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A Comparative Analysis of Machine Learning Models for Time Prediction in Food Delivery Operations

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Abstract

Accurate time estimation is crucial for ensuring customer satisfaction and operational efficiency in the growing food delivery sector. This paper focuses on comprehensively analyzing factors affecting food delivery times and assessing the effectiveness of machine learning models in forecasting delivery times. For this purpose, authors incorporated a detailed dataset from a food delivery company on the Kaggle platform, encompassing delivery address, order time, delivery time, weather conditions, traffic intensity, and delivery person's profile information. The study evaluated the effectiveness and performance of various machine learning models such as Linear Regression, Decision Trees, Random Forests, XGBRegressor and the k-nearest neighbors (KNN) regression model using metrics like MAE, RMSE, and R^2. The results demonstrate that ensemble methods— XGBRegressor—outperformed the other models in accurately predicting delivery times, achieving an R-squared score of 0.82. Additionally, a thorough analysis of feature importance uncovered the factors influencing delivery time estimation. This study offers insights into leveraging machine learning techniques to optimize food delivery operations and enhance customer satisfaction. The discoveries can assist food delivery platforms in deploying effective time estimation models and emphasizing factors for predictions.

Keywords: machine learning; time estimation; feature importance; food delivery

1. Introduction

In the last few years, food delivery has experienced major expansion with the inception of the online platforms that connect customers, delivery drivers and restaurants. One of the difficulties that customers face is the uncertainty surrounding delivery times that prompts researchers to come up with predictive models that will allow estimations of delivery duration. These models tackle issues of planning, organization, and control to optimize operations of the delivery sector [1]. Moreover, there is a substantial body of research on speeding up the delivery process by using optimization methods that help in the more efficient routing of the vehicles [1] . Studies on delivery platforms require management decisions on issues such as the delivery times and subsidy administration to radically improve profits [2]. In this regard, cutting down on the delivery times is of vital importance for improving the level of customer satisfaction and for holding an edge among competitors. The industry of food delivery is in the process of ever-changing

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trends, wherein the most attractive features are being created first in both customer service improvement and in the field of delivery process optimization, as well as towards technology exploration to provide quick and prompt service.

There are numerous factors influencing food delivery times, that their impact has been studied, such as distance to the delivery address, restaurant preparation time, traffic conditions, weather conditions, and the experience of the delivery person [3]. Within this framework, the first aim of this study is to explore the key factors influencing food delivery times. These could include variables, such as the distance to the delivery address, restaurant preparation time, traffic conditions, weather conditions, and the experience of the delivery person. The outcome seeks to aid in finding effective solutions for optimizing delivery times, which are crucial for improving operational strategies and customer service.

Machine Learning (ML) is an effective tool for providing ways out of this predicament. Within the framework of the enhancement of food delivery time, academic scholars have explored the application of ML tools. More specifically, ML algorithms can optimize delivery times by learning sophisticated patterns, making predictions based on vast quantities of data. Hence, ML models have been used to detect travel times and incorporate predictors into optimization models to resolve the last-mile delivery problem [4]. This article explores how ML can be used to analyze the elements that determine delivery times and forecast them. This work aims to identify the most effective ML approaches for predicting food delivery times and to make this information usable for improving food delivery services. This will increase customer satisfaction and improve the operational efficiency of businesses. This initiative aims to provide valuable insights to companies in the food delivery industry, enabling them to offer faster and more reliable services.

In order to achieve its objectives, this study will examine the aforementioned factors and analyze how a range of ML models can accurately predict delivery times of food. The models used include Linear Regression, Decision Trees, Random Forests, KNN and XGBoost. The performance of each model will be evaluated using various metrics to determine the most effective one.

The following sections include a literature review of the studies related with ML applied in food sector, with emphasis on the delivery element; presentation of the undertaken methodology followed by the results; and concludes with the discussion and conclusions parts.

