UrbanFlow AI: Smart Urban Mobility System - Real-Time Transit Management, AI-Driven Occupancy Prediction, and Intelligent Fleet Operations

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Abstract: Rapid urbanization has intensified pressure on public transportation networks, exposing critical deficiencies in fleet management, passenger safety, and real-time operational responsiveness. UrbanFlow AI presents a next-generation smart urban mobility platform that integrates live vehicle tracking, artificial intelligence-driven occupancy prediction, dynamic fleet reallocation, and emergency response coordination within a unified system. The platform employs bidirectional Long Short-Term Memory (BiLSTM) deep learning architectures to forecast crowd density, enabling proactive coach recommendations and route optimization. A dedicated SOS emergency module provides one-touch distress alerts covering five incident categories, while an eco-tracking layer incentivizes sustainable commuter behavior through gamified reward mechanisms. On the administrative side, a Digital Twin simulation engine allows operators to model demand surges under real-world scenarios including inclement weather, public festivals, and large-scale sporting events. An AI-powered CCTV alert system continuously monitors for overcrowding, suspicious activity, and maintenance anomalies, enabling rapid operational intervention. Experimental evaluations demonstrate that the proposed system achieves crowd prediction accuracy of 93.6%, reduces average passenger wait time by 28.3%, decreases fleet idle time by 34.0%, and achieves SOS alert dispatch latency below 3 seconds compared to conventional transit management approaches. This paper presents the system architecture, methodology, performance benchmarks, and broader implications of AI-integrated urban mobility for smarter, safer, and more sustainable cities.

Keywords: *Urban Mobility, Artificial Intelligence, Real-Time Tracking, Occupancy Prediction, Fleet Management, Digital Twin, Emergency SOS, Eco-Tracking, Smart Transportation, Deep Learning, BiLSTM, CCTV Anomaly Detection.*

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I. INTRODUCTION

Public transportation forms the foundational infrastructure of urban connectivity, yet transit systems worldwide continue to operate on reactive, schedule-driven frameworks inadequate to handle the dynamic variability of modern commuter demand. Overcrowded buses, unpredictable service delays, and insufficient emergency response capabilities erode public confidence and accelerate the societal shift toward private vehicle use, exacerbating traffic congestion and carbon emissions in already environmentally strained metropolitan environments [1].

The convergence of artificial intelligence, real-time data processing, and Internet-of-Things (IoT) sensor infrastructure now presents an unprecedented opportunity to transform public transport from a passive schedule-based service into a proactive, intelligent mobility ecosystem. Urban populations globally are projected to grow by 2.5 billion people by 2050, with more than two-thirds of humanity expected to reside in cities [2]. This demographic reality renders the modernization of public transit not merely desirable, but imperative for sustainable urban development.

Existing transit management tools characteristically address individual operational problems in isolation — a predictive occupancy system that does not communicate with fleet reallocation logic, or an emergency reporting module disconnected from real-time vehicle tracking. This fragmented architecture limits the systemic benefits achievable from any single component and prevents the feedback loops necessary for continuous operational improvement. UrbanFlow AI addresses this architectural gap by proposing a comprehensive smart mobility platform that integrates five core functional modules — live vehicle tracking, AI-driven occupancy prediction, SOS emergency response, eco-reward incentivization, and a Digital Twin administrative dashboard — within a single cohesive, deployable system.

The principal contributions of this work are as follows: (1) the design and implementation of a stacked BiLSTM occupancy prediction engine achieving 93.6% forecasting accuracy on real-world ridership data; (2) a Deep Q-Network (DQN) fleet reallocation agent reducing route imbalance by 34.1% and cutting fleet idle time by 34.0%; (3) a sub-3-second SOS emergency dispatch pipeline supporting five incident categories including a covert silent trigger; (4) a ResNet-50 CCTV anomaly detection module attaining 91.4% accuracy across overcrowding, medical, and security incident categories; and (5) a Digital Twin simulation engine enabling demand surge pre-evaluation under parameterized real-world event templates.

The remainder of this paper is organized as follows. Section II reviews relevant literature across smart transit, AI prediction, and fleet management domains. Section III presents the proposed five-layer system architecture. Sections IV and V detail the methodology and experimental results respectively. Section VI concludes with directions for future research.

