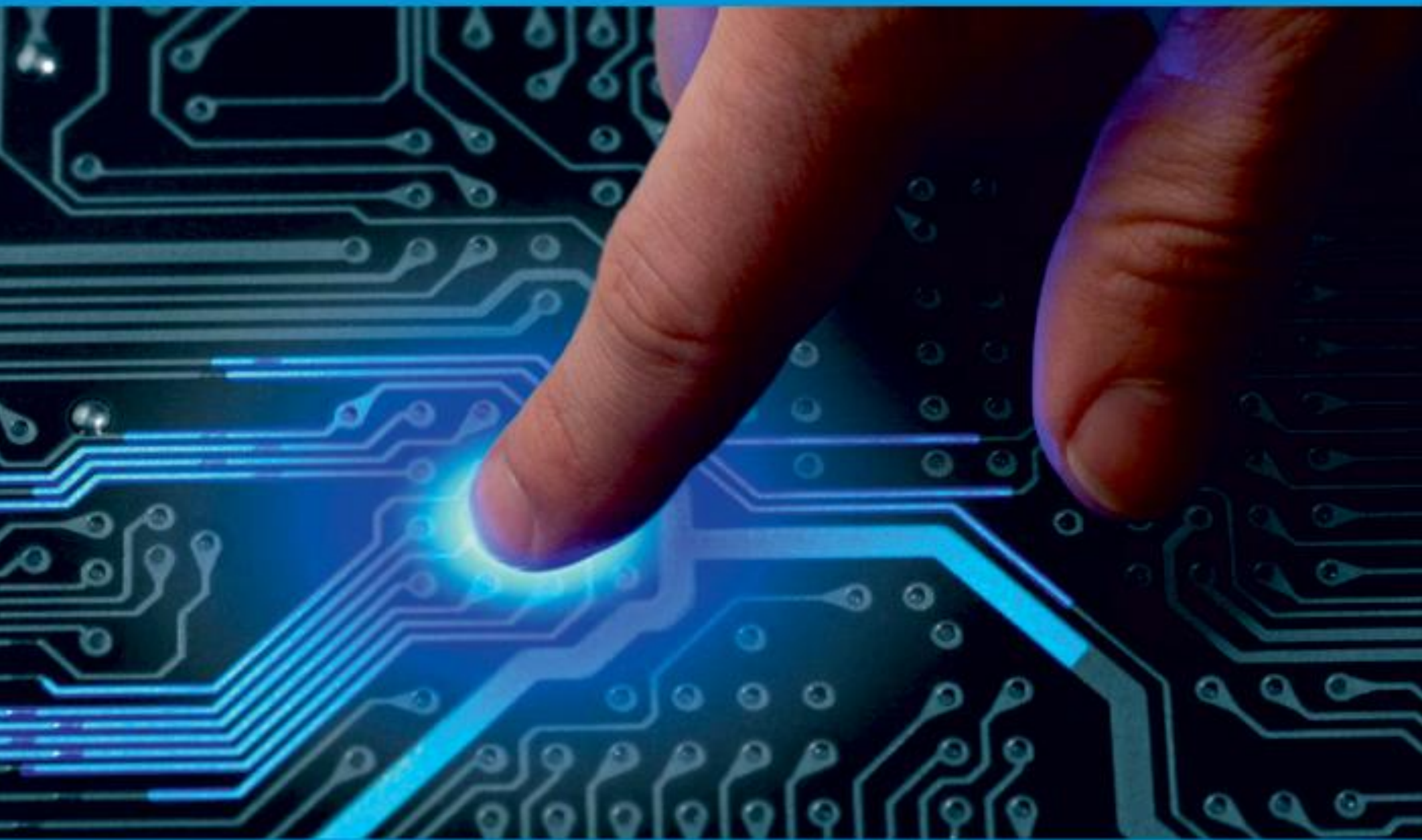
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 4, April 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