2. Literature review

This study aims to understand factors affecting food delivery times and to use these ML models for their prediction. This literature review section presents studies that have dealt with ML applications in the food sector, and particularly the food distribution aspect.

2.1. Relevant Studies

The research encompasses steps such as examining the integration of technological innovations like artificial intelligence and Machine Learning in the food industry, with a focus on the competitive food distribution sector [5]. The necessity for businesses to optimize their processes due to customers' preference for online platforms is highlighted [6]. Various studies have explored ML techniques in different contexts. For instance, an integrated approach combining mechanical modeling and ML was proposed for optimizing the thickness of frozen microwaveable foods, resulting in better heating homogeneity [7]. Liu et al. [7] discussed a framework integrating travel time predictions with order assignment optimization, emphasizing ML applications in food service delivery operations. Yang et al. [8] underscored the potential of ML in efficiently addressing challenges like delivery route decisions, food item demand forecasting, and logistic planning. They proposed a hybrid evolutionary optimization highlighting the performance advantages of ML-based algorithms for food delivery applications, focusing on package service, order selection and delivery route planning. Madani and Alshraideh [9] conducted a study on the vehicle routing problem in food order distributions, assessing the applicability of mathematical modeling and optimization techniques. The research emphasizes the potential of artificial intelligence in routing and timing to enhance the efficiency of logistics and distribution processes. They investigated the use of artificial intelligence and ML techniques to predict consumers' online purchasing decisions, providing significant insights for understanding consumer behavior and personalizing services. In their study, Maluud and Abdulazeez [10] build upon existing research highlighting the environmental, cost, and energy advantages of using e-scooters in postal and package delivery, evaluating the impact of these vehicles on delivery time and energy costs through the application of various ML algorithms. Such information can be utilized to comprehend customer preferences and behaviors in optimizing food delivery processes. The literature review process showed several approaches that were undertaken by scholars, and furthermore, a variety of factors that were explored as shown in the following Table 1.

Table 1. Studies on ML Applications in Food Delivery

Author(s)	Approach/Model	Factors Explored
Liu et al. [7]	Mechanical modeling and ML	Travel time predictions, order assignment
Zhang et al. [8]	Hybrid evolutionary optimization and ML algorithms for order selection and route planning	Order selection, delivery route planning
Madani and Alshraideh [9]	Mathematical modeling, optimization techniques, and artificial intelligence for routing and timing	Vehicle routing, delivery timing
Maluud and Abdulazeez [10]	ML algorithms for evaluating the impact of e-scooters on delivery time and energy costs, and understanding customer preferences	Vehicle mode (e-scooters), delivery time, energy costs, customer preferences
Moghe et al. [11]	Novel system based on multiple ML algorithms for enhanced delivery time estimates for batched orders	Order batching, delivery time estimates
Hildebrandt and Ulmer [12]	Offline and online-offline estimation approaches using supervised learning to improve meal arrival time estimations in restaurant meal delivery services.	Arrival time estimates, customer selections
Zhu et al. [13]	Utilization of a deep neural network (DNN) incorporating various features to enhance prediction efficacy	Order fulfillment cycle time
Gao et al. [14]	Application of deep learning using a deep network named FDNET, prediction of feasible locations, consideration of factors affecting driver behaviors, and introduction of spatiotemporal information.	Delivery route generation, time prediction, driver behaviors, spatiotemporal information
Liu et al. [15]	Integration of travel-time predictors with order-assignment optimization, reformulations of integrated models for efficient solving, and two simple heuristics for the multiperiod order-assignment problem.	Driver routing behavior, order assignment, travel time predictors
Gao et al. [16]	Applying Deep Learning Based Probabilistic Forecasting to Food Preparation Time for On-Demand Delivery Service	Food preparation time
Hughes et al. [17]	Evaluation of ML methodologies to predict stop delivery times from GPS data	Stop delivery times, duration prediction

