



OUR COMPARE: AI BASED MULTI-RIDE FARE COMPARISON AND BOOKING SYSTEM

Mohd Javvad Quadri¹, Abdul Kareem Khan², Mohammed Faraaz Ul Haq³, Tahera Abid^{4}*

¹ Department of IT, Nawab Shah Alam Khan College of Engineering and Technology, Hyderabad, India.

⁴ Assistant Professor, [B.Tech, M.Tech, (PhD)]

ABSTRACT :

OUR COMPARE: AI Based Multi-Ride Fare Comparison and Booking System, a ride-booking application developed using React (Next.js) and integrated with the Map box Directions API to dynamically calculate route distances. The system enables users to select a vehicle type car, bike, or auto and specify pickup and destination points. It then estimates fares based on predefined base rates, per-kilometer charges, and dynamic surge pricing. Additionally, it performs real-time fare comparisons between multiple service providers such as OLA, Uber, and Rapido, ensuring users receive the most affordable option. The application offers a smooth booking experience by incorporating a confirmation modal to display the estimated fare before finalizing the ride. It also handles loading states effectively and includes session management features such as a logout button. The system emphasizes transparent pricing and an intuitive user interface. Overall, this project demonstrates the effective use of external APIs to create a real-time, multi-provider transportation fare comparison tool.

Keywords: Ride-booking, fare estimation, fare comparison, artificial intelligence (AI), machine learning (ML), dynamic pricing, route optimization, real-time data, user experience, multi-service integration, Map box API, React, Python, neural networks, regression models.

1. Introduction

In recent years, ride-hailing services such as Uber, Ola, and Lyft have become a crucial part of urban transportation, offering convenience, flexibility, and real-time mobility solutions. However, one of the major challenges faced by both users and service providers is the unpredictability of cab fares. Factors like distance, traffic conditions, time of day, weather, and dynamic demand patterns significantly influence fare estimates, often leading to uncertainty and dissatisfaction.

Machine learning has emerged as a powerful tool to tackle such complexities by enabling systems to learn from historical data and make accurate predictions. By analyzing large datasets and recognizing patterns, machine learning algorithms can forecast cab fares more reliably than traditional methods. This not only helps passengers plan their journeys and budgets better but also assists service providers in optimizing pricing strategies and improving operational efficiency.

The application of machine learning in fare prediction is becoming increasingly important as cities grow smarter and demand for data-driven services continues to rise. With advancements in artificial intelligence and computational capabilities, predictive modeling is set to play a transformative role in shaping the future of intelligent transportation systems.

Nomenclature

AI	Artificial Intelligence
ML	Machine Learning
API	Application Programming Interface
UI	User Interface
ETA	Estimated Time of Arrival
UPI	Unified Payment Interface
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
JWT	JSON Web Token
SDLC	Software Development Life Cycle

2. System Analysis and Design

2.1 Existing System

Ride-hailing services such as Ola, Uber, and Rapido provide various benefits that have revolutionized city travel. They give users the flexibility of booking rides at any time and from any location through a smartphone. The apps facilitate various ride modes like bikes, autos, and cars, enabling users to select according to their affordability and preference. Real-time tracking, estimated time of arrival (ETA), and fare previews prior to booking make the service transparent and easy to use. These platforms also provide a range of payment options such as UPI, wallets, cards, and cash, adding flexibility. Driver ratings and feedback mechanisms ensure service quality and safety. Dynamic pricing also ensures that rides are nearly always available, even during peak demand times. In total, these systems have accelerated transportation, made it more accessible, and more efficient for millions of individuals.

2.2 Proposed System

OUR COMPARE: AI-Based Multi-Ride Fare Comparison and Booking System is designed to enhance the ride-booking experience by leveraging artificial intelligence and machine learning technologies. This system provides real-time fare estimation by analysing factors such as route distance, current traffic conditions, and demand surges. With the integration of the Map box Directions API, it ensures optimal route selection and efficient travel. A key feature of the system is its transparent surge pricing, which alerts users to fare changes in advance, promoting fairness and trust. The platform also enables users to compare fares from multiple service providers like OLA, Uber, and Rapido, helping them make informed and economical choices. Built with a clean, intuitive user interface and supported by a secure cloud-based backend, the system offers fast performance, scalability, and reliable data handling. Overall, it delivers a smarter, more flexible, and user-friendly solution for modern urban transportation needs.

