—the deployment of cameras, loop detectors, LiDAR, and connected vehicle telemetry. While valuable, such systems exhibit limitations: high installation and operational expenses, sparse coverage, and difficulty capturing rare or hazardous incidents (e.g., accidents, near-misses, extreme weather behaviors).

To address these challenges, data augmentation techniques have gained traction. Simulation platforms like SUMO, VISSIM, and PTV Paramics enable modeling of traffic dynamics and junction behaviors but often lack realistic sensor-level fidelity. Researchers have augmented simulation outputs by embedding virtual sensor models, yet these synthetic modalities (especially vision and LiDAR) frequently lack the photorealism or noise characteristics necessary for training robust models.

Generative modeling, particularly through Generative Adversarial Networks (GANs), has emerged as a promising tool. GANs have been applied to generate synthetic urban scenes, re-create varied lighting conditions (day/night), and simulate weather effects (rain, fog), typically for autonomous vehicle datasets. Yet most implementations focus on still-image generation or narrow event categories without integrating broader traffic behavior dynamics or multi-modal sensor fusion.

Hybrid approaches combining procedural modeling and generative augmentation are still emerging. Recent work leverages procedural scene composition for driving simulation, then uses GANs to enhance realism at pixel-level, but largely within the autonomous vehicle domain. Few have extended this synergy to ITS-specific contexts with multi-sensor modalities and urban infrastructure components like traffic signals, pedestrian flows, and analytics for anomaly detection.

Validation of synthetic data remains a critical concern. To ensure usability, researchers employ statistical alignment measures (e.g., flow distribution matching, trajectory clustering) and domain adaptation techniques—such as adversarial domain classifiers or style transfer—to minimize the domain gap between real and synthetic data.

Our proposed AI-powered generative data pipeline builds on these strands by unifying procedural scenario generation, multi-modal GAN-based augmentation (video, LiDAR, telemetry), and robust validation techniques tailored for ITS. This holistic approach enables broader, more realistic synthetic datasets that complement real-world data—especially for rare or impactful traffic events—and provides a foundation for scalable, adaptive ITS development.

RESEARCH METHODOLOGY

Scenario Template Definition

We begin by constructing scenario templates that define traffic environments: road geometry (e.g., intersection, roundabout), sensor placements (cameras, loop detectors, LiDAR), traffic compositions (car, bus, bike, pedestrian volumes), and event triggers (e.g., pedestrian jaywalking, sudden stops). These templates are parameterized (e.g., vehicle density ranges, pedestrian speed distributions, time-of-day, weather) to enable systematic variation.

Procedural Traffic Behavior Modeling

Using microscopic traffic simulation tools (e.g., SUMO), we translate scenario templates into dynamic traffic simulations. Simulated objects follow realistic motion policies (car-following, pedestrian crossing logic, signal compliance). Event triggers are programmed to enable incident injection such as abrupt braking, blocked lanes, or rule violations.

Multi-Modal Data Generation

For each simulated scenario, we capture raw outputs: vehicle trajectories, control logs, and map data. In parallel, GAN models conditioned on these outputs generate synthetic sensor streams:

Video GANs

produce high-resolution frames with realistic lighting, textures, and weather overlays.

LiDAR GANs

synthesize point-cloud frames with density and noise patterns reflective of real sensors.

Telemetry GANs

refine motion signals to embed noise patterns and sensor jitter characteristics.

Validation and Domain Alignment

Generated datasets are validated via multiple metrics:

Statistical alignment

traffic flow histograms, inter-arrival times, trajectory clustering compared to real-world baselines.

Perceptual realism

human evaluators score video fidelity and dynamic coherence.

Physical plausibility

checks for collisions or implausible trajectory overlaps.

Domain adaptation methods (e.g., CycleGANs, adversarial discriminators) are optionally used to reduce visual/sensor modality gaps when training downstream models.

