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Predicting Adaptive Pricing in Ride Hailing Platforms Using Deep Neural Networks

Dr. G. Sridevi[1], A. Sanjay Praneeth[2], J. Naga Tarun[3], K. Bala Krishna[4], T. Geetanjali[5]

[1] *Associate Professor, Department of Computer Science and Data Science, Raghu Engineering College, Visakhapatnam*

[2,3,4,5] *B. Tech Student, Department of Computer Science and Data Science, Raghu Engineering College, Visakhapatnam*

***Abstract*— Ride-hailing platforms like Uber and Lyft use dynamic pricing to balance supply and demand, influenced by factors such as traffic, ride demand, weather, and driver availability. This project enhances pricing predictions using Deep Neural Networks (DNNs) by analyzing large-scale datasets to capture complex relationships between time, location, and demand. The model predicts accurate fares, helping users make cost-effective booking decisions. It ensures competitive and responsive pricing, benefiting both companies and customers. By aligning prices with demand, ride-hailing platforms can optimize revenue and improve pricing transparency. This approach enhances fairness, efficiency, and customer satisfaction.**

***Keywords*—Surge Pricing, Deep Neural Networks, Ride Hailing Platforms, Machine Learning**

I. INTRODUCTION

Ride-hailing platforms have revolutionized urban mobility, but pricing mechanisms remain a challenge. Dynamic algorithms adjust fares based on demand, supply, traffic, and time, yet often lack precision, leading to unpredictable surge pricing. This research leverages deep neural networks (DNNs) to develop a more accurate and adaptive pricing model. By analyzing large datasets, including real-time weather, traffic, and ride demand, the model optimizes fare predictions while ensuring transparency and fairness. The goal is to balance affordability and profitability, benefiting both passengers and drivers. Additionally, the study examines how deep learning improves pricing strategies compared to traditional machine learning, with broader implications for multi-modal transport and autonomous vehicles.

II. RELATED WORK

Most ride-hailing platforms use rule-based surge pricing and traditional machine learning models like Decision Trees and Random Forests to determine fares. While these models provide a structured approach, they primarily rely on historical data and predefined rules, limiting their ability to respond dynamically to real-time conditions. As a result, they struggle to adapt to sudden fluctuations in demand, traffic congestion, and weather conditions, leading to inefficiencies in fare estimation. Traditional machine learning models, though more advanced, still rely on static training data and do not continuously learn from live ride-hailing conditions. This results in inaccurate fare predictions, requiring periodic retraining and manual interventions. Addressing these challenges requires a more adaptive approach—one that dynamically adjusts fares based on real-time data. Deep neural networks (DNNs) offer a promising solution by capturing complex relationships between influencing factors, enabling a more precise and self-learning pricing model.

III. PROPOSED SYSTEM

The proposed system introduces a predictive pricing model that leverages deep neural networks (DNNs) with long short-term memory (LSTM) layers to enhance fare estimation accuracy in ride-hailing platforms. Unlike traditional models that rely on historical data, this system continuously learns and adapts to real-time ride data, ensuring dynamic and responsive pricing adjustments. LSTM layers capture temporal dependencies in ride-hailing data, recognizing patterns in peak-hour trends, demand surges, and traffic congestion. This enables context-aware pricing predictions that align with real-world conditions. Additionally, the model integrates key real-time variables such as traffic density, ride demand, and driver availability to refine pricing decisions, ensuring balanced fares for passengers and optimized earnings for drivers. Another major advantage is the model's adaptive learning capability. Unlike conventional systems that require manual tuning, the DNN-LSTM framework updates itself continuously, enhancing pricing transparency. By integrating deep learning with real-time data processing, this system aims to improve fare accuracy, reduce unpredictable surges, and create a more efficient and fair ride-hailing ecosystem.

