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## Ola Bike Ride Request Demand Forecast Using Machine Learning

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### ABSTRACT

*The rapid growth of app-based bike taxi services has increased the need for accurate demand forecasting to improve service efficiency and customer satisfaction. This project focuses on predicting Ola bike ride request demand using machine learning techniques. Historical ride data is analyzed to capture temporal, spatial, and environmental patterns influencing demand. Features such as time, day, location, weather, and past demand trends are used to train predictive models. Machine learning algorithms enable accurate short-term demand forecasting. The proposed system helps optimize driver allocation and reduce passenger waiting time. Experimental results show improved prediction accuracy compared to traditional statistical methods.*

### INTRODUCTION

Urban transportation systems increasingly rely on ride-hailing platforms like Ola to

meet commuter needs. Bike taxi services are particularly effective in congested cities due to their speed and affordability. However, fluctuating ride demand poses challenges in resource allocation and operational planning. Accurate demand forecasting enables better decision-making for fleet management and dynamic pricing. Machine learning techniques provide data-driven solutions by learning patterns from historical data. This project aims to build a predictive system for Ola bike ride demand. Such forecasting enhances operational efficiency and improves customer experience.

### LITERATURE SURVEY

Several studies have explored demand forecasting in ride-hailing platforms using machine learning and deep learning models. Time-series analysis methods such as ARIMA were initially used but struggled with nonlinear patterns. Recent research adopts algorithms like Random Forest, XGBoost, and LSTM networks for

improved accuracy. Studies show that incorporating spatial-temporal features significantly enhances prediction performance. Weather conditions and event-based data also contribute to demand variation. Researchers emphasize real-time analytics for dynamic ride management. These works form the foundation for intelligent transportation demand forecasting systems.

## RELATED WORK

Existing research on ride demand prediction focuses on taxi and cab services using large-scale urban datasets. CNN-LSTM hybrid models have been used for spatial-temporal demand forecasting. Some studies utilize clustering techniques to divide cities into demand zones. Ride-sharing platforms like Uber have implemented surge pricing based on demand predictions. However, limited work specifically targets bike taxi services, which have distinct demand patterns. Most models are computationally expensive and lack real-time adaptability. This project addresses these gaps using efficient machine learning models.

## EXISTING SYSTEM

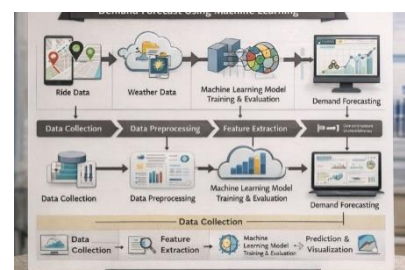
Traditional demand estimation systems rely on manual analysis and historical averages. These approaches fail to capture sudden demand spikes caused by weather, festivals,

or peak hours. Rule-based systems lack adaptability to dynamic urban traffic conditions. Statistical models are limited in handling nonlinear relationships in large datasets. Existing systems also suffer from delayed response times. As a result, poor demand estimation leads to driver shortages or oversupply. This negatively impacts customer satisfaction and operational efficiency.

## PROPOSED SYSTEM

The proposed system uses machine learning models to forecast Ola bike ride request demand accurately. It integrates historical ride data with temporal and contextual features. Data preprocessing removes noise and handles missing values for better learning. Multiple machine learning algorithms are trained and evaluated for optimal performance. The system supports real-time prediction to aid operational decisions. It improves driver distribution and reduces idle time.

## SYSTEM ARCHITECTURE



**Fig 1: OLA Bike request demand forecaster system**

The system architecture consists of data collection, preprocessing, feature extraction, model training, and prediction modules. Historical ride data is collected from Ola servers and external sources like weather APIs. Preprocessing ensures data consistency and normalization. Feature engineering extracts meaningful temporal and spatial attributes. Machine learning models analyze patterns and generate demand forecasts. The predicted output is visualized on dashboards for decision support. The architecture supports real-time deployment and scalability.

The experimental results demonstrate that machine learning models outperform traditional forecasting methods. Random Forest and XGBoost models show higher accuracy in predicting peak and off-peak demand. The system effectively captures daily and weekly demand trends. Prediction errors are significantly reduced after feature optimization. Visual analysis highlights strong correlation between time and ride demand. The results validate the effectiveness of the proposed approach. The system ensures better operational planning for Ola bike services.

