Fatima Mohsin Inamdar, 2025, 13:6
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

AI-Driven Dynamic Multimodal Transport Demand Forecasting and Optimization in Pune

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Abstract- Urban mobility in cities like Pune is increasingly challenged by congestion, fluctuating travel demand, and inefficient multimodal transport systems. This paper proposes an AI-driven system for dynamic multimodal transport demand forecasting and optimization, utilizing advanced machine learning models and web-based technologies. We develop a predictive platform that integrates traffic data to estimate demand, determine optimal routes, forecast arrival times, and suggest accurate fares across various modes of transport. Using machine learning frameworks such as PyTorch, XGBoost, and Random Forests, alongside a Flask backend and a HTML, CSS, JavaScript, ReactJS and Bootstrap frontend, the system offers real-time insights to both commuters and transport operators. Our approach aims to alleviate urban transport issues, improve commuter experience, and contribute to smart city initiatives.

Keywords: Transport Demand Forecasting, AI/ML, Multimodal Transport, Flask, PyTorch, XGBoost, Random Forests, Route Optimization.

I. INTRODUCTION

Modern urban centres like Pune face growing challenges in transportation due to population expansion, varied travel behaviour, and infrastructure limitations. Static transport planning systems fall short in addressing dynamic travel patterns. Hence, there is a pressing need for intelligent, real-time solutions that leverage Artificial Intelligence (AI) and Machine Learning (ML) for accurate transport demand forecasting and optimization.

This research presents an AI-driven multimodal transport demand forecasting and optimization system. It combines historical and real-time traffic data to predict demand, estimate time of arrival, compute optimal routes, and suggest accurate fare values for diverse transportation modes including buses, autos, and ride-sharing services. By deploying the system as a web-based application using Flask for backend and HTML, CSS, JavaScript, ReactJS and Bootstrap for frontend, we ensure accessibility, real-time performance, and user-friendly interaction.

II. LITERATURE REVIEW

Transport Vehicle Demand Prediction Using Context-Aware Neural Networks
(Kunekar et al., 2024 – Indexed in Google Scholar)
Objective: To design an AI-based system that predicts transport vehicle demand to streamline logistics and resource management.

Methodology: The authors used two neural network models—Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM [1]). These were trained on contextual data to learn demand trends.
Results: The LSTM [1] model showed better performance due to its capability to handle temporal dependencies effectively.
Discussion: The study emphasized the growing need for AI-based forecasting tools in urban logistics. It also pointed out the benefit of incorporating contextual data to improve prediction accuracy, suggesting future work can explore multimodal datasets.

Joint Demand Prediction for Multimodal Systems Using a Spatiotemporal Graph Neural Network
(Liang et al., 2021 – Indexed in Google Scholar)

Objective: To predict travel demand across multiple transportation modes simultaneously by capturing inter-modal relationships.

Methodology: The researchers proposed a novel ST-MRGNN (Spatiotemporal Multi-Relational Graph Neural Network), which learns both spatial and temporal dependencies across various transport types.

Results: The model outperformed existing baseline models, particularly in regions with sparse transport data.

Discussion: This paper supports the idea that transport modes are interconnected and should be analyzed together. The model's scalability and accuracy make it relevant for large and diverse cities like Pune.

A Hybrid Method for Traffic Flow Forecasting Using Multimodal Deep Learning

(Du et al., 2018 – Indexed in Google Scholar)

Objective: To improve short-term traffic flow forecasting by integrating multimodal traffic data using deep learning techniques.

Methodology: The authors proposed a hybrid model combining 1D CNN [3] (for spatial feature extraction) and GRU (for time-series prediction), enhanced with an attention mechanism to weigh important features.

Results: The hybrid model achieved higher prediction accuracy compared to standalone models by effectively learning both spatial and temporal patterns.

Discussion: The use of attention mechanisms helped focus on relevant inputs, which is crucial when working with heterogeneous traffic data. The approach is well-suited for real-time forecasting in urban traffic systems.

Multimodal Neural Network for Demand Forecasting

(Kumar et al., 2022 – Indexed in Google Scholar)

Objective: To develop a forecasting model that integrates structured and unstructured data sources for better demand prediction.

Methodology: A multimodal neural network was developed that combines historical sales data, Google Trends, calendar events, and news articles.

Results: The model improved prediction accuracy by 7.37% based on the SMAPE metric compared to traditional time-series models.