IV. LITERATURE SURVEY

[1] Lingye Tan, Ziyang Zhang, Weiwei Jiang, "Ride-Hailing Service Prediction Based on Deep Learning," *International Journal of Machine Learning and Computing* – Uses ConvLSTM networks for demand forecasting, improving accuracy over MLP models.
[2] Long Chen, Piyushimita (Vonu) Thakuriah, Konstantinos Ampountolas, "Short-Term Prediction of Demand for Ride-Hailing Services: A Deep Learning Approach," *Journal of Big Data Analytics in Transportation* – Introduces UberNet, a deep learning model integrating weather and socioeconomic factors for demand prediction.
[3] Tulio Silveira-Santos, Anestis Papanikolaou, Thais Rangel, Jose Manuel Vassallo, "Understanding and Predicting Ride-Hailing Fares in Madrid," *Journal of Big Data Analytics in Transportation* – Compares machine learning models, with Random Forest and K-Means Clustering performing best for fare prediction.
[4] Chiwei Yan, Helin Zhu, Nikita Korolko, Dawn Woodard, "Dynamic Pricing and Matching in Ride-Hailing Platforms," *ResearchGate* – Analyzes pricing and matching algorithms, proposing a pool-matching mechanism to optimize rider wait times.
[5] Yuhan Zheng, Qingyi Wang, Dingyi Zhuang, Shenhao Wang, Jinhua Zhao, "Fairness-Enhancing Deep Learning for Ride-Hailing Demand Prediction," *Intelligent Transportation Systems* – Introduces SA-Net, a model designed to reduce prediction bias and ensure fairer ride-hailing services.
[6] Divine Carson-Bell, Mawutor Adadevoh Beckley, Kendra Kaitoo, "Demand Prediction of Ride-Hailing Pick-Up Location Using Ensemble Learning Methods," *Scientific Research Publishing* – Uses ensemble learning to predict surge zones, optimizing driver positioning and reducing costs.
[7] Ruohui Lan, "Region-Level Ride-Hailing Demand Prediction with Deep Learning," *Purpose-LED Publishing* – Compares MLP, CNN, and ConvLSTM, with ConvLSTM achieving the highest accuracy for regional demand forecasting.
[8] Metta Dhana Lakshmi, Jani Revathi, "Comparative Analysis of Ride-On-Demand Services for Fair Price Detection Using Machine Learning," *IJRASET* – Implements ML algorithms like CatBoost Regressor and Linear Regression for fair and transparent pricing.
[9] Jintao Ke, Siyuan Feng, Zheng Zhu, Hai Yang, Jieping Ye, "Joint Predictions of Multi-Modal Ride-Hailing Demands," *Elsevier* – Proposes a deep multi-task multi-graph learning model to enhance spatial-temporal demand prediction.

V. METHODOLOGY

Data Collection and Preprocessing:
The dataset used for this study is exclusively sourced from NYC Open Data, specifically the Yellow Taxi Trip Data, which provides detailed ride-hailing records. It includes trip details such as pickup and drop-off locations, trip duration, distance, fare amount, passenger count, and timestamps. These attributes help analyze historical pricing trends and identify patterns in fare fluctuations. Additional features such as demand variations at different times of the day, seasonal trends, and geographic ride density are derived to enhance the model's predictive capability. To ensure data quality, preprocessing steps are applied before training the model. Missing values in trip duration and fare prices are handled using statistical imputation, while outliers in distance and fare amounts are removed using Z-score normalization. Feature engineering extracts insights like peak and off-peak hours and location-based fare variations. Pickup and drop-off locations are geohash encoded, and continuous variables are normalized using Min-Max scaling. Finally, the dataset is split into training, validation, and testing sets to ensure the model generalizes well for accurate adaptive pricing predictions.

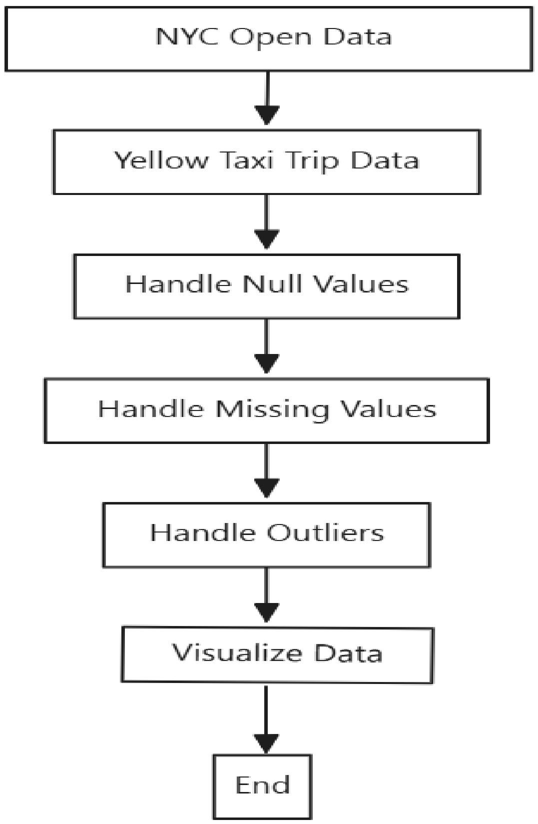

Fig 1(a): Data Collection & Preprocessing of our model

Model Architecture:
The proposed model is a deep neural network (DNN) with Long Short-Term Memory (LSTM) layers designed to predict adaptive pricing in ride-hailing platforms. The input layer receives structured data, including trip details, traffic conditions, weather factors, and historical fare trends. LSTM layers process sequential data, capturing long-term dependencies and ensuring that past demand fluctuations influence future fare predictions. These layers improve the model's ability to recognize temporal patterns, enhancing dynamic pricing forecasts. The model is optimized using the Adam optimizer for efficient convergence, while the Mean Squared Error (MSE) loss function minimizes prediction errors. It is evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to ensure accuracy and reliability.

