

AI-ENABLED PREDICTIVE PUBLIC TRANSPORTATION OPTIMIZATION SYSTEM FOR URBAN MOBILITY IN BENGALURU

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Introduction:

Urban transportation systems in cities like Bengaluru face challenges such as traffic congestion, unpredictable travel times, and inefficient fleet utilization. Existing systems rely on static scheduling and lack predictive intelligence, resulting in delays and reduced commuter satisfaction.

This project proposes an AI-Enabled Predictive Public Transportation Optimization System (AI-PTOS) that integrates deep learning, data analytics, and API-based routing to enhance urban mobility. A Long Short-Term Memory (LSTM) model is implemented to forecast congestion patterns by learning temporal dependencies in time-series traffic data.

Due to restricted access to real-time BMTC operational datasets, the system utilizes publicly available APIs such as TomTom and Google Maps, along with simulated datasets, to replicate real-world transportation conditions. The system further incorporates a fleet analytics module, an alert notification system, and an AI-based recommendation engine, with outputs visualized through an interactive dashboard for data-driven decision-making.

Objectives:

1. To develop an LSTM-based time-series model for predicting traffic congestion patterns.
2. To design a fleet analytics and alert system for monitoring route efficiency and operational performance.
3. To implement a real-time route optimization and recommendation system using API-based traffic data.

Methodology:

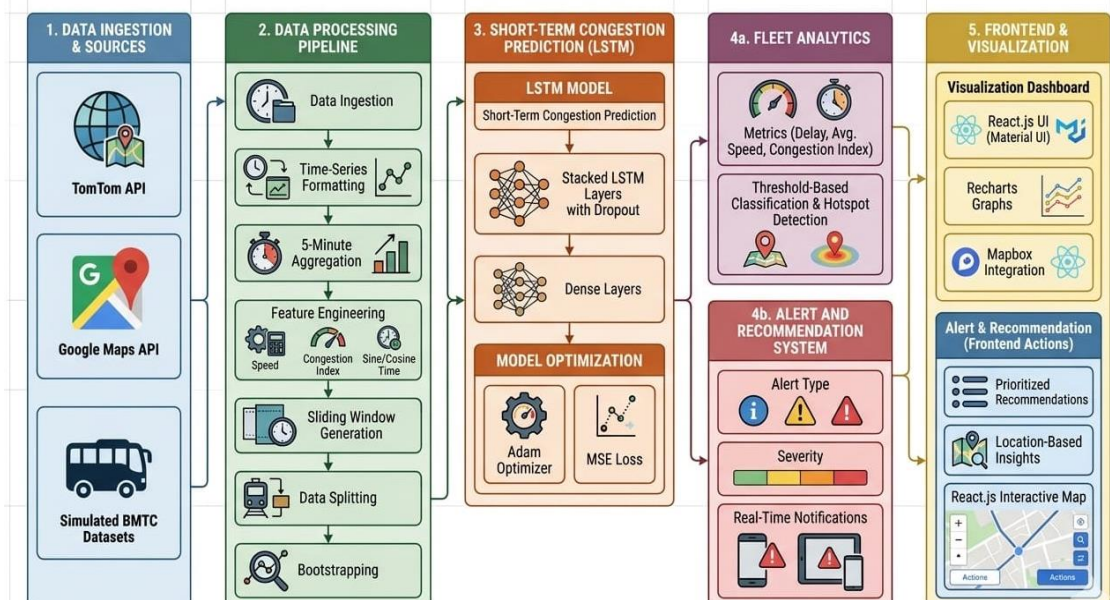
The project is based on multi-stage approach:

- 1. Data Collection:** The proposed system follows a modular, data-driven architecture integrating preprocessing, machine learning, analytics, and visualization. Traffic data is collected using external APIs such as TomTom and Google Maps and converted

into structured time-series format. Since direct BMTC data access is unavailable, simulated datasets are used to approximate real-world conditions.