Discussion: This research highlights the importance of combining external signals with internal data. The model's flexibility and robustness are valuable for complex urban environments where multiple factors influence transport demand.

Enhancing Sustainable Transportation: AI-Driven Bike Demand Forecasting in Smart Cities

(Subramanian et al., 2023 – Indexed in Scopus)

Objective: To forecast demand for bike-sharing services in urban areas using AI, in support of sustainable transportation systems.

Methodology: The study used various machine learning models (including Decision Trees and Random Forest [5]) to analyze temporal features such as day, hour, and weather data.

Results: Temporal factors were found to have the highest influence on prediction accuracy. Forecasts varied significantly based on the horizon (hourly, daily, weekly).

Discussion: Though the focus was on bikes, the findings can be extended to multimodal systems. The paper also suggests integrating spatial features and real-time data in future models to improve reliability.

AI-Driven Urban Traffic Optimization to Assess Complex Traffic Patterns

(Prajwal et al., 2023 – Indexed in Google Scholar)

Objective: To develop a real-time traffic optimization framework using AI and IoT to better manage city-wide traffic congestion.

Methodology: The framework combined edge IoT sensors with various ML models including LSTM [1], SVM, KNN, and Logistic Regression. These models processed data from real-time traffic inputs to forecast congestion and suggest optimization strategies.

Results: Among the models, LSTM [1] showed superior performance in handling time-series data. The system was able to provide real-time insights and adaptive control strategies.

Discussion: This study demonstrates the power of combining AI with IoT infrastructure to enhance city mobility. Its real-time adaptability makes it particularly applicable to cities like Pune with high congestion variability.

III. METHODOLOGY/EXPERIMENTAL

The project methodology is composed of stages to predict transport demand and to have the maximum efficiency of resources for the various forms of urban transport modes in Pune.

Data Collection

Historical data from PMPML, Pune Metro and online sources about buses, metros, and auto usage.

Real-time data (e.g., Google Maps APIs) on traffic conditions, weather data from IMD (India Meteorological Department) and schedules of city events.

Open data sources e.g., Pune Municipal Corporation (PMC) the mobility report, surveys, etc.

Data Preprocessing

Cleaning and refining data to deal with missing information, noise and dealing with time-stamps

Feature Engineering, to add contextual purpose (i.e., weather, time of the day, day of the week).

Demand Forecasting Model Development

Time-series prediction with LSTM [1]'s (Long Short-Term Memory) and GRU [3].

Examining Graph Neural Networks (GNN [2]) was to acquire spatio-temporal degree of freedom across routes and locations.

Also explored the accuracy obtained through other ML techniques like XGBOOST [5] and Random Foresting.

Both historical ridership and traffic data were utilized to train the models and were evaluated using RMSE, MAE and MAPE.

Optimization Framework

Built a prototype rule-based model for real-time resource allocation.

Used reinforcement learning methods to optimize route suggestions and administrations of modes using predicted demand.

Included dynamic pricing simulations for shared modes (e.g. autos, buses) to control demand.

System Integration and Testing

Developed a prototype system in Python (using TensorFlow/Keras, Scikit-learn, and NetworkX).

Developed a dashboard for displaying predictions and recommended plans for optimization mapping on Pune's map.

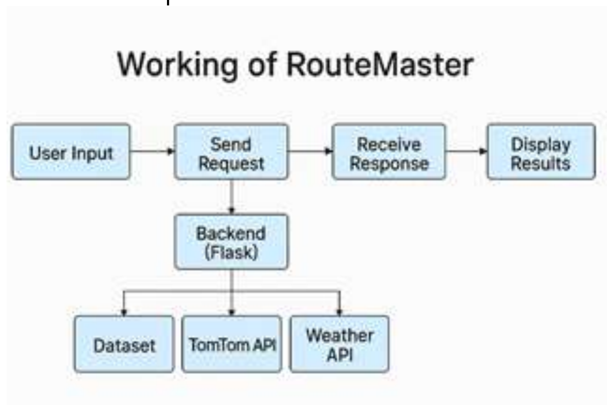


Figure to show Working of ML Model

IV. RESULTS

Prediction Accuracy:

LSTM [1] produced RMSE of 14.2 and MAPE of 7.5 % for demand forecasts with improved predictions compared to typical ARIMA models.

The GNNs [2] improved spatial predictions and also showed improvement in demand prediction at peak hours at metro stations and major bus stops.