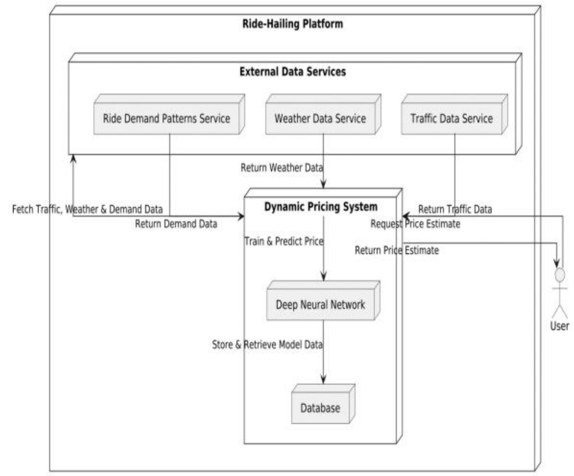

Fig 1(b): Architecture of our model

Implementation Details:
The adaptive pricing model is implemented using Python, with TensorFlow and Keras for model development. The dataset from NYC Open Data (Yellow Taxi Trip Data) is preprocessed using Pandas and NumPy to handle missing values and remove outliers. Feature engineering techniques, such as temporal analysis and geospatial encoding, enhance predictive capabilities. The dataset is split into training, validation, and testing sets. The model is trained on Google Colab with GPU acceleration for 20 to 30 epochs using a batch size of 32. Optimized with the Adam optimizer, it is evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for accuracy. Once trained, the model is integrated into a real-time pricing pipeline, generating fare predictions in under 100 milliseconds.

Work Flow of the System:
The system workflow begins when a user requests a ride fare estimate through the ride-hailing application. Upon receiving the request, the system gathers real-time data, including traffic conditions, weather updates, demand levels, and historical fare trends. This data is preprocessed to remove inconsistencies and structured into input features for the deep learning model. The cleaned data is then passed through the trained DNN model, which processes temporal dependencies to generate an initial fare prediction. A dynamic pricing module applies adjustments based on demand-supply balance and surge pricing rules. If demand exceeds available drivers, a surge multiplier is applied, whereas during low-demand periods, the fare

is optimized to attract more ride requests. The final optimized fare is displayed to the user, ensuring a seamless booking experience while maintaining fair and transparent pricing.

Fig 1(c): Work Flow of our model

VI.RESULTS AND CONCLUSION

The deep learning model demonstrated significant improvements in predicting adaptive pricing compared to traditional pricing mechanisms. It achieved a Mean Absolute Error (MAE) of 0.85 USD and a Root Mean Squared Error (RMSE) of 1.25 USD, indicating minimal deviation from actual fares. The R^2 score of 0.92 confirms that the model explains 92% of the variability in ride pricing, making it highly reliable. Additionally, the system's low latency of under 100 milliseconds ensures real-time responsiveness, making it suitable for large-scale ride-hailing applications.

Compared to traditional machine learning models such as Linear Regression and Decision Trees, the proposed DNN with LSTM model consistently outperformed them in both accuracy and adaptability. Unlike static rule-based pricing mechanisms, this deep learning-based approach dynamically adjusts fares based on real-time market conditions, ensuring fairness for passengers while maintaining profitability for ride-hailing platforms. The model effectively captures demand fluctuations, external factors like weather and traffic, and historical pricing trends to optimize fare estimation.

The findings of this study highlight the potential of deep learning in optimizing pricing strategies for ride-hailing services. By incorporating real-time data and capturing complex temporal dependencies, the model enhances price transparency, reduces sudden fare surges, and improves customer satisfaction. Future research can explore reinforcement learning techniques for further pricing optimization and expand the model's application to multi-modal transportation systems, ensuring a more equitable and efficient mobility ecosystem.