II. REVIEW OF LITERATURE

A substantial body of research has explored individual components of smart urban mobility, though comprehensive integrated systems remain comparatively understudied in the literature. The relevant body of work spans occupancy forecasting, fleet reallocation optimization, anomaly detection, and passenger experience enhancement.

A. *Occupancy Prediction and Demand Forecasting*

Chen and Xu [3] demonstrated that LSTM-based deep learning models substantially outperform traditional ARIMA forecasting in predicting bus occupancy levels, achieving a mean absolute percentage error of 6.2% on real-world datasets from Shenzhen's public bus network. Their work highlighted the critical importance of incorporating auxiliary contextual features — specifically weather conditions and event calendars — to improve model robustness during atypical demand periods. This finding informed the multi-source feature engineering adopted in UrbanFlow AI's prediction pipeline.

Cilingiroglu [4] investigated quantitative approaches to AI-based sequential data forecasting, demonstrating that neural networks incorporating Natural Language Processing (NLP) for sentiment extraction from external data sources achieve prediction precision beyond what quantitative data alone can deliver. This work directly supports the multi-modal data integration strategy employed in the proposed system.

B. *Fleet Management and Route Optimization*

Sharma, Patel, and Reddy [5] evaluated dynamic vehicle reallocation strategies using reinforcement learning, finding that Q-learning agents reduced average route imbalance by 31% compared to static scheduling baselines. The study identified convergence speed as a practical challenge for real-time deployment in large networks — a limitation specifically addressed in UrbanFlow AI through the adoption of a Deep Q-Network architecture with prioritized experience replay. Kotecha [6] further established that AI-driven fleet management innovations, when integrated with commuter experience layers, yield compound operational and satisfaction improvements exceeding those achievable through isolated optimization.

C. *Safety, Anomaly Detection, and Passenger Experience*

Kumar and Nair [7] examined AI-driven anomaly detection in public transport CCTV systems, reporting that convolutional neural network classifiers achieved 91.4% accuracy in identifying overcrowding events and 87.8% accuracy in detecting suspicious behavior patterns. Their research underscored the critical need for low-latency inference pipelines to support operational response time requirements — a design constraint explicitly incorporated into the UrbanFlow AI CCTV module's architectural specifications.

Mehta [8] conducted a user study demonstrating that personalized coach recommendations significantly increased passenger satisfaction scores by 22% and reduced boarding time by an average of 47 seconds per vehicle stop. Abbas, Cohen, and Mosk [9] further contextualized AI integration in smart city systems, noting that real-time data fusion across heterogeneous urban infrastructure sources enables qualitatively superior operational decision-making compared to siloed analytics platforms.

D. *Digital Twin and Simulation*

Gupta [10] analyzed Digital Twin applications in urban mobility planning, establishing that network simulation under parameterized event scenarios enables transit operators to proactively evaluate fleet deployment strategies before actual

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demand surges materialize. This evidence base directly motivated the Digital Twin sub-module incorporated within UrbanFlow AI's administrative control tier, as well as the empirically calibrated demand multiplier framework applied to event-based simulation templates. Despite these individual advances, no unified framework combining predictive occupancy management, SOS emergency coordination, eco-incentive tracking, and Digital Twin simulation has been proposed for public transit systems. UrbanFlow AI addresses this integration gap comprehensively.

III. PROPOSED SYSTEM ARCHITECTURE

UrbanFlow AI is structured around a five-layer architecture that separates data ingestion, AI inference, operational decision-making, user interaction, and administrative oversight into clearly defined functional tiers while enabling bidirectional data flow between layers. This layered design ensures that insights generated at the fleet management layer propagate in real time to passenger-facing recommendation interfaces, creating operational feedback loops that continuously improve both system efficiency and commuter experience. Fig. 1 presents the high-level architectural overview.

A. *Data Layer*

The Data Layer forms the sensory foundation of the entire platform. It aggregates real-time telemetry from GPS transponders installed on buses and trains (providing vehicle position updates at 10-second intervals), ultrasonic passenger count sensors at boarding points, CCTV video streams from onboard and station cameras, weather condition feeds from public meteorological APIs, and structured event schedules from municipal event management calendars. A unified data ingestion pipeline normalizes heterogeneous input formats, applies timestamp alignment, and routes validated streams to the AI processing tier through a high-throughput message broker. Data quality monitoring continuously flags sensor dropout events and activates fallback imputation routines to maintain pipeline continuity.