Many studies primarily examine operational factors such as travel times, order assignments, and driver behavior, with limited consideration of external factors. Nevertheless, the analysis does not delve deeply into external factors like weather conditions, traffic patterns, and events that may affect delivery times. Moreover, certain studies acknowledge the drawback of not considering real-time factors, indicating the necessity of integrating real-time data (such as traffic updates and weather conditions) into predictive models to enhance the accuracy and adaptability of delivery time estimation. There is also a potential gap in the current research when it comes to incorporating customer preferences and behavior into predictive models. While some studies have touched on this topic, there is room for more extensive exploration of customer-related factors such as order preferences, historical data, and feedback. By incorporating these factors, we can enhance delivery efficiency and ultimately improve customer satisfaction.

This study focuses on optimizing food delivery times through ML approaches, while specifically exploring new factors and methods not previously addressed in the literature. It aims to extend beyond the examination of previously defined factors like traffic intensity, weather conditions, and the delivery person's experience, to delve into less explored dimensions such as the relationship between customer satisfaction and waiting time. Particularly, this research intends to offer strategic improvements in delivery processes by conducting an in-depth analysis of various data features affecting delivery times and comparing different ML methods. This approach expands the existing literature by testing the applicability of advanced algorithms and providing innovative solutions to the complexities and uncertainties of delivery processes. The contributions of this study have the potential to enhance the efficiency and customer satisfaction of food delivery operations, offering directly applicable insights for industry practice.

3. Methodology

This study follows a comprehensive methodology to identify factors affecting food delivery times and predict these times using Machine Learning models. Our methodology includes data collection, preprocessing, modeling, and evaluation, followed by the analysis of the results that Part 4 will present.

3.1. Data Collection

The dataset used in this research is from a food delivery company on the Kaggle platform [18]. It includes various features like delivery address, order time, delivery time, weather conditions, traffic intensity, and delivery person's profile information.

Food delivery adapts rapidly to today's dynamic lifestyle as a courier service. Offered by restaurants, stores, and specialized food delivery companies, customers usually place orders online via a restaurant's website, mobile app, or food ordering services. The delivery process involves various factors from start to end, directly affecting efficiency.

Delivered products may include main dishes, appetizers, beverages, desserts, and grocery items. They need to be transported safely and intact, often in boxes, bags, or thermal carriers. The delivery person's vehicle choice significantly impacts delivery speed and efficiency. Vehicle selection varies with geographic conditions and city structure; agile transport like bicycles or motor scooters in large cities, while cars are more common in wider, open areas.

3.1.1. Dataset Content

The dataset used in this study encompasses extensive data related to food delivery processes. Variables like the delivery person's identity, age, rating scores, coordinates of the restaurant and delivery point, order and delivery times, weather conditions, traffic intensity, condition of the delivery vehicle, and delivery type are analyzed to understand

and predict delivery times. These data are collected to thoroughly examine factors influencing food delivery times and predict them using Machine Learning models.

Table 2. Dataset Content

Variable Name	Data Type	Description
ID	object	Unique identifier for each delivery record.
Delivery_person_ID	object	Identifier for the delivery personnel involved in the delivery.
Delivery_person_Age	object	Age of the delivery personnel, typically a numerical value but listed as an object due to possible non-numeric entries
Delivery_person_Ratings	object	Ratings given to the delivery personnel, typically on a scale, but listed as an object due to possible non-numeric entries.
Restaurant_latitude	float64	Geographical latitude of the restaurant from where the order is dispatched.
Restaurant_longitude	float64	Geographical longitude of the restaurant from where the order is dispatched.
Delivery_location_latitude	float64	Geographical latitude of the delivery location
Delivery_location_longitude	float64	Geographical longitude of the delivery location.
Order_Date	object	The date on which the order was placed.
Time_Orderd	object	The time at which the order was placed.
Time_Order_picked	object	The time at which the order was picked up by the delivery personnel.
Weatherconditions	object	Descriptive information about the weather conditions during delivery.
Road_traffic_density	object	Information about the density of road traffic during delivery.
Vehicle_condition	int64	A numerical rating or categorization of the vehicle's condition used for delivery. This could represent various states of vehicle functionality and may impact delivery efficiency.
Type_of_order	object	Type or category of the order.
Type_of_vehicle	object	Type of vehicle used for the delivery.
multiple_deliveries	object	Indicator of whether the delivery person is handling multiple deliveries simultaneously.
Festival	object	Indicator of whether the delivery occurred during a festival.
City	object	The city in which the delivery took place.
Time_taken(min)	object	The time taken for the delivery, typically a numerical value but listed as an object due to possible non-numeric entries.