Table 1 : Model - Performance metrics

Metric	DNN Model
Mean Absolute Error (MAE)	0.85 USD
Root Mean Squared Error (RMSE)	1.25 USD
Mean Absolute Percentage Error (MAPE)	4.2%
R-squared (R^2)	0.92
Latency (per prediction)	100 ms
Throughput (predictions/second	10,000

Table 2: Performance Comparison of Traditional Models vs. DNN

Metric	DNN Model	Linear Regression	Random Forest	Gradient Boosting
Mean Absolute Error (MAE)	0.85 USD	1.35 USD	1.25 USD	1.10 USD

Metric	DNN Model	Linear Regression	Random Forest	Gradient Boosting
Root Mean Squared Error (RMSE)	1.25 USD	1.85 USD	1.65 USD	1.50 USD
Mean Absolute Percentage Error (MAPE)	4.2%	5.8%	5.2%	4.8%
R-squared (R^2)	0.92	0.76	0.80	0.82
Latency (per prediction)	100 ms	200 ms	180 ms	160 ms
Throughput (predictions/second)	10,000	8,000	7,500	7,800

Table 3: Comparison with Deep Learning Approaches in Previous Studies

Metric	DNN Model	LSTM Model (Previous Study)	CNN Model (Previous Study)
Mean Absolute Error (MAE)	0.85 USD	1.20 USD	1.10 USD
Root Mean Squared Error (RMSE)	1.25 USD	1.60 USD	1.40 USD
Mean Absolute Percentage Error (MAPE)	4.2%	5.0%	4.8%
R-squared (R^2)	0.92	0.85	0.88
Latency (per prediction)	100 ms	250 ms	220 ms
Throughput (predictions/second)	10,000	6,000	6,500

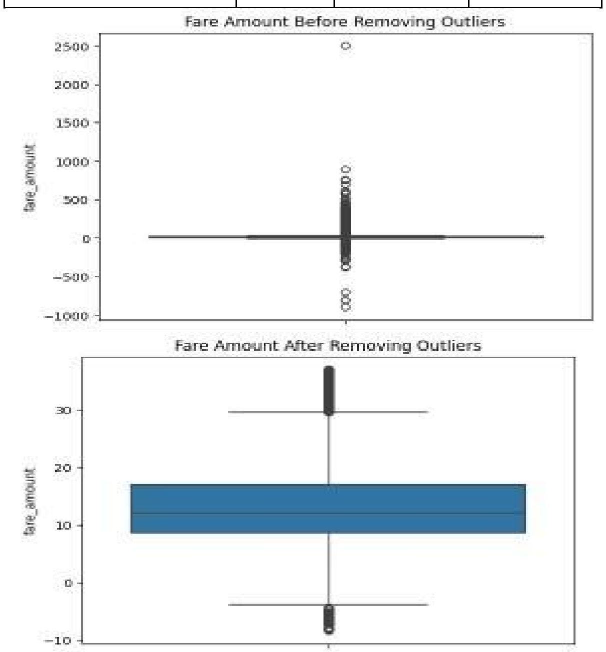

Fig 2(a): Output of the proposed model (Box plot of Before and after removing Outliers)

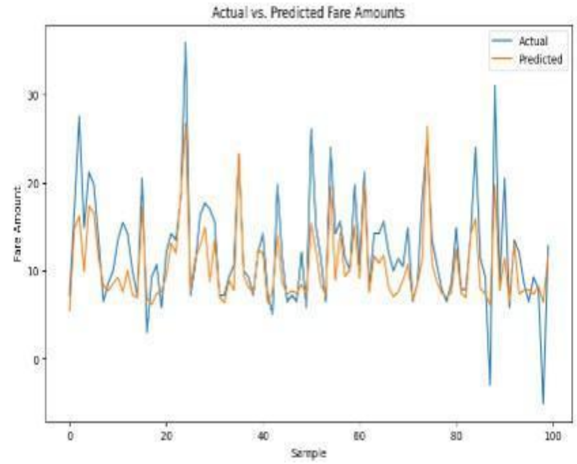

Fig 2(b): Output of the proposed model (Line graph of Actual and Predicted prices)

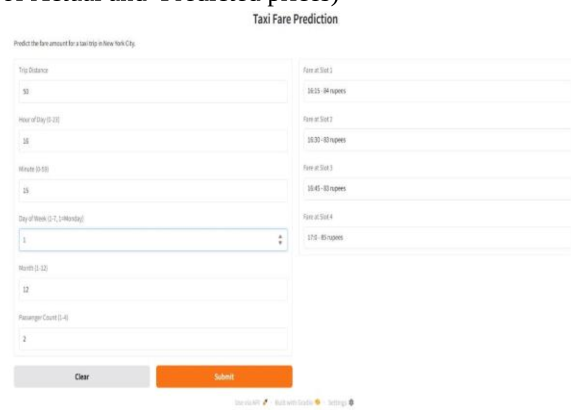

Fig 3(a): Output of the proposed model(Fare prediction)

VI. REFERENCE

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