B. *AI Inference Layer*

The AI Inference Layer hosts three specialized computational modules. The Occupancy Prediction Engine employs a stacked bidirectional LSTM architecture that processes 24-hour sliding window sequences of historical and real-time ridership observations to generate multi-horizon crowd density forecasts. The Anomaly Detection Module applies a fine-tuned ResNet-50 convolutional neural network to CCTV frame sequences, classifying events across four incident categories: overcrowding, medical emergency, suspicious behavior, and infrastructure anomaly. The Route Optimization Agent implements a Deep Q-Network trained in a simulated transit environment modeling vehicle capacity constraints, inter-stop travel time distributions, and spatiotemporal demand variability. All three modules are served through containerized inference endpoints supporting horizontal scaling under peak demand.

C. *Operations Layer*

The Operations Layer translates AI inference outputs into actionable fleet management decisions. This tier generates dynamic vehicle reallocation recommendations, coach-level capacity advisories, and SOS alert dispatch triggers. The Digital Twin sub-module within this layer models the transit network as a directed weighted graph where nodes represent stops and edges encode empirically calibrated travel time distributions. Scenario simulation applies demand multipliers corresponding to predefined event templates — Heavy Rain, Major Festival, and Cricket Match scenarios — enabling operators to evaluate fleet deployment strategies before demand surges materialize. Simulation outputs are rendered as occupancy heat overlays on the administrative map view.

D. *User Interface Layer*

The User Interface Layer delivers a responsive, dark-themed progressive web application to commuters, providing live vehicle markers on an interactive map, AI-generated personalized coach recommendations, integrated ticket booking functionality, SOS emergency activation, and eco-reward point tracking. The interface is designed with accessibility standards compliance and renders across mobile and desktop form factors. All real-time map updates and capacity alerts are delivered through persistent WebSocket channels to ensure sub-second display latency for safety-critical notifications.

E. *Admin Dashboard Layer*

The Admin Dashboard exposes fleet-level monitoring views, live CCTV alert feeds, AI reallocation suggestions, Digital Twin scenario simulation controls, and incident response coordination tools to transit operators. Role-based access controls differentiate between route-level operator permissions and network-wide supervisory access. All inter-layer communications are orchestrated through a RESTful API gateway with JWT authentication, while WebSocket channels serve real-time data streams requiring sub-200ms delivery guarantees.

IV. METHODOLOGY

A. *Data Collection and Preprocessing*

Training data was compiled from three primary sources: historical ridership records spanning 24 months across 18 bus routes and 6 metro lines in a mid-sized Indian city; GPS trajectory logs providing vehicle position updates at 10-second intervals; and anonymized passenger boarding event logs timestamped to the minute. Supplementary contextual features — daily temperature, precipitation intensity, and local event schedules — were obtained from public meteorological and municipal APIs. After aggregation, deduplication, and cleaning, the combined dataset comprised approximately 4.2 million hourly ridership records representing a comprehensive operational cross-section.

Raw ridership counts were normalized using Min-Max scaling to bound all inputs within the [0, 1] range, eliminating scale disparities between routes with structurally different ridership volumes. Missing values arising from sensor dropout events were imputed using forward-fill interpolation to preserve time-series continuity, a strategy empirically validated as superior to mean imputation for sequential transit data. Outlier observations exceeding three standard deviations from rolling weekly means were identified through a sliding z-score procedure and replaced with locally smoothed estimates generated by exponentially weighted moving averages. Input sequences of 24 consecutive hourly observations were constructed as overlapping sliding windows for LSTM model training, with prediction horizons spanning 1 to 6 hours ahead to support both immediate dispatch decisions and advance fleet positioning.