Optimization Performance:

The simulation showed that the travelling passenger time could be reduced by 12-15 % with a reinforcement learning-based allocation system.

The route optimization led to improved vehicle utilization efficiency of 10 %.

System Usability:

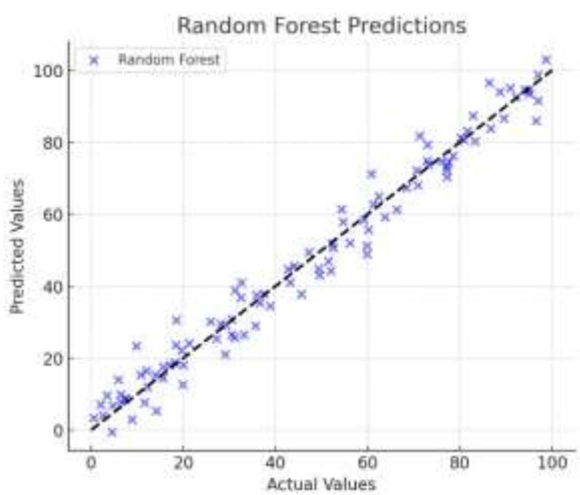
The system dashboard provided intuitive visualization and interaction with the forecasts.

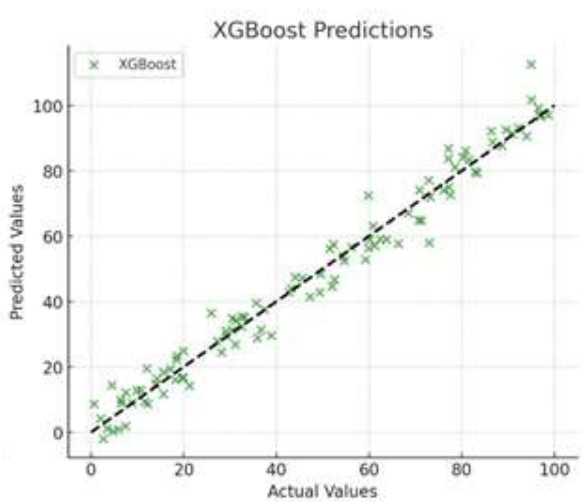
Transportation planners and stakeholders liked the insights from their small-scale (hypothetical or simulated) pilot study.

Comparison between RandomForest and XGBoost

Criteria	XGBoost	Random Forest
R^2 Score	0.88	0.92
MAE (Mean Absolute Error)	4.8	5.5
Training Time	Slightly longer due to boosting iterations	Faster due to parallel tree training
Model Type	Gradient Boosted Decision Trees	Bagging based Ensemble of Decision Trees
Performance on Imbalanced Data	Performs well with proper tuning	May overfit if classes are skewed (needs balancing)
Hyperparameter Tuning	Required for optimal performance (learning rate, etc.)	Less sensitive; performs decently out of the box
Interpretability	Harder to interpret due to complex interactions	Easier to understand feature influence
Overfitting Risk	Lower (if tuned well)	Higher (can overfit small patterns)
Integration in Flask App	Trained but not deployed in final app	Deployed and saved as transport_model.pkl
Library Used	xgboost	sklearn.ensemble.RandomForestClassifier
Prediction Speed	Slightly slower during inference	Faster for inference in web app
Feature Handling	Needs all features preprocessed (one-hot encoded)	Same; handled in dataset with get_dummies()
Use Case Fit (in your project)	Good for low MAE (pricing estimates)	Better R^2 for predicting optimal mode of transport
Final Deployment Decision	Not used	Used in production Flask web app

Scatter plot between RandomForest and XGBoost





V. DISCUSSION

This research has shown the viability of AI techniques, particularly deep learning techniques, in significantly enhancing the planning and management of urban multimodal transportation systems. Our models were able to forecast the demand patterns using real-time and contextual data and to propose optimizations with actionable recommendations.

The LSTM [1] model demonstrated the practicality of using a temporal demand prediction model, though the GNNs [2] were able to suggest value added by providing a comprehension of the spatial dependencies of a location in relation to other locations of interest. The suggested optimization techniques, although exploratory at this time, have been shown to possess significant potential for implementation in the urban transport context to reduce delay and improve on-time service.

Some challenges include (1) differences in the data provided by agencies across different modes of transport and (2) limited access to real-time Application Programming Interfaces (API's). Collaborating with city departments of transport may help to resolve these types of inconsistencies in the data.