9940 572 462 6381 907 438 ijircce@gmail.com www.ijircce.com

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204249 |

Car Price Fluctuation Prediction using Machine Learning

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ABSTRACT: The automative industry is subject to dynamic changes influenced by various factors, including economic conditions, consumer preferences, technological advancements, and regulatory policies. Predicting Fluctuations in car prices is crucial for manufactures, dealers, and consumers to make informed decisions regarding buying, selling and public tourism plans. Many cab services have fixed prices regardless of demand or time of day. This means that users may end up paying more than necessary during peak hours or special events when demand is high. The Price of travel is adjusted daily based on demand for public transportation services. This dynamic pricing strategy allows the fare to fluctuate according to factors such as time of day, day of the week, seasonality, and special events. This Study proposes a machine learning-based approach to predict car price fluctuations. The proposed model leverages historical data on car prices along with relevant features such as destination, sources, fuel, timestamp, cab type and technological innovations. Through data preprocessing, feature engineering, and model selection techniques, the model aims to capture the complex relationships between these variables and car prices. The effectiveness of the proposed approach is assessed through comprehensive experimentation and performance evaluation using real-world car price datasets and also weather dataset. The results demonstrate the potential of machine learning models in accurately forecasting car price fluctuations, thereby providing valuable insights for public.

KEYWORDS: Random Forest, Price Prediction, Cab Fare Fluctuation, Prediction.

I.INTRODUCTION

Many organizations do not have a direct role in travel and tourism but offer related products and services. Some examples would be offering travel insurance, parking facilities at airports, theatre and event tickets, car hire, and travel by rail or coach to airports, etc. at competitive rates. There are various different forms of dynamic pricing: 1. Peak Pricing – This is a strategy that is common in transportation businesses. Airlines are a good example. Airlines often charge a higher price to travel during rush hour mostly on weekdays and sometimes on weekends. 2. Surge Pricing – Companies such as Uber respond dynamically to changes in supply and demand in order to price their services differently. Like most of us have noticed, this frequently happens on stormy evenings and nights when more people request for cabs. Taxify also not so long ago introduced dynamic pricing to ensure the drivers are encouraged to go online and offer services when the demand is high. Every day the price of travel was changed due to the demand for public uses. The framework developed for the price prediction is analysed for the travel plans. For the same travel plan offered at a fixed price for a particular group of customers, our proposed model saw a final fare with a lesser number of errors in predicting customer planning.

II.SYSTEM MODEL AND ASSUMPTIONS

Cab price prediction typically falls within the domain of regression analysis, where the goal is to estimate a continuous target variable in this case, the fare price based on one or more predictor variables, such as time of day, day of the week, location, and demand-supply dynamics. Regression models in machine learning, such as linear regression, decision trees, and ensemble methods, are commonly used for this purpose.
Feature engineering plays a crucial role in predicting cab price fluctuations. It involves selecting, transforming, and creating new features from the raw data to improve the predictive performance of the model. Features such as time-

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related variables (e.g., hour of the day, day of the week), weather conditions, traffic patterns, and events in the vicinity can significantly impact cab fares and thus need to be carefully engineered.
Predicting cab price fluctuations using the Random Forest algorithm involves several key steps. Firstly, historical data on cab prices, alongside relevant features like time of day, day of the week, location, weather conditions, and demand-supply dynamics, is collected and pre-processed. This preprocessing phase includes handling missing values, encoding categorical variables, and scaling numerical features as necessary. Next, feature selection and engineering techniques are applied to identify the most influential features and potentially create new ones.
The successful implementation of this system involves several key components, including thorough data acquisition, preprocessing, model development, and continuous monitoring and maintenance. Data must be collected from a variety of sources, pre-processed for consistency and quality, and fed into the Random Forest model to train and validate predictions.