3.2. Data Preprocessing

The dataset underwent a data preprocessing process that included filling missing values, converting categorical data into numerical format, and cleaning outlier values. It was transformed into a DataFrame and consists of three CSV files: Sample_Submission, train, and test. Our studies were completed on the train dataset, which has 45,593 rows ranging from 0 to 45,592, indicating its comprehensiveness. There are a total of 20 columns observed, with names and data types including ID, Delivery_person_ID, Age, Ratings, Order_Date, and Time_taken(min), among others. Most columns were of the object type, typically used for categorical and textual information. However, columns like "Age", "Ratings", and "Time_taken(min)" were converted to the correct data types as they contain numerical data. Missing values were observed in some columns, and their correct imputation was crucial as it significantly impacts the analysis results.

3.3. Feature Selection and Engineering

In this study, the feature engineering process was comprehensively addressed. Initially, categorical data such as weather conditions and road traffic density were converted into a numerical format suitable for Machine Learning algorithms through Label Encoding. Subsequently, time-related features that could potentially impact delivery times were extracted from order dates, providing new information like day, month, and year. Additionally, delivery distances were calculated using the coordinates of restaurants and delivery points.

For feature selection, we applied the XGBRegressor model's built-in feature importance calculation method. This method evaluates the importance of each feature based on how much it contributes to the prediction accuracy of the model. The feature importances are calculated using the mean decrease in impurity (MDI) criterion, which measures the decrease in node impurity (weighted impurity decrease) for each feature when it is used for splitting in the decision trees that make up the XGBRegressor model.

All these features played a crucial role in enhancing the model's predictive capability and accuracy in estimating food delivery times. The process of identifying factors critical to the predictive accuracy of ML algorithms is a key step in feature engineering [3]. The detailed and comprehensive approach to feature engineering significantly improved the accuracy of the results and the overall performance of the model.

3.4. Model Development

Various Machine Learning models were developed and compared to predict delivery times. Machine Learning is the area of study that deals with the development of the algorithms and the statistical models that help computers to learn, and make inferences, as well as decisions, based on data without them being explicitly programmed. It is the process of using sophisticated mathematical models to process and interpret data, detect relationships, and make decisions or predictions based on the results. ML models have shown various remarkable results in learning highly intricate patterns from the data and then making future predictions for unseen data [19].

In this study, four different ML models were employed to predict the food delivery times. Each model has distinct characteristics and offers solutions for different types of data structures and complexities. These models include Linear Regression, Decision Trees, Random Forests, XGBoost, and KNN Regression:

1. Linear Regression: A basic and widely used statistical estimation method to model the relationship between independent variables and a dependent variable. It takes a weighted sum of the independent variables to predict a continuous output. This method deals with linear relationships between variables and provides an effective starting point for predicting food delivery times [10].
2. Decision Trees: These work by splitting the dataset into segments using simple decision rules, allowing them to model complex data structures. Decision trees are

non-parametric supervised learning algorithms [20]. Each decision node splits the data set into two or more homogeneous subsets, leading to predictions at the end.