B. *Occupancy Forecasting Model — BiLSTM Architecture*

The occupancy forecasting model employs a stacked bidirectional LSTM architecture comprising two hidden layers with 128 and 64 units respectively, capturing both forward and backward temporal dependencies within each sliding input window. A fully connected linear output layer maps the final hidden state to the multi-step prediction horizon. Dropout regularization at a rate of 0.3 was applied between LSTM layers to mitigate overfitting on the training distribution. The model was trained using the Adam optimizer with an initial learning rate of 0.001, cosine annealing learning rate decay, and early stopping based on validation Mean Absolute Error with a patience threshold of 10 epochs to prevent over-training. Batch size was set to 256 to balance gradient estimation quality against computational training efficiency. The final model was trained for 87 epochs before early stopping activation.

C. *Fleet Optimization — Deep Q-Network Agent*

The route optimization agent was implemented as a Deep Q-Network trained within a discrete-state simulated transit environment modeling vehicle capacity constraints, inter-stop travel time distributions sampled from empirical GPS logs, and stochastic passenger demand distributions calibrated to training data statistics. The DQN employs a replay buffer of 50,000 experience tuples and target network soft-update with a Polyak averaging coefficient of $\tau = 0.005$ to stabilize training dynamics. The reward function penalizes route imbalance (unequal load distribution across vehicles serving a route segment), fleet idle time, and passenger wait time violations, providing the agent with a composite incentive structure aligned with operator objectives. After 2.4 million simulated timesteps of training, the converged policy was exported for integration into the Operations Layer.

D. *CCTV Anomaly Detection — ResNet-50 Classifier*

The CCTV anomaly detection component was built on a ResNet-50 backbone pre-trained on ImageNet, fine-tuned on a purpose-labeled dataset of 12,000 annotated CCTV frames across four incident categories: Overcrowding, Medical Emergency, Suspicious Behavior, and Infrastructure Anomaly. Data augmentation during fine-tuning included random horizontal flipping, brightness jitter (±20%), and Gaussian noise injection to improve robustness against real-world camera artifacts and variable lighting conditions. The model was trained with a categorical cross-entropy loss, SGD optimizer with momentum 0.9, and a cosine-annealed learning rate initialized at 0.01. Inference is performed on 5-frame temporal clips sampled at 2 Hz from each monitored camera feed to capture short-duration event signatures.

E. *SOS Emergency Module*

The SOS system supports five incident categories: Women Safety, Medical Emergency, Robbery, Fire, and General Distress. Upon activation through the mobile interface, the module packages the commuter's GPS coordinates, vehicle identifier, route code, current timestamp, and incident category into a cryptographically signed JSON alert payload. This payload is simultaneously dispatched to the transit control center dashboard and the relevant emergency service API endpoints within a target latency of 3 seconds under standard network conditions. A covert silent SOS trigger, activated by a triple-shake gesture pattern, provides an alternative activation mechanism for situations where overt button interaction would be unsafe, such as robbery or harassment scenarios requiring discretion.

F. *Digital Twin Simulation Engine*

The Digital Twin module represents the transit network as a directed graph $G = (V, E)$ where vertices V correspond to stops and edges E encode empirically calibrated travel time probability distributions derived from 24 months of GPS log data. Scenario simulation applies multiplicative demand scaling factors to specific route segment-time window combinations corresponding to three predefined event templates:

Heavy Rain (demand increase of 1.4–1.8× on shelter-providing trunk routes), Major Festival (1.6–2.2× increase on routes proximate to venue), and Cricket Match (1.8–2.5× increase on stadium-adjacent services). Simulation results are rendered as color-encoded occupancy heat overlays on the administrative map view, enabling operators to visually identify anticipated bottleneck segments and pre-position spare capacity vehicles before demand materializes.

V. RESULTS AND PERFORMANCE EVALUATION

The UrbanFlow AI system was evaluated against a held-out test set covering 90 days of unseen ridership data across all 18 bus routes and 6 metro lines included in the training corpus. Performance was systematically assessed across five evaluation dimensions: occupancy prediction accuracy, fleet efficiency, passenger experience, emergency response latency, and CCTV anomaly detection. In each case, results from the proposed BiLSTM-based UrbanFlow AI system are compared against two baselines: a conventional schedule-based approach

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representing current operational practice, and a standalone Random Forest model representing the intermediate machine learning benchmark.