III. EXISYTING SYSTEM

The traditional model for cab services, which primarily relies on fixed pricing or manually adjusted fares, exhibits several shortcomings that can lead to inefficiencies and customer dissatisfaction. Fixed pricing does not account for fluctuating demand throughout the day or during special events, often resulting in users paying more than necessary during off-peak times or excessively high rates when demand spikes. This rigidity offers little room to adapt fares in response to real-time variables such as traffic congestion or weather conditions, potentially leading to missed opportunities for revenue optimization and inefficient resource allocation. Additionally, the lack of real-time data integration means that pricing may not accurately reflect the actual costs associated with variables like travel distance, time spent, or current demand, which can result in either overcharging or undercharging customers. This inaccuracy, coupled with a general opacity regarding how fares are calculated, particularly during surge pricing, may erode trust and leave customers feeling frustrated due to the absence of clear, transparent fare algorithms. Furthermore, this unpredictability in pricing complicates budgeting and planning for users, especially during emergencies or unforeseen events, adding an extra layer of difficulty in managing transportation expenses. Overall, the existing fixed pricing system in many cab services appears increasingly misaligned with customer expectations and dynamic market conditions.

IV.PROPOSED SYSTEM

Proposed model introduces several significant advantages over traditional fixed pricing systems by utilizing dynamic pricing optimization and advanced predictive capabilities. By dynamically adjusting cab fares based on real-time demand and other relevant factors such as weather, traffic, and special events, our system not only maximizes revenue for service providers but also ensures fair pricing for users. This is achieved through sophisticated machine learning algorithms that accurately capture the complex relationships between input variables and cab fares, significantly improving the accuracy of fare predictions compared to the older fixed pricing models. Moreover, our approach enhances transparency in the pricing process. Users receive clear explanations regarding fare adjustments, which are based on objective, understandable criteria. This transparency fosters trust and confidence among users, distinguishing our service in a competitive market. Additionally, the dynamic pricing model incentivizes drivers to be available during peak times, which optimizes resource allocation, reduces passenger wait times, and increases the overall efficiency of the cab service. This model not only refines operational efficacy but also continuously evolves.

V. RESULT AND DISCUSSION

In the fig 1, The home page serves as the main entry point for users, providing an overview of the cab price fluctuation prediction system and its features. The home page contains the brief information about the project.

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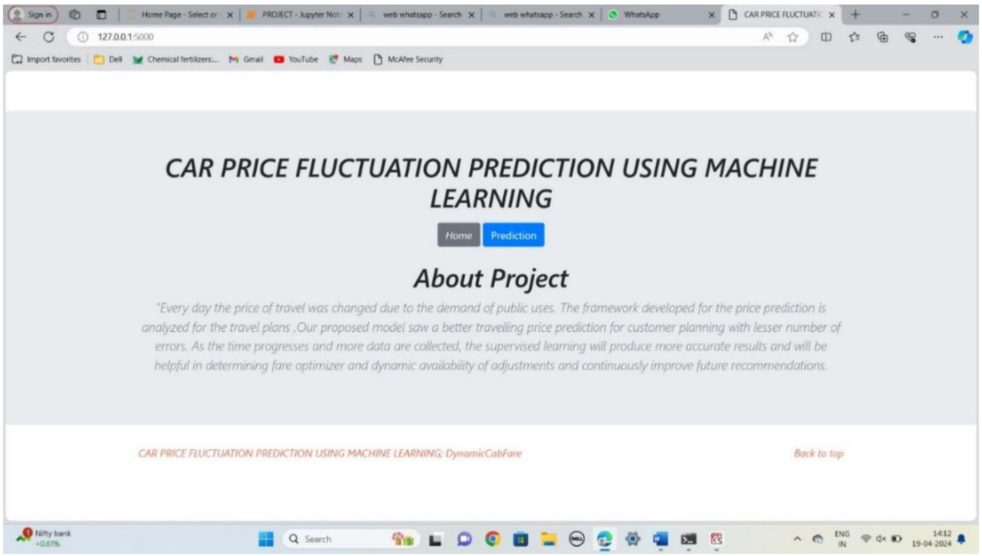