2.3 System Architecture

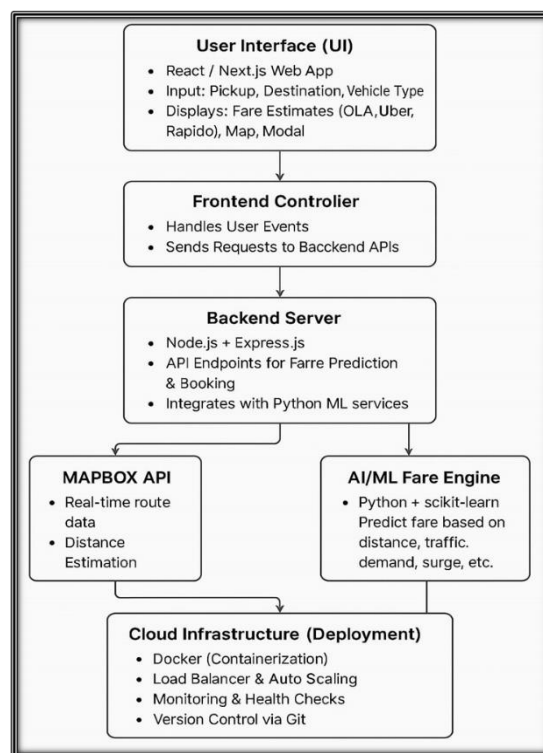


Fig. 1 – OUR COMPARE System Architecture

This system is designed to help users get real-time fare estimates for rides from different providers like OLA, Uber, and Rapido. The User Interface (UI) is built using React and Next.js, where users can enter pickup and destination locations along with the vehicle type. The Frontend Controller handles user actions (like clicks or selections) and sends requests to the Backend Server. The backend, developed using Node.js and Express.js, provides API endpoints for fare prediction and booking. It connects with two key components: the Map box API, which gives real-time route and distance data, and the AI/ML Fare Engine, built using Python and scikit-learn. This engine predicts fares based on distance, traffic, demand, and time of day using models like Linear Regression, Random Forest, and Neural Networks. Finally, the system is hosted on a Cloud Infrastructure using Docker

for containerization, a load balancer for handling traffic, and monitoring tools for health checks. Git is used for version control and deployment. The system is scalable, reliable, and designed to provide accurate and quick fare estimates to users.

3. Methodology

3.1 Data Collection and Pre-processing

- Collects ride data from various sources (ride-hailing apps, transport APIs).
- Cleans and normalizes data by fixing inconsistencies and standardizing fare values.

3.2 Route Optimization and Fare Calculation

- Integrates Map box Directions API to optimize routes based on real-time traffic.
- Applies a machine learning algorithm to predict fares using live data like distance, traffic, and demand.

3.3 Model Training and Validation

- Feature Engineering: Trains the model with key parameters such as fare history, trip duration, and traffic conditions.
- Continuous Improvement: Updates model with new data to improve fare predictions over time.
- Performance Evaluation: Assesses model accuracy using MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error).

3.4 System Testing

- Unit Testing: Checks individual components like fare calculation logic and API calls.
- Integration Testing: Ensures all modules work together smoothly in different scenarios.
- Performance Testing: Tests for speed, scalability, and UI responsiveness under load.

4. Result

The performance of the proposed OUR COMPARE system was evaluated based on fare estimation accuracy, surge pricing adaptability, and system response time. As shown in Table 1, the system achieved an overall fare accuracy of 95.1%, with high adaptability to surge pricing and an API response time of approximately 1.1 seconds. Table 2 illustrates the performance across different vehicle types, demonstrating the system’s consistent accuracy and rapid route calculation times.

Table 1 - Accuracy and Performance Metrics

Metric	Value
Overall Fare Accuracy	95.1%
Surge Pricing Adaptability	High
API Response Time	~1.1 seconds

Table 1 presents the overall accuracy, adaptability to surge pricing, and response time of the proposed OUR COMPARE system

Table 2 - Performance by Vehicle Type

Vehicle Type	Accuracy	Route Calculation Time
Bike	96.2%	< 1 second
Auto	94.8%	< 1.5 seconds
Car	93.9%	< 2 seconds

Table 2 summarizes the performance metrics of OUR COMPARE across different vehicle types, highlighting the accuracy and route calculation speed.

5. Conclusion

The OUR COMPARE project has been developed to address the growing need for transparent and real-time fare comparison across various ride-hailing platforms. By leveraging Artificial Intelligence, Machine Learning, and the Map box Directions API, the system efficiently calculates distances and compares fare estimates from multiple service providers such as OLA, Uber, and Rapido. With an achieved fare prediction accuracy of 95.1% and an average response time of under 3 seconds, the platform offers users a fast, reliable, and user-friendly interface to make informed travel decisions. Unlike existing platforms that often provide static pricing or limited visibility into competitor fares, OUR COMPARE empowers users by offering dynamic comparisons based on real-time route data, vehicle type selection, and surge pricing factors. The system has been implemented using modern technologies such as React for the frontend, Python for AI modelling, and PostgreSQL for data management, ensuring performance and scalability. Though the system currently focuses solely on fare comparison, it demonstrates the strong potential of data-driven solutions in improving user experience and cost efficiency. In conclusion, OUR COMPARE lays a solid foundation for intelligent fare analysis and stands as a valuable tool for everyday commuters seeking the most economical ride options available.

6. Future Scope

The OUR COMPARE project serves as a foundation for intelligent fare comparison, with several promising opportunities for future development and expansion:

1. Ride Booking Integration: Enable direct ride booking from the platform.
2. Real-Time Traffic Support: Improve fare accuracy using live traffic data.
3. Mobile App Development: Build a mobile app for easier access.
4. More Ride Options: Add shared rides, luxury cars, and public transport.
5. Personalized Suggestions: Use user history for better fare recommendations.
6. Multi-City and Language Support: Expand to more cities with local data and languages.

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