3. Random Forests: Developed by Breiman [21] they combine multiple decision trees to create a 'forest' using ensemble learning techniques. Each tree is built from a random subset of the dataset, and the final prediction is made by averaging the predictions of all trees or by a majority vote. This approach reduces the risk of overfitting and usually produces more reliable and robust predictions than a single decision tree.
4. XGBoost (eXtreme Gradient Boosting): A high-performance gradient boosting library offering powerful algorithms for making predictions on complex datasets. Built on decision trees, XGBoost sequentially constructs trees, each learning from the errors of its predecessors. This model is favored for scalability, speed, and performance and often achieves high success in ML competitions and industrial applications [22].
5. K-Nearest Neighbors (KNN) Regression: A non-parametric algorithm that predicts the value of a data point based on the values of its nearest neighbors in the feature space. KNN regression finds the K closest training examples to the input and averages their output values [23].

Each model was trained using cross-validation and hyperparameters were tuned with GridSearchCV. A critical step in our model optimization process is identifying the most suitable parameters for different machine learning algorithms using GridSearchCV. GridSearchCV evaluates every combination within specified parameter ranges to select those that maximize the model's accuracy score. This procedure is applied to each model, aiming to enhance both its accuracy and generalization capacity. The selection of parameters such as depth (max_depth) for decision trees affects the complexity of the trees and thus the learning capacity of the model, while parameters like the number of trees (n_estimators) used in ensemble algorithms aim to increase the stability and reliability of the predictions. These parameters have been carefully adjusted to enhance our models performance [24].

3.5. Model Evaluation

In this phase, three primary statistical metrics were used to evaluate the prediction performance of the machine learning models regarding food delivery times, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). These metrics measure how accurate the model's predictions are and how well they fit the actual data.

1. Mean Absolute Error (MAE):

Mean Absolute Error (MAE) is a measure of how much the predictions of a model deviate from the actual values. For each prediction, the absolute difference from the real value is calculated, and the average of these differences is computed. Mathematically, it can be expressed as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

Here, y_i represents the actual values, and $\hat{y}_i$represents the model's predictions.n is the number of observations. This metric is crucial for understanding the accuracy of the model in predicting the outcomes [25].

2. Root Mean Squared Error (RMSE):

Root Mean Squared Error (RMSE) is a metric used to measure the magnitude of errors in a model's predictions. It calculates the square root of the average of the squares of the prediction errors, giving more weight to larger errors. RMSE offers a comprehensive assessment of model performance. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

In this formula, y_i represents the actual values $\hat{y}_i$ represents the predicted values, and n is the number of observations. RMSE is particularly useful in quantifying the error in terms of the units of the observed data [26].

3. R-squared (R²):

R-squared (R²) is a statistical measure that represents the proportion of variance for the dependent variable that's explained by the independent variables in a regression model. It ranges between 0 and 1 and is used as a measure of how close the model's predictions are to the actual values [27]. A higher R² value indicates that the model captures the data well. The formula for R² is:

$$R^2 = 1 - \frac{\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2}{\Sigma_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3}$$

Here y_i presents the actual values, $\hat{y}_i$ the model's predictions, and $\bar{y}_i$ the average of the actual values. These metrics have been used to evaluate the model's success in predicting food delivery times. Each metric addresses different aspects of the model and, when they are used together, they provide a balanced and comprehensive assessment. It is recommended to use these metrics in conjunction to gain a thorough understanding of the model's predictive capabilities and accuracy [28]. The success of ML algorithms is directly related to how low the values of the performance metrics used are [29].

4. Results

This analysis has identified the features that are most decisive in predicting food delivery times. It provides critical information for developing strategies to more effectively forecast delivery times and enhance delivery processes. These findings offer deeper insight into the factors significantly affecting delivery times, laying the groundwork for future research by providing valuable insights. The analysis of the collected training data thoroughly evaluated how well the models could adapt to different situations and accurately predict outcomes. Parameter tuning, done through GridSearchCV, tested how well the models performed with different settings to identify the most effective ones [20]. Using cross-validation scores, GridSearchCV helped choose the best model setup, preventing overfitting and improving performance. We assessed model performance by examining the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2). These measures assessed how close the models' predictions were to the actual values and their effectiveness in explaining differences in delivery times. Assessing performance was vital for understanding prediction errors and how well the models could handle variations in the dataset. The achieved results are presented below.