Fig. 1 Home Page

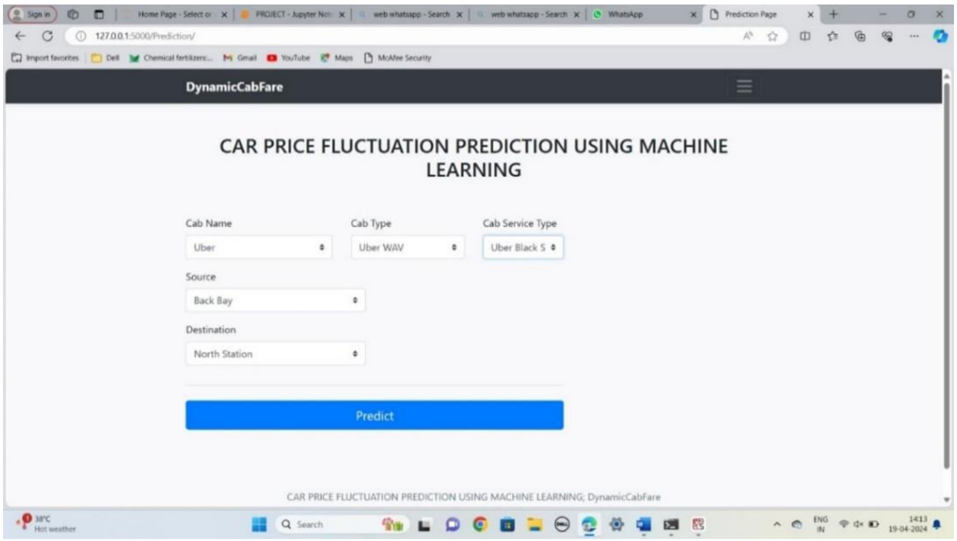

Fig. 2 Prediction Page

- In the fig 2, The above prediction page we can fill the details of of car name, Source, Destination, Cab Type and cab service type.

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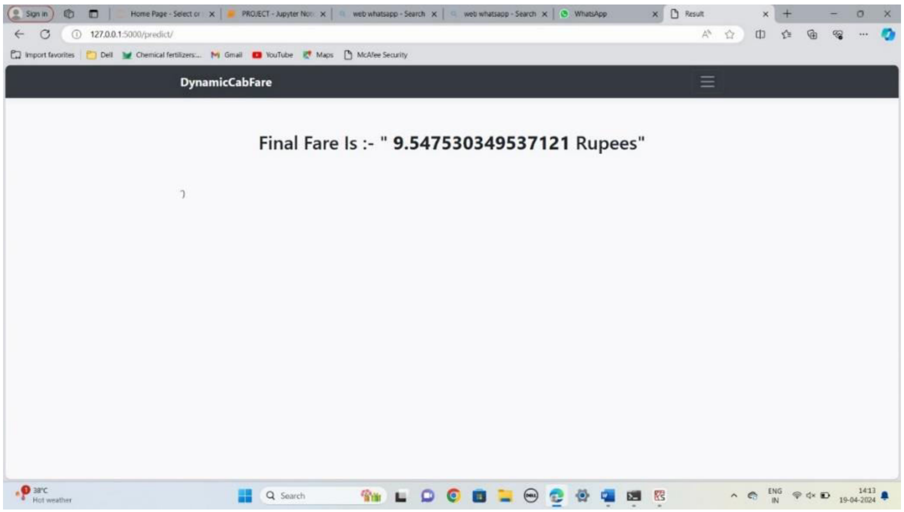

Fig .3 Final Fare Prediction

In Fig 3, In the final fare prediction page through the given information, we can predict the price travelled from source to destination in the cab.

VI. CONCLUSION

In conclusion, the cab price fluctuation prediction system using machine learning and the Random Forest algorithm offers a significant advancement in the way transportation services manage pricing strategies. By applying machine learning to analyse historical data and real-time information, the system accurately predicts cab fare fluctuations, reflecting demand patterns, time of day, location, and external factors such as traffic and weather conditions.

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[5] Cab Fare Prediction Using Machine Learning (ResearchGate) details a system for trip fare prediction using deep neural networks and location data [6] **Machine Learning for Ridesharing** by Nikhil Krishnan [6] (You can find relevant research papers through this resource).

[7] Explore research repositories like arXiv or IEEE Xplore for recent publications on cab fare prediction using keywords like "taxi fare prediction," "machine learning,"

[8] A Deep Ensemble Learning Model for Taxi Demand Prediction by Qin et al. (2019) explores using ensemble learning models for improved taxi demand prediction [1].