Table 1: Comparative Performance Evaluation of UrbanFlow AI System

Evaluation Metric	Baseline (Schedule-Based)	ML Baseline (Random Forest)	UrbanFlow AI (BiLSTM)
Occupancy Prediction Accuracy (%)	61.3%	79.8%	93.6%
Mean Absolute Error (passengers)	14.2	8.6	3.1
Route Imbalance Reduction (%)	—	18.4%	34.1%
Average Wait Time Reduction (%)	—	11.2%	28.3%
SOS Alert Dispatch Latency (s)	N/A	N/A	2.8
CCTV Anomaly Detection Accuracy (%)	—	74.5%	91.4%
Fleet Idle Time Reduction (%)	—	15.7%	34.0%
R^2 Score	0.54	0.79	0.95

A. *Occupancy Prediction Performance*

The BiLSTM occupancy prediction model achieved 93.6% accuracy on the held-out test set, representing a 13.8 percentage-point improvement over the Random Forest baseline and a 32.3 percentage-point improvement over the schedule-based approach. The Mean Absolute Error of 3.1 passengers per reading represents a 64.0% reduction relative to the Random Forest baseline (8.6 passengers), confirming that the proposed architecture delivers not only directionally correct forecasts but quantitatively precise load estimates suitable for fine-grained fleet positioning. The R^2 score of 0.95 confirms that the model captures approximately 95% of the variance in passenger load across all tested routes and time horizons, including atypical demand periods corresponding to public holidays and weather events. Prediction horizon analysis reveals that forecast accuracy decreases gracefully from 95.2% at the 1-hour horizon to 89.7% at the 6-hour horizon, remaining operationally useful across the full planning window.

B. *Fleet Efficiency and Passenger Experience*

Fleet reallocation recommendations generated by the DQN agent reduced average route imbalance by 34.1% relative to the current schedule-based baseline, substantially exceeding the 18.4% achieved by the static Random Forest policy. Fleet idle time decreased by 34.0%, representing meaningful fuel savings and reduced operational costs at scale. When reallocation suggestions were actively applied by operators during the evaluation period, passenger average wait times decreased by 28.3%, compared to 11.2% for the Random Forest baseline. These compounding efficiency gains validate the architectural decision to couple the predictive occupancy layer directly with the fleet management decision layer, enabling the information feedback loops that single-module approaches structurally cannot achieve.

C. *Emergency Response Performance*

The SOS module consistently achieved alert dispatch within 2.8 seconds of trigger activation across all tested network conditions, comfortably meeting the sub-5-second threshold established by urban emergency response standards as necessary for effective intervention. Payload delivery was confirmed for 99.97% of test activations, with the 0.03% failure rate attributable exclusively to severe network connectivity interruptions in tunnel segments. The covert triple-shake gesture trigger was correctly identified in 98.4% of activations across a diverse test panel of 45 participants spanning varying device models and grip patterns, demonstrating robustness to user variability in the safety-critical silent activation pathway.

D. *CCTV Anomaly Detection Performance*

CCTV anomaly detection attained an overall accuracy of 91.4% across all four incident categories, matching the benchmark reported by Kumar and Nair [7] for overcrowding detection while extending comparable performance to additional incident types. Category-level analysis reveals that overcrowding detection achieved the highest precision at 94.1%, reflecting the relative visual distinctiveness of high-density crowd formations in camera frame space. Suspicious behavior classification achieved the lowest precision at 87.2%, consistent with the inherently greater visual ambiguity of behavioral anomaly patterns compared to density-based events. Medical emergency detection attained 92.6% precision and infrastructure anomaly classification achieved 89.8%, with both categories benefiting from the ResNet-50 backbone's strong spatial feature extraction capabilities.

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Table 2: CCTV Anomaly Detection Performance by Incident Category

Incident Category	Precision (%)	Recall (%)	F1-Score (%)
Overcrowding Detection	94.1%	93.8%	93.9%
Medical Emergency	92.6%	91.9%	92.2%
Infrastructure Anomaly	89.8%	90.4%	90.1%
Suspicious Behavior	87.2%	86.5%	86.8%
Overall	91.4%	90.7%	91.0%

E. *Digital Twin Simulation Validation*

The Digital Twin simulation engine was validated by comparing predicted demand patterns against historical ridership observations for 12 documented high-impact event days within the dataset — four festival events, four major cricket matches, and four weather disruption episodes. Simulated demand surge patterns showed a mean absolute deviation of 6.8% from observed ridership across the validated event scenarios, confirming that the empirically calibrated demand multiplier framework provides operationally reliable surge estimates. Operator feedback collected during a two-week controlled pilot indicated that pre-simulation of event scenarios reduced reactive reallocation decisions by an estimated 41%, as operators were able to pre-position spare vehicles before demand peaks materialized.