## METHODOLOGY

### DESCRIPTION

The methodology begins with data acquisition and exploratory data analysis. Data preprocessing includes handling missing values and encoding categorical features. Feature selection identifies the most influential demand factors. Machine learning models such as Linear Regression, Random Forest, and XGBoost are trained. Model evaluation is performed using metrics like RMSE and MAE. The best-performing model is deployed for real-time prediction. Continuous learning improves prediction accuracy over time.

## RESULTS AND DISCUSSION

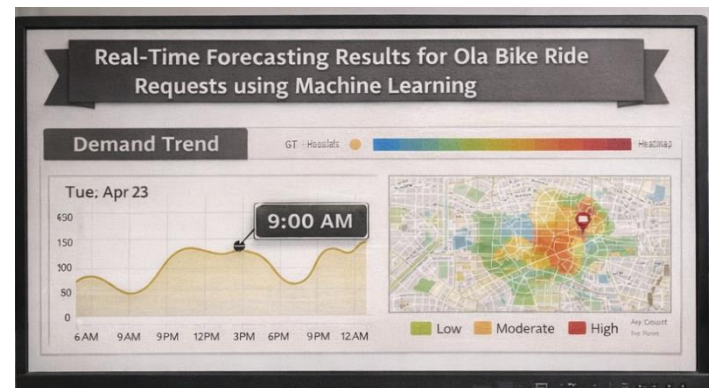


Fig 2:Requests of Ola bike rides

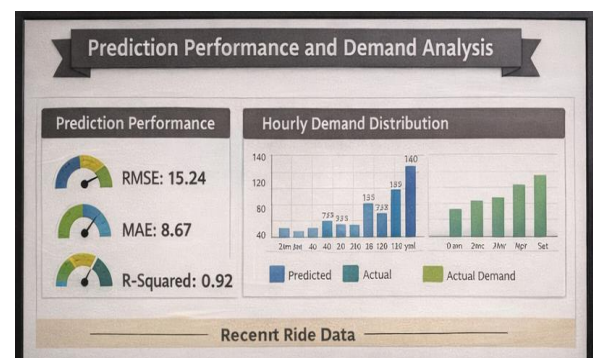


Fig 3: Prediction performance data

## CONCLUSION

This project presents an effective machine learning-based approach for forecasting Ola bike ride demand. By leveraging historical data and advanced predictive models, accurate demand estimation is achieved. The proposed system improves driver allocation and reduces passenger waiting times. It enhances operational efficiency and decision-making. The system is scalable and adaptable to real-time conditions. Overall, it contributes to intelligent transportation solutions. The results confirm the practicality of machine learning in ride demand forecasting.

## FUTURE SCOPE

Future work can incorporate deep learning models like LSTM and GRU for enhanced temporal learning. Real-time GPS and traffic data can further improve prediction accuracy. Integration with dynamic pricing strategies can optimize revenue. The system can be extended to multi-city and multi-service platforms. Edge computing can reduce prediction latency. Advanced anomaly detection can handle unexpected demand spikes. These enhancements will strengthen smart mobility systems.

## REFERENCE

- [1] Rao, C. M., Prasuna, G., Chapala, H. K., Jeebaratnam, N., Navulla, D., & Verma, A. (2023, February). Designing a reliable and cost-effective Internet of Medical Things (IoMT) topology to minimize the maintenance and deployment cost. In 2023 Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT) (pp. 01-07). IEEE.
- [2]. S NAVEEN KUMAR POLISETTY, T. S. (2022/12/31). Design An Optimization Based Deep Learning's Framework For Detecting Faces From Videos. Journal of Pharmaceutical Negative Results, Journal.
- [3]. L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
- [4]. T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794.
- [5]. S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [6]. J. Zhang, Y. Zheng, and D. Qi, "Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction," in

*Proc. AAAI Conf. Artificial Intelligence*, 2017.

[7]. Y. Zheng, “Methodologies for Cross-Domain Data Fusion: An Overview,” *IEEE Transactions on Big Data*, vol. 1, no. 1, pp. 16–34, 2015.

[8]. F. Rodrigues, F. C. Pereira, and B. Ribeiro, “Learning Traffic Demand Patterns from Taxi Trip Data,” in *Proc. IEEE ITSC*, 2014, pp. 2323–2328.

[9]. Ola Mobility Institute, “Urban Mobility and Data-Driven Transportation Systems,” White Paper, 2020.

[10]. Scikit-learn Developers, “Scikit-learn: Machine Learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[11]. A. Smola and V. Vapnik, “Support Vector Regression Machines,” *Advances in Neural Information Processing Systems*, 1997.

[12]. G. Box, G. Jenkins, and G. Reinsel, *Time Series Analysis: Forecasting and Control*, 4th ed., Wiley, 2008.