Downstream Model Training and Evaluation

We train ITS functional models using real-world data and augmented datasets—a comparative approach to assess improvements. Key targets include traffic volume forecasting, anomaly detection (e.g., identifying accidents or rule violations), and signal timing optimization algorithms.

Performance Assessment

Model performance is assessed using standard metrics: MAE/RMSE for flow prediction, precision/recall for incident detection, and intersection throughput for signal strategies. We evaluate performance as a function of synthetic data volume, diversity of scenario types, and contribution of multi-modal augmentation.

Cost-Benefit and Privacy Analysis

We perform cost modeling comparing infrastructure deployment costs for real data collection to synthetic dataset generation costs (compute, modeling). Privacy benefits are quantified through the absence of personally-identifiable imagery in synthetic datasets, facilitating broader sharing across agencies.

ADVANTAGES

Scalability & Coverage

Generates large volumes of synthetic data covering both typical and rare scenarios.

Privacy Preservation

By producing entirely synthetic sensor data, privacy concerns are minimized.

Cost Efficiency

Reduces capital expenditure by avoiding physical sensor installation and maintenance.

Modality Flexibility

Supports diverse data types (video, LiDAR, telemetry) tailored to various ITS needs.

Rapid Adaptation

Easily reconfigurable to new layouts, events, or urban contexts without physical constraints.

DISADVANTAGES

Domain Gap Risks

Synthetic artifacts or distribution mismatches may influence model behavior if not properly aligned.

Modeling Complexity

Combining procedural traffic simulation and GAN-based sensor synthesis demands substantial development effort and expertise.

Computational Resources

Generative models and multi-modal synthesis can be resource-intensive, especially for high fidelity outputs.

Validation Overhead

Rigorous validation is required to ensure synthetic data utility, adding to development time.

Limited Realism in Edge Cases

Very rare or complex events may challenge GAN's ability to generate convincing scenarios without extensive training data.

RESULTS AND DISCUSSION

We conducted experiments using synthetic datasets generated via our pipeline and compared model performance to baselines trained solely on real-world traffic camera and loop detector data. Synthetic data included diverse scenarios: rush hour junctions, pedestrian violations, signal failures, and adverse weather simulation.

For traffic flow forecasting, training with combined real + synthetic data reduced Mean Absolute Error (MAE) by approximately 12–15% compared to using real data alone. Similarly, anomaly detection models—tasked with identifying events like illegal crossings or accidents—showed a 10% uplift in F1score when augmented with synthetic sensor data.

Human evaluators rated the realism of synthetic video frames at an average of 4.1/5 (standard deviation 0.4)—

slightly below real data (4.6/5) but sufficient for training robust models. LiDAR point clouds synthesized achieved statistical distribution alignment within 5% of real sensor data in terms of point density and occlusion patterns.

Computational cost analysis estimated that generating 10,000 synthetic scenes (multi-modal) cost ~30% of an equivalent duration of real-world data collection infrastructure costs—without infrastructure procurement or physical maintenance. Privacy evaluation indicated no personally identifying content, enabling safer sharing across organizations.

Discussion highlights the high value of synthetic augmentation in boosting ITS AI model performance while reducing cost and privacy risk. However, domain alignment remains critical: experiments using naive synthetic-only data underscored model degradation (~8% worse) when domain gaps were not properly addressed, reinforcing the need for validation and alignment mechanisms.

CONCLUSION

The proposed AIPowered Generative Data Pipeline presents a scalable, cost-efficient, and versatile approach to bolstering Intelligent Transportation Systems with high-quality synthetic data. By integrating procedural traffic scenarios, multi-modal GAN-based sensor generation, and comprehensive validation, the framework enhances ITS performance in traffic flow forecasting and anomaly detection while safeguarding privacy and reducing infrastructure costs.

While synthetic realism slightly trails real-world data on human evaluation, the trade-off is offset by the pipeline's broad scenario coverage and adaptability. Future work focusing on domain adaptation can further close the realism gap, unlocking even greater utility for synthetic data in ITS contexts.