VI. DISCUSSION

The experimental results collectively demonstrate that the integrated architecture of UrbanFlow AI delivers performance improvements substantially exceeding those achievable through isolated module optimization. The 93.6% occupancy prediction accuracy represents a 13.8 percentage-point improvement over the standalone Random Forest baseline, yet the more significant operational gains emerge from the system-level coupling between the prediction and fleet management layers. The 34.1% route imbalance reduction — nearly double the 18.4% achieved by the Random Forest policy alone — reflects the compounding value of feeding real-time occupancy forecasts directly into the DQN reallocation agent rather than operating the two components independently.

The SOS emergency module's 2.8-second dispatch latency and 99.97% delivery reliability represent a categorical improvement over existing passive reporting mechanisms that depend on commuter phone calls or manual operator observation. The covert silent trigger's 98.4% activation recognition rate demonstrates that safety-critical features can be designed for reliability under the physical stress conditions typically accompanying genuine emergency activations, including elevated heart rate, grip pressure variability, and device orientation inconsistency.

Several implementation challenges merit acknowledgment. The computational requirements of real-time multi-stream inference — simultaneously processing occupancy prediction across all routes, CCTV frame classification across all camera feeds, and DQN policy evaluation for reallocation decisions — impose substantial infrastructure demands in large metropolitan deployments. Distributed inference architectures and edge computing deployments at station level represent promising directions for managing this computational load without increasing central processing costs proportionally to network scale. Data privacy considerations arising from continuous passenger tracking and behavioral monitoring represent a critical governance challenge requiring transparent policy frameworks and technical anonymization measures beyond those implemented in the current prototype.

The eco-reward tracking module, while not the primary focus of this paper's quantitative evaluation, represents a behaviorally significant component of the platform's long-term sustainability contribution. By translating measurable reductions in private vehicle substitution into tangible commuter incentives, the module creates a positive-sum alignment between individual utility maximization and collective environmental benefit — an alignment conspicuously absent from most existing transit management frameworks.

VII. CONCLUSION AND FUTURE WORK

This paper has presented UrbanFlow AI, a comprehensive smart urban mobility platform integrating real-time vehicle tracking, AI-driven occupancy prediction, dynamic fleet reallocation, SOS emergency response, eco-reward incentivization, and Digital Twin simulation within a unified, deployable architecture. Experimental results confirm substantial improvements across all evaluated dimensions: crowd prediction accuracy of 93.6%, fleet idle time reduction of 34.0%, wait time reduction of 28.3%, and SOS alert dispatch latency of 2.8 seconds. These outcomes demonstrate that an integrated AI approach to urban mobility management delivers compounding operational and commuter-experience benefits that are structurally unavailable to systems addressing individual transit challenges in isolation.

The contribution of this work extends beyond the performance metrics themselves to the architectural insight that transit AI systems achieve their greatest impact through tightly coupled inter-module information flows rather than through improvements to any single predictive component. The feedback loop from occupancy forecasting through fleet reallocation to commuter recommendation to behavioral eco-

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tracking creates a self-reinforcing cycle of efficiency gains whose cumulative operational value exceeds the sum of individual module improvements.

Future research will pursue three primary directions. First, federated learning approaches will be explored to enable multi-city model training without centralizing sensitive ridership data at a single infrastructure provider, addressing both data privacy concerns and the geographic generalization limitations inherent in single-city training corpora. Second, the integration of autonomous vehicle coordination protocols will be investigated for next-generation mixed fleets incorporating both human-operated and autonomous transit vehicles. Third, adaptive SOS incident category learning from operator-validated incident outcome feedback loops will be developed to enable the system to evolve its emergency classification capabilities as incident type distributions shift with changing urban demographics and infrastructure configurations. UrbanFlow AI represents a concrete contribution toward the vision of fully intelligent, citizen-centric public transportation in which data-driven insight empowers both commuters and operators to make smarter, safer, and more sustainable mobility decisions.

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