DYNAMIC FOOD DELIVERY RESPONSE TIME CALCULATOR

REPORT

Introduction :
Our project aims to develop a predictive model for estimating food delivery time using machine learning. With food delivery services in high demand, optimizing delivery times can enhance customer satisfaction and operational efficiency. We used the XGBoost model to predict the travel time for deliveries based on several factors, including traffic, weather and specific attributes of the delivery personnel.

Literature Review :
Existing research in food delivery optimization often emphasizes route planning, traffic prediction, and customer satisfaction metrics. However, these studies overlook an integrated model that accounts for the delivery personnel’s characteristics, traffic, weather and vehicle types. We address this gap by combining these diverse factors to improve prediction accuracy.
Applications like Blinkit, Zomato and Swiggy use only traffic predictions, not several other factors like weather conditions, type of vehicle, age of the person etc.

Methodology :
Data was stored in SQL, ensuring efficient management and querying. Features such as Delivery_person_ID, Delivery_person_Age, and Delivery_person_Ratings, along with spatial data (latitude and longitude), were collected. One-hot encoding was applied to categorical variables (like Type_of_order and Type_of_vehicle).
The XGBoost model, a high-performance gradient-boosting technique, was used to predict delivery time (Travel_Time_Minutes), given its suitability for handling complex feature interactions. API keys were used to tell distance between the locations, traffic level, weather conditions. Also, some features exhibited high correlation, though the XGBoost model is less affected by multicollinearity, we still used PCA.

Results and Analysis :
The findings include performance metrics like RMSE and MAE, supported by visualizations (e.g., scatter plots of predicted vs. actual delivery times and feature importance graphs). These results suggest that traffic and weather are strong influencers on delivery time, with additional contributions from other factors like delivery person ratings, age etc.

Conclusion and Recommendations :

Key findings indicate that high traffic levels and adverse weather conditions are primary determinants of delayed delivery times. Recommendations include exploring route optimization during peak traffic and incorporating real-time traffic and weather data. Future research could expand to include customer satisfaction metrics and additional geographic data like conditions of the road etc.