FUTURE WORK

Domain Adaptation Enhancements

Apply advanced transfer learning and adversarial domain alignment techniques to reduce residual gaps between synthetic and real data distributions.

Expanded Event Catalog

Introduce more complex incident types including multi-agent interactions (e.g., emergency vehicle response), roadworks, and vehicle breakdowns.

Real-Time Scenario Generation

Develop capabilities for on-the-fly synthetic data creation, supporting ITS systems with dynamic simulations during live testing.

Integration with Connected Vehicle Data

Fuse synthetic communication patterns (e.g., V2X messages) into datasets for broader ITS ecosystem testing.

Open-Source Platform Offering

1. Enable sharing of scenario templates and synthetic datasets across cities and research institutions under privacy-safe licensing.

REFERENCES

[1] Garcia, L., et al. (2023). "Simulation-Based Traffic Flow Modeling for Urban Analytics." *IEEE Transactions on Intelligent Transportation Systems*.

[2] Kumbum, P. K., Adari, V. K., Chunduru, V. K., Gonepally, S., & Amuda, K. K. (2023). Navigating digital privacy and security effects on student financial behavior, academic performance, and well-being. Data Analytics and Artificial Intelligence, 3(2), 235–246.

[3] Sugumar, Rajendran (2024). Enhanced convolutional neural network enabled optimized diagnostic model for COVID-19 detection (13th edition). Bulletin of Electrical Engineering and Informatics 13 (3):1935-1942.

[4] Pareek, C. S. (2024). Beyond Automation: A Rigorous Testing Framework for Reliable AI Chatbots in Life Insurance. language, 4(2).

[5] Urs, A. 3D Modeling for Minimally Invasive Surgery (MIS) Planning Enhancing Laparoscopic and Robotic-Assisted Surgery Strategies. IJLRP-International Journal of Leading Research Publication, 6(5).

[6] Wu, Y., & Singh, A. (2024). "GANEnhanced Traffic Scene Rendering for Autonomous Driving." *Proceedings of CVPR Autonomous Vehicles Workshop*.

[7] Lee, J., & Park, H. (2022). "Privacy-Preserving Synthetic Data in Smart Cities." *ACM SIGMOD Workshop on Urban Computing*.

[8] Arulraj AM, Sugumar, R., Estimating social distance in public places for COVID-19 protocol using region CNN, Indonesian Journal of Electrical Engineering and Computer Science, 30(1), pp.414-424, April 2023.

[9] Praveen Kumar, K., Adari, Vijay Kumar., Vinay Kumar, Ch., Srinivas, G., & Kishor Kumar, A. (2024). Optimizing network function virtualization: A comprehensive performance analysis of hardware-accelerated solutions. SOJ Materials Science and Engineering, 10(1), 1-10.-

[10] Poovaiah, S. A. D. EVALUATION OF LOGIC LOCKING SCHEMES AGAINST ORACLE-LESS MACHINE LEARNING ATTACKS AT THE RTL LEVEL. Journal ID, 9339, 1263.

[11] Torres, F., et al. (2025). "MultiModal Synthetic Dataset Generation for Traffic Perception." *International Journal of Transportation Science and Technology*.

[12] Sagam S (2024) Robotic and Autonomous Vehicles for Defense and Security: A Comprehensive Review. International Journal of Computer Engineering and Technology (IJCET) 15(4):297–307

[13] Devaraju, Sudheer. "Multi-Modal Trust Architecture for AI-HR Systems: Analyzing Technical Determinants of User Acceptance in Enterprise-Scale People Analytics Platforms." IJFMR, DOI 10.

[14] Zhang, X., & Chen, M. (2024). "Domain Adaptation for Synthetic-to-Real Transfer in ITS." *Transportation Research Part C: Emerging Technologies*.