2. **Data Preprocessing:** The preprocessing pipeline is implemented using Python libraries such as TensorFlow/Keras, Pandas, and NumPy. Raw data is aggregated into fixed 5-minute time windows and transformed using min-max normalization to scale features such as speed and congestion index. Feature engineering techniques generate meaningful inputs including normalized speed, congestion index, and temporal features (sine and cosine transformations) to capture daily traffic patterns. A sliding window approach is used to convert data into sequential inputs (sequence length = 3) suitable for LSTM modeling, and bootstrapping techniques are applied to handle sparse datasets.
3. **LSTM-Based Prediction:** A deep learning model based on LSTM architecture is developed using TensorFlow/Keras. The model consists of stacked LSTM layers with dropout regularization followed by dense layers, trained using the Adam optimizer and Mean Squared Error loss function. This enables accurate short-term congestion prediction by capturing temporal dependencies in traffic data.
4. **Fleet Analytics:** Fleet analytics is implemented using a data-driven analytical approach, where key metrics such as delay, average speed, and congestion index are computed using derived formulas. Traffic conditions are classified using threshold-based logic, allowing identification of congestion hotspots and inefficient routes. Industry-grade platforms such as Samsara were studied; however, their operational cost (approximately ₹2000–₹4200 per vehicle per month depending on subscription and hardware) makes them less feasible for academic deployment, leading to the adoption of a simulation-based approach.
5. **Alert & Notification System:** The system includes an alert and notification module that generates real-time alerts based on conditions such as high congestion, excessive delays, or abnormal route behavior. Each alert includes parameters such as type, severity, and location, enabling effective monitoring.
6. **AI-Based Recommendation System:** An AI-based recommendation system is also implemented to provide route optimization suggestions and operational insights. The system analyzes predicted congestion levels and route performance metrics to generate prioritized, data-driven recommendations, including expected impact and priority levels.
7. **Frontend & Visualization:** The frontend is developed using React.js with a component-based architecture. Material UI is used for responsive design, and Recharts is used for data visualization. The system includes an interactive map module implemented using Leaflet.js for real-time route visualization. The architecture is designed to support integration with advanced mapping platforms such as the Google Maps API for enhanced routing and traffic intelligence in future deployment.

INTEGRATED TRANSPORTATION CONGESTION PREDICTION & FLEET MANAGEMENT ARCHITECTURE



Result and Conclusion:

The system demonstrates the effectiveness of combining LSTM-based time-series prediction with real-time analytics and decision support mechanisms. The LSTM model successfully captures temporal traffic patterns and predicts congestion trends with high reliability.

Fleet analytics enables identification of inefficient routes and delay patterns, while the alert system provides timely notifications of critical conditions. The recommendation system enhances decision-making by suggesting optimized routes and operational strategies.

Even with simulated datasets, the system effectively replicates real-world transportation behavior, validating the feasibility of AI-driven smart transportation solutions.

Project Outcome and Industry Relevance:

The project successfully delivers an AI-enabled system for optimizing urban transportation through predictive analytics and real-time data integration. By combining LSTM-based congestion forecasting with API-driven routing and fleet analytics, the system provides actionable insights for improving traffic flow and operational efficiency. The inclusion of environmental factors such as rainfall and waterlogging enhances the system's real-world applicability, especially for cities like Bengaluru. The dashboard enables transport authorities to monitor congestion levels, delays, and route performance dynamically. The alert and recommendation modules support proactive decision-making, reducing travel time and improving commuter experience. The system aligns with smart city initiatives by promoting data-driven urban mobility solutions. It can be applied in public transport systems such as BMTC, ride-sharing platforms, and logistics operations. Compared to expensive industry tools, the solution offers a cost-effective and scalable alternative. The modular architecture allows integration with IoT devices and real-time sensors in future. Overall, the

project demonstrates strong industry relevance in traffic management, smart mobility, and urban planning domains.

Working Model vs Simulation/Study:

The project is developed as a functional working prototype that integrates both real-time data and simulated components. The routing and map visualization modules operate using real-world APIs, enabling accurate route generation and traffic-based navigation. However, due to limited access to official BMTC datasets, certain components such as fleet data and historical traffic patterns are simulated to replicate real-world scenarios. The LSTM model is trained on structured and pre-processed datasets to perform short-term congestion prediction. The system also incorporates real-time weather data to enhance realism in features like waterlogging detection. While the analytics and visualization modules function dynamically, some backend data sources are approximated for academic implementation. This hybrid approach ensures that the system remains both practical and feasible within project constraints. The prototype effectively demonstrates how a fully real-world system would operate when integrated with live data sources. Hence, the project bridges the gap between simulation and real-world deployment.

Project Outcomes and Learnings:

The project resulted in the successful development of an end-to-end AI-based transportation analytics system. It provided hands-on experience in implementing time-series forecasting using LSTM models and understanding their real-world applications. The team gained practical knowledge of data preprocessing techniques such as normalization, feature engineering, and sequence generation. Integration of external APIs helped in understanding real-time data handling and system design. The development of alert and recommendation systems enhanced problem-solving and decision-making capabilities. The project also improved skills in frontend development using React.js and data visualization techniques. Working with simulated and real data highlighted the importance of data availability and quality in predictive systems. The team learned how to design scalable and modular architectures for future expansion. Additionally, the project strengthened analytical thinking by linking multiple factors such as traffic, weather, and congestion. Overall, it provided a comprehensive learning experience across machine learning, system integration, and real-world application development.