a. Calculation of Feature Importances:

After training, the feature importances were determined. These scores reflect the weight each feature has in the model's decision-making process. To obtain a better comprehension of the importance levels, these numbers were visualized in a bar graph form (see Figure 1). Every bar on the graph illustrates a feature, and the height of the bar illustrates the importance of that particular feature. This visualization allows us to instantly identify the most critical features of the model easily, and thus to understand the underlying information on which the model is built [21]. Visualization is a tool that helps us to better understand the intricate decision-making process within Machine Learning models. This can be vividly depicted by the visualization of different features and their effect on the model prediction as illustrated by Breiman [21] during the analysis of 5 million orders at Ele.me where it becomes easier for us to grasp these complicated processes. Moreover, this method not only broadens our understanding of the modeling process but also succinctly and clearly presents how the data affects the model predictions.

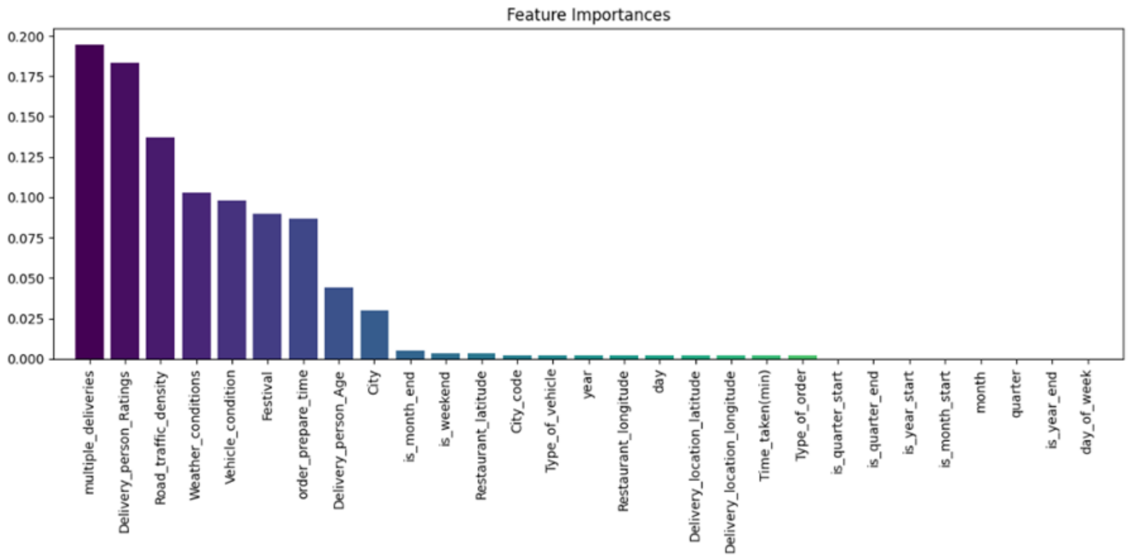

Figure 1. Feature Importance

b. Model Comparison Results:

GridSearchCV was used to find the optimal parameters for each model to enhance performance on the dataset. More specifıbcally, the optimal parameter values chosen were max_depth of 7 for DecisionTreeRegressor, n_estimators of 300 for RandomForestRegressor, and n_estimators of 20 with a max_depth of 9 for XGBRegressor. The best number of neighbors (n_neighbors) for KNeighborsRegressor was set as 7. These parameters control the complexity and learning capacity of the model. The models were trained on the training dataset (X_train, y_train), allowing them to learn patterns and relationships in the dataset.

Once training was complete, predictions were made on the test dataset (y_pred = model.predict(X_test)), and each model's performance was evaluated by comparing it to the actual delivery times (y_test). Table 3 presents the outcomes of this evaluation based on the three primary statistical metrics that were defined in the methodology part, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2).

Table 3. Model Comparison Results

ML Model	MAE	RMSE	R^2
Linear Regression	5.74	7.15	0.417
Decision Trees	4.24	5.58	0.7172
Random Forests	3.21	4.09	0.8126
XGBRegressor	3.16	3.98	0.82
KNN	5.53	7.05	0.43

Linear regression seems to have relatively high errors compared to other models, indicating that it might not capture the underlying patterns in the data well. Decision trees show better performance compared to linear regression, with lower errors and a higher R^2 value, indicating better fitting to the data. Random forests further improve the performance over decision trees, with even lower errors and a higher R^2 value, suggesting a better fit to the data and improved predictive power. Linear Regression and KNN performed relatively poorly compared to other models, with higher errors and a lower R^2 value, suggesting that they may not be the best choice for this dataset. These metrics demonstrate the superiority of the XGBRegressor in predicting food delivery times, having the best performance in all three metrics:

- Mean Absolute Error (MAE): Indicating the average deviation of the model's predictions from the actual values, with an MAE of 3.16, suggesting the model's predictions deviate from the actual values by an average of about 3.16 units.
- Root Mean Squared Error (RMSE): The square root of the MSE, providing the typical magnitude of errors, was calculated to be 3.98.
- R-squared (R^2) Score: Indicating how much of the variance in delivery times the model can explain, an R^2 of 0.82 suggests the model can explain 82% of the variance in the dataset.

Moreover, Figure 2 presents the performance comparison of the different machine learning models based on R-squared scores. The best parameters for each model and the highest R-squared scores achieved are indicated. The high R^2 score for the XGBRegressor indicates it can capture a large part of the variance in the dataset and effectively model the factors affecting delivery times.

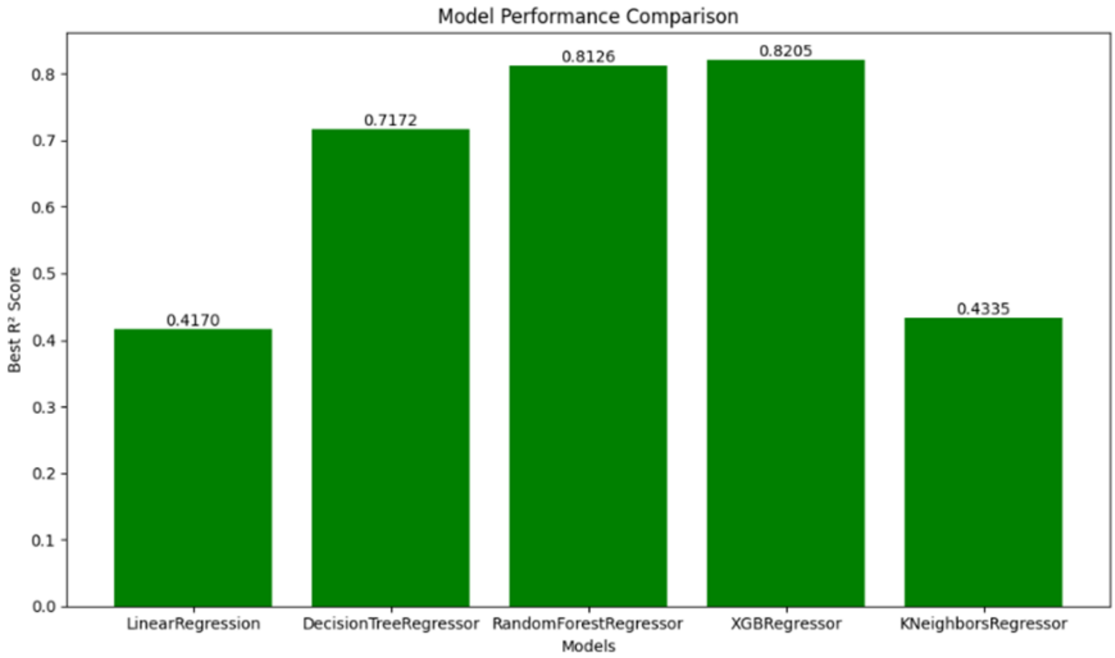

Figure 2. Model Performance Comparison

5. Discussion

This study showed the efficiency of machine learning models, particularly XGBRegressor, in modelling correctly the delivery times of food. The investigation indicates that as a group, ensemble methods are superior to the other models, e.g. Linear Regression, Decision Trees, and Random Forests. The result comes in line with existing literature suggesting that ensemble methods overall outperform in complex prediction assignments owing to their capacity to pick up most intricate patterns and relationships within the data set.

The XGBRegressor model achieved an impressive R-squared score of 0.82, indicating that it can explain 82% of the variance in delivery times. This high explanatory power is a testament to the model's capability in capturing the nuances of the dataset and the factors influencing delivery times. The low values of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) further reinforce the model's accuracy and reliability.

Compared to current state-of-the-art methods, the XGBRegressor model outperformed techniques used in similar studies. For instance, Liu et al. [15] achieved an R-squared of 0.76 for travel time prediction, while the present study attained a higher R-squared of 0.82 for delivery time estimation. Additionally, the proposed approach incorporates a comprehensive set of features, including weather conditions, traffic intensity, and delivery person's profile, which were not considered in some previous works [12, 13].

Feature importances analysis yields very useful information on the factors that are highly correlated to delivery times. This visualization provides for the user an immediate understanding of the most influential features and stakeholders can subsequently focus on optimizing those critical factors. To achieve operational efficiency and customer satisfaction goals, food delivery providers can prioritize the top-ranked features and implement targeted strategies.

It is necessary to keep in mind that the XGBRegressor model gave excellent results but there would be fluctuations in the results depending on the specific dataset used and also the region or operational context in which the model is applied. Consequently, it is suggested to test the model's performance on various datasets and consider the specific features of the target delivery setting.

6. Conclusion

This study aimed to identify the most effective machine learning models for predicting food delivery times and to understand the key factors influencing these times. The results demonstrate that the XGBRegressor model from the XGBoost library outperformed other models, achieving an R-squared score of 0.82 and low values of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). This highlights the model's ability to accurately predict delivery times and capture the complex relationships within the dataset.

As a result, featured importance analysis detected the main factors affecting delivery times. This data is board to a food delivery company to highlight and optimize its operations, thus leading to better customer satisfaction and efficiency of operation.

This study contributes to the already existing body of knowledge on machine learning models for forecasting food delivery times by offering a complete analysis on the critical factors that affect such times. The research outcomes can be exploited by delivery-food companies to boost their businesses and establish a competitive edge in the ever-growing food delivery market. While this study has provided significant insights into the application of machine learning for predicting food delivery times, there are several avenues for future research.

Particularly, the research of the current study was concentrated on a particular group of factors like temperature, traffic, and courier background. Research studies could seek to develop more features which will eventually improve the prediction accuracy of the models. For example, the use of live traffic data, road construction details, or consumer feedback can help improve the services.

Moreover, this research work mainly covered traditional machine learning models. Nevertheless, future analysis can develop deep learning methods like CNNs or RNNs to predict food delivery times. Deep learning models have demonstrated remarkable progress in several domains and could provide additional inputs or higher performance.

Although this research has focused on predicting the delivery times, a future research study can investigate the integration of these predictions with optimization techniques for route planning, resource allocation and operational decision-making. Conjunction of machine learning models with optimization algorithms may eventually result in more efficient and cost-effective food delivery operations.

Finally, within the framework of reinforcing the results and evaluating the implications for the practice, the forthcoming research should include the deployment of the developed models in real-life food delivery operations. Such evaluation will facilitate the assessment of, and refinement of models as based on real life feedback and constraints. Through this future research approach, food delivery optimization can be taken to the next level, resulting in satisfied customers, efficient business operations, and a sustainable food delivery industry.

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