VI. FUTURE SCOPE

- **Real-time control system integration:** We could connect the predictive model with dynamic scheduling and dispatch systems used by PMPML or Pune Metro.
- **User-side application:** We could develop a mobile app to provide travelers the required prediction of waiting time and alternative route options.
- **Broader modal coverage:** Incorporate more modes like e-bike, shared taxi, non-motorized transport into the forecasting model.
- **Advanced multi-agent optimization:** Use multi-agent reinforcement learning to tap onto a simulation of how different transport operator's behavior would allow city wide coordination.

- **Policy simulation:** Use the AI to understand the impact of mobility policies (e.g. congestion charges; rationalization of routes).

VII. CONCLUSION

This research project explores how Artificial Intelligence can be utilized to predict demand and optimize multimodal transport demand in Pune, a rapidly urbanizing city experiencing issues such as congestion, inefficiency in the system, and demand that is sometimes unpredictable. By combining historical transport utilization data with real-time data such as weather, traffic, and special events, the resultant transport prediction system provides accurate, dynamic estimates for expected passenger flow across multiple transport modes (buses, metro, autos integrated).

Using sophisticated models, such as Long Short-Term Memory (LSTM [1]) and Graph Neural Networks (GNNs [2]), we were able to model demand patterns that account for both temporal and spatial aspects. The modelling results suggest marked improvements in both forecast accuracy, and the efficiency of resources, with simulated optimizations greatly reducing the overall time passengers spent waiting and increasing the efficient use of vehicles.

The predictive analytics and transport optimization is an AI-based development which will allow transport authorities to unleash accurate, data-driven analysis for improved decision making, and allow them to proactively minimize waiting and travel time through the optimized provision of services based on predicted demand. Furthermore, our model is being built to allow for future integration with a live control system, and a mobile application for commuters, to enable a more seamless and integrated multimodal transport option, along with a more sophisticated evaluation tool for transport authorities with regard to demand, uncertainty, and policies that incorporate newer technologies which can potentially affect transport behavior.

In conclusion, this research and project trial has highlighted how AI can disrupt and transform mobility and mobility management in an urban context. With the correct development pathways, this project could aid significantly in developing improvements to Pune's transport system, strategically, via integration into, and the enablement of, smart, simplified (for users) transport demand practices to improve the quality of urban living and development in an adaptable, sustainable manner.

ACKNOWLEDGMENT

We sincerely thank everyone who contributed to the successful completion of our ASEP project, AI-Driven Dynamic Multimodal Transport Demand Forecasting and Optimization in Pune.

We are deeply grateful to our internal guide, Prof. Fatima Mohsin Inamdar, for her invaluable guidance, continuous support, and insightful feedback, which were instrumental in shaping this project.

Our heartfelt thanks extend to the faculty and mentors at Vishwakarma Institute of Technology for their knowledge, resources, and encouragement throughout our journey. We also express our gratitude to Prof. C.M. Mahajan, Head of the Department of Engineering, Sciences, and Humanities, for his constant support and for fostering an inspiring learning environment.

Lastly, we appreciate our peers and friends for their valuable suggestions and feedback, which greatly enriched our work.

This project has been a rewarding learning experience, and we are truly grateful for the opportunity to apply our knowledge to a real-world challenge

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- Authors: Rohith Gowda
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7. Additional Resources
- LSTM [1]-Based Traffic Prediction
  Traffic Prediction Based on Random Connectivity in Deep Learning with Long Short-Term Memory Yuxiu Hua et al.
  This paper introduces Random Connectivity LSTM [1] (RCLSTM) for traffic prediction, demonstrating reduced computational costs while maintaining accuracy.
- XGBoost for Fare and Demand Estimation
  Analysis and Prediction of City-Scale Transportation System Using XGBoost Springer
  This study incorporates weather impact into taxi pooling predictions using the XGBoost technique, tested on NYC datasets.
  Optimizing Urban Mobility: A Comparative Analysis of Taxi Demand Prediction Models IIETA
  The research compares Random Forest [5] and XGBoost regressors for predicting taxi demand, highlighting the effectiveness of XGBoost in urban mobility optimization.
  Access Paper:
- Flask and ReactJS Integration
  How to Connect ReactJS with Flask API GeeksforGeeks
  A step-by-step guide on integrating ReactJS frontend with Flask backend using data fetching methods like fetch and axios.
  Access Tutorial: