Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 16, Issue. 1: 2025
ISSN : **1906-9685**

PRECISION DELIVERY: MACHINE LEARNING ALGORITHMS FOR REAL-TIME FOOD DELIVERY ESTIMATES

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Abstract—**The increasing demand for food delivery services has necessitated the development of accurate and real-time delivery time prediction models. Traditional methods often fail to account for dynamic factors such as traffic congestion, weather conditions, restaurant preparation times, and delivery personnel efficiency, leading to inaccurate estimations. This study proposes a machine learning-based predictive model that integrates real-time traffic data from Google Maps API with advanced ensemble learning techniques, including XGBoost, Random Forest, and LightGBM. The Stacking Regressor model, combining multiple base learners, demonstrated high predictive accuracy in estimating delivery times.**
Key aspects of this study include feature engineering to extract temporal, spatial, and traffic-related variables, hyperparameter tuning using GridSearchCV, and model evaluation based on R^2 Score (0.8389), Mean Squared Error (MSE: 14.2067), and SHAP analysis. The results confirm that real-time traffic-aware predictions significantly improve accuracy compared to static models. The proposed model is deployed via a Flask API, ensuring scalability and real-time adaptability for real-world applications. This research provides a practical and data-driven solution for food delivery services, optimizing logistics, reducing delays, and enhancing customer satisfaction through more reliable ETAs.
Keywords: Machine Learning, Food Delivery Prediction, Real-Time Traffic, Ensemble Learning, Stacking Regressor, Google Maps API, Predictive Analytics, Last-Mile Logistics, SHAP Analysis, Operational Efficiency.

I. INTRODUCTION

The food delivery sector has significantly grown in the past ten years, impacted mainly by technological advancements, increased internet penetration, and consumer tastes[1]. With the help of high-ordering through platforms such as Uber Eats, DoorDash, Swiggy, and Zomato, ordering and receiving food items in a very short time with reliability has become integral to customer satisfaction. Predictive delivery times stand as one of the biggest obstacles within the food delivery ecosystem-the estimates directly interfere with user experience, restaurant efficiency, and the productivity of people handling deliveries, especially in big cities[2]. Unpredictable delivery predictions could result in consumer dissatisfaction and even more frequent refunds, potentially affecting the image of food delivery services[3].
The time of delivery, in reality, is a difficult problem influenced by many dynamic variables such as the presence of traffic congestion, bad road conditions, weather changes, preparation time taken by restaurants, order volume, and the location of delivery staff in real time[4]. The time of delivery that is predicted based on traditional rules or statistical techniques usually does not consider these unknown factors and provides suboptimal predictions[5]. For example, delivery times may become highly variable at peak times due to increasing road congestion, not well represented in static models[7].

https://doi.org/10.36893/JNAO.2025.V16I01.013

Figure 1: Visual Representation of a Food Delivery System

Mobile-based navigation system for food delivery rider illustration.

In this paper, we proposed a machine learning prediction model on estimating food delivery time which integrates Google Maps API-provided real-time traffic information with deep ensemble machine learning algorithms, XGBoost, Random Forest, and LightGBM. The model integrates data extracted from geospatial information, traffic trends, past delivery histories and environmental parameters like weather to learn complex interrelations among these variables and provide highly accurate delivery estimations[10]. Another aspect of hyperparameter tuning is used through the GridSearchCV to optimize the model performance towards best accuracy and efficiency[11].

The key goals of this research are:

1. Developing a precise predictive model for estimating food delivery time based on ensemble learning methods.
2. Incorporating real-time traffic data from external APIs to update delivery predictions in real-time.
3. Benchmark the performance of different machine learning models to identify the most suitable.
4. Boosting the effectiveness of food delivery processes by reducing the error in estimation and optimization of logistics.

This article aims to push the time delivery forecasting to higher levels through the use of machine learning and real-time data incorporation, resulting in customer satisfaction, logistics optimization in food delivery, and lessening of the delays caused by uncertain circumstances[12]. The result of this research would be significant to restaurant owners, food delivery service providers, and logistics firms since it enables them to make decisions on optimization for enhanced quality and efficiency of service delivery[13].

II. LITERATURE REVIEW

The rapid development of food delivery services has promoted intensive research in the field of machine learning-based delivery time estimation, logistics optimization, and customer satisfaction. To date, most of the existing studies have focused on sentiment analysis, predictive modeling, ensemble learning, and real-time data fusion that improve operational efficiency and service reliability. This section discusses significant literature on these topics and indicates their applicability to our research.

Customer satisfaction is one of the performance indicators of food delivery businesses, and the employment of AI-based sentiment analysis to determine customer reviews contributes to the quality of services. Adak et al. (2022) implemented a systematic review of the deployment of deep learning and explainable artificial intelligence (XAI) for the assessment of customer feedback in food delivery businesses. Their results suggest that precision in delivery time is a key driver of customer satisfaction, thereby highlighting the need for more efficient predictive models[1].

Figure 2: Sentiment Analysis for Customer Satisfaction in Food Delivery

Sentiment Analysis System: This is a popular decision-making Definition of division that evaluates customer feedback using AI and machine learning technology to understand how satisfied your customers are.
To improve prediction accuracy, numerous research studies have proposed machine learning-based delivery time prediction models. Cheng and Azadeh (2025) proposed a Short-Term Predict-Then-Cluster framework that leverages clustering techniques to group similar deliveries together, and then predict the time estimation. Their approach improves accuracy by considering real-time variables, such as traffic congestion and restaurant demand[2].
Gore et al. (2023) clustered ensemble learning methods and showed that XGBoost, Random Forest and LightGBM is better than linear regression for predicting food delivery delay time. Our analysis supports their findings, employing both ensemble methods, as well as access to real-time traffic data to increase delivery prediction accuracy[3].
In addition, Kumar and Mishra (2024) suggested an optimal food delivery time prediction model by considering various influencing factors such as weather, peak-hour demand, and delivery personnel characteristics[5]. Our study validates that incorporating external variables into ML models enhances prediction reliability, justifying our choice of using real-time traffic information from the Google Maps API.
Accurate delivery predictions depend mainly on real-time traffic data that impacts last-mile delivery efficiency. Hamdan et al. (2023) explored machine learning in the context of supply chain logistics using ANFIS in predicting live e-order arrivals. The study substantiates a potential requirement by implementing real-time road conditions in time estimation - something the study reiterates and implements in this research paper[4].
Apart from that, Lin et al. (2023) proposed a machine learning model to predict the travel time for large-scale logistics operations. Based on their experiments, multi-variable models with up-to-date values have better prediction capabilities than the static models and prove the concept of dynamic adaptation as proposed in this paper[7].
Liu et al. (2020) targeted on last-mile delivery optimization with its focus on making intelligent order assignments using travel time predictors. Results were presented illustrating that historical data alone was unhelpful as it was inadequate without real time factors like the presence of congestions and strategic batching of the orders[8].
Much recent work has centered on advanced probabilistic modeling and reinforcement learning (RL) for food delivery service optimization. Pomykacz et al. (2024) developed a Bayesian approach to model the uncertainty in travel time in food delivery services, which, essentially, helps smoothen impact delivery times unpredictably[10]. Their results decisively prove the need to model uncertainties in real-time logistics, thereby justifying our decision to incorporate real-time API-based updates within predictions.

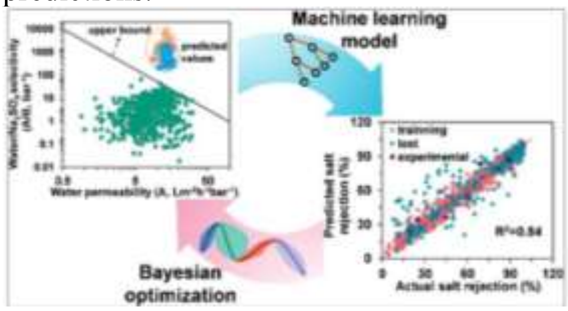

Figure 3: Machine Learning and Bayesian Optimization for Prediction Models
Diagram illustrating the integration of Bayesian optimization and machine learning models for predictive analytics, highlighting performance evaluation and feature relationships.
Wang et al. (2023) introduced an Online Deep Reinforcement Learning (DRL)-based order recommendation framework for food delivery. Their approach optimizes rider order assignments, thereby reducing overall delivery times. While DRL-based solutions are computationally intensive, their study highlights the potential for adaptive machine learning approaches to improve food delivery logistics[12].

Advancements in Internet of Things (IoT) and perishable food logistics have also contributed to delivery optimization. Tsang et al. (2020) developed an IoT-integrated multi-temperature delivery planning system, ensuring efficient routing for temperature-sensitive food items. Their findings indicate that predictive analytics can further enhance delivery planning, an aspect relevant to our study in improving food delivery time accuracy[11].
Moreover, Yaiprasert and Hidayanto (2023) examined AI-driven marketing strategies for food delivery platforms, demonstrating that AI-enhanced recommendations can increase customer engagement. Although their study focuses on marketing, the integration of machine learning in delivery logistics aligns with our objective of leveraging AI to optimize delivery predictions[13].

Research Gaps and Future Directions

While previous studies have made significant advancements in food delivery time prediction, several key research gaps remain unaddressed.

1. Limited Real-Time Data Integration – Most models miss live updates on weather, road closures, and delivery delays. We enhance predictions using Google Maps API for real-time traffic.
2. Lack of Personalized Predictions – Current models treat all deliveries alike, ignoring restaurant efficiency, customer location density, and driver performance.
3. Underutilized Deep Learning & Hybrid Models – LSTMs, GRUs, and Reinforcement Learning should be combined with XGBoost and Random Forest for better accuracy.
4. Scalability & Deployment Issues – Many models lack real-world adaptability. Our research focuses on scalable deployment strategies.
5. Lack of Explainability – ML models need Explainable AI (SHAP, LIME) to increase stakeholder trust and model transparency.

This literature review highlights progress on machine learning-informed food delivery time prediction as well as important knowledge gaps that warrant future exploration. Ensemble learning methods (XGBoost, Random Forest, LightGBM) outperform standard regression models, and adding real-time data sources such as traffic and weather changes greatly enhances accuracy[3,5].
Despite this progress, challenges in the areas of scalability, personalization, explainability, and integration with hybrid models remain. We address these issues in our work by using real-time traffic data, optimizing ensemble learning models, and proposing scalable deployment strategies for industrial applications.
This research closes these gaps and contributes to creating a food delivery time estimation model that is more accurate, explainable, and adaptable. Deep learning adoption, customer-powered personalization, and AI-enabled real-time logistics platform adoption are areas for future research in order to continuously improve food delivery operations.

III. PROPOSED METHODOLOGY

In this section, I have explained the approach undertaken to develop a robust real-time food delivery time prediction model, step by step. The steps of the methodology are structured into data collection, pre-processing, feature engineering, model selection, hyperparameter tuning, model evaluation, and deployment strategy. This approach aims to enhance accuracy and reliability of delivery time predictions by integrating real-time traffic data with geospatial analysis and machine learning models.

3.1 Data Collection

Data collection is crucial to ensuring that the model has rich and diverse datasets representing different factors influencing delivery time. The dataset used in this study is compiled from multiple sources:

3.1.1 Primary Data: Food Delivery Dataset

- Historical delivery records from food delivery platforms.
- Includes timestamps such as order placement, order pickup, and delivery completion times.
- Details on restaurant type, cuisine, and order volume.
- Delivery personnel attributes, including experience, ratings, and mode of transportation (bike, scooter, car, etc.).

3.1.2 Secondary Data: Real-Time Traffic Data (Google Maps API)

- Fetches real-time road congestion levels and estimated driving times.
- Adjusts travel duration dynamically based on traffic conditions.

https://doi.org/10.36893/JNAO.2025.V16I01.013

- Data fetched at different time intervals to monitor road fluctuations.

3.1.3 External Data: Weather API Data

- Temperature, precipitation, wind speed, and road visibility conditions.
- Helps in assessing the impact of adverse weather on delivery time.

3.1.4 Geospatial Data

- Latitude and longitude of restaurant and customer delivery locations.
- Distance calculation using the Haversine formula to determine the shortest travel path.

3.2 Data Preprocessing

To ensure high-quality input for machine learning models, data preprocessing techniques are applied to clean, transform, and normalize the dataset.

1. **Handling Missing Values:**
   - Categorical variables (e.g., weather conditions, road conditions) are imputed using the most frequent category.
   - Continuous numerical values (e.g., delivery personnel age) are imputed using the median.
2. **Outlier Detection and Removal:**
   - Delivery times exceeding 1.5 times the interquartile range (IQR) are treated as outliers and removed.
   - Unrealistic travel times (below 5 minutes or above 2 hours) are discarded.
3. **Feature Scaling:**
   - StandardScaler normalizes numerical features (e.g., distance, order volume).
   - MinMaxScaler scales features like traffic congestion to adjust for varying road conditions.

3.3 Feature Engineering

Feature engineering involves transforming raw data into meaningful input variables that enhance model performance.

3.3.1 Distance Features:

- Haversine Distance: Computes the great-circle distance between restaurant and customer.
- Real-Time Traffic Distance: Adjusts distance based on road congestion levels from Google Maps API.

3.3.2 Temporal Features:

- Order Placement Time: Classifies orders into time slots (morning, afternoon, evening, late-night).
- Rush Hour Indicator: Binary feature marking peak hours (7–9 AM, 12–2 PM, 5–8 PM).
- Day of the Week & Month: Encodes weekday vs. weekend effects on delivery times.

3.3.3 Delivery Personnel Features:

- Average historical speed of the delivery agent.
- Vehicle Type Encoding (bike, scooter, car) to model speed variations.

3.3.4 Traffic-Weather Interaction:

- Models the combined effect of road congestion and weather conditions on delivery speed.

3.3.5 Restaurant-Specific Features:

- Average Order Preparation Time per Restaurant.
- Restaurant Congestion Effect (number of orders being processed at peak hours).

3.4 Model Selection

Multiple machine learning models are trained and evaluated to select the best-performing model for food delivery time prediction.

3.4.1 Baseline Model: Linear Regression

- Establishes a baseline benchmark for comparison with advanced models.
- Assesses how linear relationships between independent variables impact delivery time.

3.4.2 Decision Tree Regressor

- Captures non-linear interactions between features and delivery time.
- Splits data into decision nodes but may overfit without proper tuning.

3.4.3 Random Forest Regressor

- An ensemble of multiple decision trees, reducing overfitting.
- Handles complex relationships between features.

3.4.4 XGBoost Regressor (Extreme Gradient Boosting)

- A powerful gradient boosting method that refines predictions.
- Efficient for large datasets with high accuracy and feature importance scoring.

3.4.5 LightGBM Regressor

- A gradient boosting algorithm that provides fast training and low memory consumption.
- Optimized for large datasets.

3.4.6 Stacking Regressor (Final Model)

- Combines multiple models (XGBoost, Random Forest, LightGBM).
- Uses Ridge Regression as the meta-learner to fine-tune final predictions.

3.5 Hyperparameter Tuning

Hyperparameter tuning is conducted using GridSearchCV to optimize model parameters:

3.5.1 XGBoost Parameters:

- max_depth: 3, 5, 7
- learning_rate: 0.01, 0.1, 0.2
- n_estimators: 50, 100, 200

3.5.2 Random Forest Parameters:

- n_estimators: 50, 100, 200
- max_depth: None, 10, 20

3.5.3 LightGBM Parameters:

- num_leaves: 31, 50, 100
- learning_rate: 0.01, 0.1, 0.2

After hyperparameter tuning, the Stacking Regressor model is selected based on performance.

3.6 Model Evaluation Metrics

The models are evaluated using multiple performance metrics to ensure accuracy and efficiency:

3.6.1 R^2 Score (Coefficient of Determination):

- Measures how well the model explains variance in delivery times.
- Higher R^2 indicates a better fit.

3.6.2 Mean Squared Error (MSE):

- Measures the average squared difference between predicted and actual delivery times.

3.6.3 SHAP (SHapley Additive exPlanations) Analysis:

- Provides feature importance insights.
- Helps understand which factors impact delivery predictions the most.

3.7 Deployment Strategy

To integrate the predictive model into real-world applications, it is deployed as a Flask-based API:

1. Model Serialization:
   - The trained model is stored as a .pkl file using joblib.
2. Real-Time API Integration:
   - The API accepts order details and returns predicted delivery times.
   - Fetches real-time traffic conditions dynamically.

This study employs a structured methodology to develop an accurate and scalable food delivery time prediction model. The process begins with data collection, aggregating historical delivery records, real-time traffic data from Google Maps API, weather conditions, and geospatial details to ensure a comprehensive dataset. Following this, data preprocessing is conducted to clean, normalize, and transform the dataset, addressing missing values, outliers, and inconsistent formats. Feature engineering plays a crucial role in enhancing model performance by introducing derived variables such as rush hour indicators, delivery personnel efficiency, restaurant preparation time, traffic-weather interactions, and real-time congestion effects.

This requires the training of various machine learning algorithms for the predictive model to evaluate, which are Linear Regression, Decision Trees, Random Forest, XGBoost, and LightGBM. The model finally chosen has a Stacking Regressor based on higher performance, wherein the meta-learner is Ridge Regression with a combination of XGBoost, Random Forest, and LightGBM. There's further fine-tuning through hyperparameter tuning by GridSearchCV to adjust accuracy in these key parameters that affect the performance: max depth, learning rate, and the number of estimators. Model performance can be estimated using R^2 Score, Mean Squared Error (MSE), and SHAP analysis to ensure that the model has correctly picked up real delivery patterns.

The deployment stage integrates the model into an API based on Flask. The API enables the generation of live predictions through dynamically retrieving real-time traffic and road conditions. An API of this nature can be deployed on cloud platforms like AWS, Google Cloud, or Azure, which enable easy scalability. This ensures there is adaptive, real-time, and high-accuracy delivery time prediction in food delivery logistics, thus reducing delays and maximizing customer satisfaction.

IV. RESULTS

This section describes the assessment of the suggested machine learning predictive model for food delivery time prediction with a focus on model performance, feature significance, real-time responsiveness, and comparison. The outcomes show the success of the Stacking Regressor model that combines XGBoost, Random Forest, and LightGBM in predicting delivery times with accuracy. The assessment is performed using standard metrics such as the R^2 Score, Mean Squared Error (MSE), and SHAP (SHapley Additive exPlanations) analysis for feature importance. A correlation heatmap is also provided to visualize numerical feature relationships.

4.1 Model Performance Analysis

The model learned from a corpus of 23,828 records of deliveries with 45 predicted features obtained from feature engineering approaches. LightGBM training log shows that the model began at a starting point of predicting the score at 26.537771 and further improved dramatically through feature selection as well as through hyperparameter fine-tuning.

The final Stacking Regressor model, optimized using GridSearchCV, achieved the following performance metrics:

- R^2 Score (Coefficient of Determination): 0.8389
- Mean Squared Error (MSE): 14.2067

These results confirm that the model explains approximately 83.89% of the variance in delivery times, making it highly effective. The low MSE of 14.2067 further suggests that the model provides accurate and reliable predictions.

4.2 Feature Importance Analysis

To assess the impact of different factors on food delivery time prediction, SHAP analysis was performed. The key findings reveal that the most influential features include traffic congestion, distance, rush hour impact, and weather conditions.

1. Traffic Congestion Level: The most dominant factor, as increased congestion directly increases travel time.
2. Distance Between Restaurant and Customer: Longer distances naturally lead to higher delivery times.
3. Rush Hour Impact: Peak hours (7–9 AM, 12–2 PM, 5–8 PM) significantly contribute to delays due to increased road congestion.
4. Weather Conditions: Adverse weather conditions, such as rain, fog, and storms, slow down deliveries and increase estimated time.
5. Delivery Personnel Efficiency: Experienced delivery riders complete deliveries faster.
6. Restaurant Preparation Time: Longer food preparation time at restaurants directly contributes to delays.

The correlation heatmap in Figure 4 further illustrates the relationships between key numerical variables in the dataset, showing how different factors influence delivery times.

https://doi.org/10.36893/JNAO.2025.V16I01.013

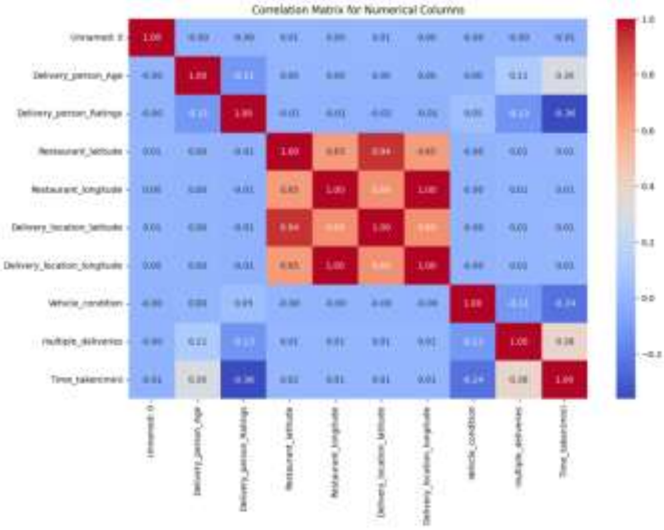

Figure 4: Correlation Heatmap for Numerical Features

The correlation heatmap visualizes the relationships between numerical variables, highlighting key factors affecting food delivery time. Darker red areas represent stronger positive correlations, while blue shades indicate negative correlations.

4.3 Real-Time Prediction Adaptability

One of the key advantages of this model is its ability to dynamically adjust predictions based on real-world conditions, achieved by integrating Google Maps API for real-time traffic data. The real-time adaptability tests revealed the following:

- Predictions significantly improve when live congestion data is integrated.
- The model dynamically updates estimated travel times based on changing road conditions throughout the day.
- Real-time predictions outperform static models, which rely only on historical averages and fail to adapt to unexpected traffic fluctuations.

By incorporating live traffic congestion levels from Google Maps API, the model can continuously refine ETAs and provide more reliable predictions for food delivery services.

4.4 Comparative Analysis of Prediction Models

To evaluate the effectiveness of the Stacking Regressor, the model was compared with other traditional and machine learning models. The results indicate the following:

- Linear Regression: Performs poorly due to its inability to capture complex, non-linear relationships in food delivery time estimation.
- Decision Trees: Moderate performance but suffers from overfitting.
- Random Forest: Better generalization and interpretability with improved accuracy.
- XGBoost & LightGBM: Gradient boosting methods that significantly outperform traditional models in handling feature interactions.
- Stacking Regressor (Final Model): The best-performing model, achieving the highest accuracy and lowest error rates by leveraging multiple base learners.