References:

1. Ravichandran, S., Shieh, C., Horng, M., Ramu, A., & Sasi, A. (2025). *Designing Machine Learning Driven Dual Adjacency Graph Based Spatiotemporal Traffic Prediction for Smarter Urban Mobility and Congestion Management in Bengaluru City*. <https://doi.org/10.21203/rs.3.rs-7174769/v1>
2. Poonam, KM. (2024). AI-Driven Predictive Analysis for Urban Traffic Management: A Novel Approach. *International Journal of Innovative Science and Research Technology*, 2270–2277. <https://doi.org/10.38124/ijisrt/ijisrt24oct1444>

3. Sarkar, S. R., & Tahura, S. (2025). AI-Enhanced Public Transportation Systems for Urban Sustainability. *Advances in Computational Intelligence and Robotics Book Series*, 97–116. <https://doi.org/10.4018/979-8-3693-9770-1.ch005>
4. Artificial intelligence -driven adaptive infrastructure for urban mobility. (2023). *International Journal of Developmental Research*, 64509–64513. <https://doi.org/10.37118/ijdr.27837.12.2023>
5. Vemuri, N. M., Tatikonda, V. M., & Thaneeru, N. (2024). Enhancing Public Transit System Through AI and IoT. *International Journal of Scientific Research and Management*, 12(02), 1057–1071. <https://doi.org/10.18535/ijsrcm/v12i02.ec07>
6. Murari, K. (2024). Enhancing urban mobility through machine learning-driven traffic management in smart cities. *ShodhKosh Journal of Visual and Performing Arts*, 5(1). <https://doi.org/10.29121/shodhkosh.v5.i1.2024.6386>
7. Zrigui, I., Khouilji, S., & Kerkeb, M. L. (2025). *Integrated Strategy for Urban Traffic Optimization: Prediction, Adaptive Signal Control, and Distributed Communication via Messaging*. <https://doi.org/10.48550/arxiv.2501.02008>
8. Sivakumar, V., Vadivel, S. R. S., Titus, A., Krishnaswamy, R., Yadav, J. K. P. S., & Meenakshi, B. (2025). *Deep Q-Network-Powered Optimization of Urban Public Transit for Sustainable Mobility and Efficiency*. 1214–1219. <https://doi.org/10.1109/icscsa66339.2025.11171157>
9. Owoade, S. J., Uzoka, A., Akerele, J. I., & Ojukwu, P. U. (2024). Optimizing urban mobility with multi-modal transportation solutions: A digital approach to sustainable infrastructure. *Engineering Science & Technology Journal*, 5(11), 3193–3208. <https://doi.org/10.51594/estj.v5i11.1729>
10. Desai, A., & Sharma, A. K. (2025). Ai-driven solutions for urban traffic efficiency in bengaluru. *International Journal of Scientific Research*, 44–45. <https://doi.org/10.36106/ijsr/3428182>
11. Nardi, S. (2023). Smart Passenger Center: Real-Time Optimization of Urban Public Transport. *Proceedings of the ... International Florida Artificial Intelligence Research Society Conference*, 36. <https://doi.org/10.32473/flairs.36.133300>
12. Anson, A. M., & Amirah. (2025). Machine Learning-Based Route Optimization for Smart Urban Transportation Systems. *Journal of Computer Science Application and Engineering*, 3(2), 31–36. <https://doi.org/10.70356/josapen.v3i2.65>
13. Rajendran, S. P., Sundaramoorthy, S., & venkat, P. (2025). *AI Enabled Intelligent Traffic Management and Adaptive Transportation Systems for Congestion Reduction and Efficiency*. 163–192. <https://doi.org/10.71443/9789349552241-06>
14. Selvi, M. V., Upadhyay, P., Revathi, A., Punitha, N., Reshma, S., & Saravanakumar, M. (2025). *Enhancing Urban AI-Powered Transportation Systems With Machine Learning*. 363–382. <https://doi.org/10.4018/979-8-3693-7984-4.ch020>
15. Vineeth, K. S. S., Naresh, K., Reddy, G. B., & Naresh, R. (2024). *Dynamic Traffic Optimization through Cloud-Enabled Big Data Analytics and Machine Learning for Enhanced Urban Mobility*. 835–841. <https://doi.org/10.1109/icdici62993.2024.10810771>

Future Scope:

The future scope of this project includes:

1. Integration of real-time GPS devices, IoT sensors, and live data sources to improve accuracy and enable real-time tracking.
2. Adoption of advanced deep learning models such as Transformers and reinforcement learning for improved prediction performance and dynamic fleet scheduling.
3. Enhancement of the alert system into predictive alerts and development of a fully AI-driven adaptive recommendation engine.
4. Scalability of the system for deployment across multiple cities, supporting large-scale intelligent transportation infrastructure.