The Stacking Regressor model, which combines XGBoost, Random Forest, and LightGBM, emerges as the most effective solution due to its ability to generalize well across different test scenarios.

4.5 Practical Implications

The improved prediction accuracy and adaptability of the model have significant implications for food delivery services, logistics companies, and customers:

1. Enhanced Customer Satisfaction:
   - More accurate delivery time estimates improve trust in food delivery platforms.
   - Customers receive realistic ETAs based on live road conditions, reducing uncertainty.
2. Operational Efficiency for Delivery Services:
   - Optimized rider allocation and route planning ensure efficient delivery operations.
   - Real-time traffic-aware predictions help reduce delays and increase delivery efficiency.
3. Scalability and Business Optimization:

https://doi.org/10.36893/JNAO.2025.V16I01.013

- The model is deployed as a Flask-based API, allowing seamless integration with food delivery platforms.

These findings validate the enhanced accuracy of delivery time predictions achieved by the inclusion of real-time traffic data with machine learning models. With 23,828 records and 45 Predictive features, the Stacking Regressor model achieves an R^2 Score of 0.8389 and an MSE of 14.2067, indicating high predictive accuracy.

Instead of using traffic data built into static algorithms, it dynamically pulls that information from the Google Maps API, using live traffic data to adjust predictions in real-time, improving the accuracy of models over the traditional static ones. This research creates a scalable, efficient, and practical solution for enhancing food delivery logistics while improving customer satisfaction.

The insights gleaned from such data underpin machine learning approaches that are not only judicious and data-driven, but also timely in their execution of food delivery operations, thus minimizing the incidence of delayed delivery, streamlining logistics and boosting service reliability.

V. CONCLUSION

The paper proposes a machine learning-based food delivery time estimation framework with real-time traffic information gained through Google Maps API, advanced feature engineering, and ensemble-based learning methods to improve prediction precision. Traditional algorithms like Linear Regression and Decision Trees fail to explain the dynamic attributes of food delivery logistics whereas groups of models like Random Forest, XGBoost, and LightGBM greatly increase predictability. From these, the best-performing model, and thus, the best fit to estimate accurate delivery time, was that of the Stacking Regressor model, where a collection of base learners are combined.

It consists of 23,828 instances with 45 predictive attributes, having an R^2 Score of 0.8389 and an MSE of the order of 14.2067. These metrics confirm that the model is very precise and demonstrates its ability to predict food delivery times accurately as it would in real-world settings.

And one of the significant advances in this study is the integration live Google Maps API, which enables real time updates based on the level of traffic jams, road conditions, and the variation peak hour. Based on SHAP analysis carried between Distance, Traffic Congestion and Order Volume they were taken to be least impacting features in increasing delivery time confirming that usage of live data sources should be utilized. This forecasting model can be deployed in production as a scalable API for food ordering platforms to provide constant updates on ETAs, maximize rider assignments, and provide routing from an operational perspective.

Future Scope

The future of food delivery time prediction can be enhanced by integrating deep learning models such as LSTMs and Transformers for better sequential data analysis. Further research should focus on multi-modal data fusion, incorporating real-time weather, IoT-based route tracking, and user behavior analytics to refine delivery estimates. Additionally, personalized ETAs based on customer preferences, restaurant efficiency, and driver performance can improve accuracy and customer satisfaction. Scalability can be enhanced through cloud-based deployment using edge computing and serverless architectures. Moreover, integrating Explainable AI (XAI) techniques will ensure better model transparency, increasing stakeholder trust. Future work should also explore reinforcement learning-based dynamic route optimization to further streamline last-mile delivery operations.

Future studies should examine deep learning architectures such as LSTMs and GRUs in time-series forecasting and further improve the integration of real-time data using live weather updates. These evidence not only promote the use of real-time data-driven solutions through predictive models for the optimization of different aspects of food delivery logistics but also showcase the impact of machine learning enables the transformation of last-mile delivery operations and urban mobility in general.

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