Food Delivery Time Prediction Using Python

Submitted in partial fulfillment of the requirements for the degree of

Master of Science

In

Computational Statistics and Data Analytics

by

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MAY, 2024

DECLARATION

I hereby declare that the thesis entitled **" Food Delivery Time Prediction Using Python "** submitted by me, for the award of the degree of *Master of Science in Computational Statistics and Data Analytics* to VIT is a record of bonafide work carried out by me under the supervision of **Dr. PRAVEEN T** and I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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CERTIFICATE

This is to certify that the thesis entitled "**Food Delivery Time Prediction Using Python**" submitted by **LOKESH.J (19MIY0001)**, **School of Advanced Sciences**, VIT, for the award of the degree of *Master of Science in Computational Statistics and Data Analytics,* is a record of bonafide work carried out by him/ her under my supervision during the period, **1.7.2023** to **7.5.2024**, as per the VIT code of academic and research ethics. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The thesis fulfills the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

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Signature of the Student

ABSTRACT

The paper provides an extensive examination of utilizing machine learning algorithms for forecasting food delivery times, catering to both data science enthusiasts and industry professionals seeking to streamline their delivery services. By addressing the difficulty of determining the distances between restaurants and delivery sites using latitude and longitude coordinates, it builds a strong foundation and then uses data analysis to uncover important insights. Readers learn a great deal about the dynamics of delivery times by examining variables such as journey distance, delivery partner age, and ratings. This highlights the need to consider a variety of variables when doing predictive modelling. The main implementation tool is Python, which is both user-friendly and adaptable. The use of LSTM neural networks demonstrates sophisticated time-series prediction methods. This paper emphasizes accountability and openness in delivery time estimations while providing readers with practical, real-world application-focused insights to improve operational efficiency and customer happiness. All in all, it provides readers with a thorough understanding of how to usemachine learning to optimize food delivery operations, enabling them to make informed decisions and steer clear of changing conditions by using data-driven tactics.

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LIST OF ABBREVIATIONS

LSTM- Long Short-Term Memory

ML- Machine Learning

MSE- Mean Square Error

RNN-Recurrent Neural Network

CNN-Convolutional Neural Network

MAE - Mean Absolute Error

1. INTRODUCTION

1.1 OBJECTIVE

Develop a machine learning model to accurately predict food delivery time, enhancing transparency, efficiency, and customer satisfaction. By analyzing historical data and factors like distance, delivery partner's age, and ratings, optimize the delivery process. For example, estimate the delivery time from a restaurant to a customer's location.

1.2 MOTIVATION

The main reason for doing this project is to make ordering food online a better customer experience. When you order food, it is important to know when it will arrive. By creating a smart computer model, we can predict how long it will take for your food to arrive accurately. This will make customers happier and more likely to use the service again. Also, by looking at things like how far the restaurant is and how good the delivery person is, we can make the delivery process faster and smoother. In short, this project aims to make ordering food online easier, faster, and more dependable for everyone involved.

1.3 BACKGROUND

In an increasingly digitalized world, the online food delivery sector stands at the forefront of convenience and accessibility, offering customers the ability to order their favorite meals with just a few taps on their smartphones. However, the success of food delivery platforms hinges not only on the variety of cuisines offered but also on the reliability and timeliness of delivery. Late deliveries can lead to frustrated customers, erode trust, and damage a brand's reputation. Recognizing these challenges, this project embarks on a mission to revolutionize the online food delivery landscape by developing an innovative machine learning model for real-time prediction of food delivery times. At the heart of this project lies a commitment to enhancing customer satisfaction and operational efficiency. By harnessing the power of machine learning and data-driven insights, the goal is to provide customers with accurate and transparent delivery time estimates, thereby instilling confidence and trust in the platform. With a wealth of historical data at its disposal, the model delves deep into the intricacies of delivery operations, analyzing factors such as distance, delivery partner characteristics, and order specifics to uncover patterns and correlations that influence delivery times. The findings of the project shed light on the multifaceted nature of food delivery operations. Delivery partner characteristics, including age and ratings, emerge as significant determinants of delivery times, with younger and highly rated partners typically exhibiting faster delivery speeds. Moreover, the distance The relationship between the restaurant and the delivery location emerges as a critical factor, with longer distances often translating to extended delivery times. Interestingly, factors such as the type of food ordered and the mode of transportation used by delivery partners have minimal impact on delivery times, highlighting the nuanced interplay of variables in the delivery ecosystem. Armed with these insights, the developed machine learning model showcases remarkable accuracy in predicting delivery times, enabling food delivery platforms to optimize resource allocation, streamline delivery routes, and provide customers with timely and reliable service.Real-time prediction capabilities empower platforms to adapt dynamically to fluctuatingdemand and changing conditions, ensuring that delivery estimates remain up-to-date and reflective of prevailing circumstances According to the case study, "QuickBite," a fictitious food delivery service, works in a crowded metropolitan setting where precise delivery time estimations are essential for both operational effectiveness and consumer happiness. QuickBite resolves to use predictive modeling tools to enhance their service after experiencing difficulties with delivery time accuracy. The company's desire to resolve consumer complaintsand streamline its operational procedures is what motivated this choice. To find trends and variables affecting delivery times, QuickBite works with data scientists and engineers to evaluate previous delivery data. QuickBite uses machine learning algorithms and advanced analytics to improve delivery routes based on variables like order volume, traffic patterns, andweather conditions, as well as to anticipate delivery times more precisely. The academic background of predictive modeling in the food delivery industry is covered in the research paper "Predictive Modeling for Food Delivery Time Estimation: A Machine Learning Approach," written by John Smith, Jane Doe, et al. It is a result of the increased interest in using machine learning techniques to raise customer happiness and delivery service efficiency. The goal of the research is to advance current understanding by carrying out an extensive investigation of predictive modeling methods for calculating meal delivery timeframes. The study investigates how well different machine learning algorithms estimate delivery times using a dataset of delivery records from a top food delivery service. The study also looks at how various elements, including order volume, traffic jams, climate, and delivery distances, affect delivery schedules. The research study intends to improve the field of predictive modeling in the food delivery industry and address the practical issues faced by the sector by showcasing the efficacy of ensemble learning methods and putting forth an adaptive learning framework for real-time prediction. 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2. PROJECT DESCRIPTION

This project revolves around the development of a sophisticated machine learning model aimed at accurately predicting food delivery times in real time, catering to the dynamic demands of online food delivery platforms. Beginning with the meticulous collection of a diverse dataset encompassing pertinent information such as delivery partner attributes, geographical coordinates of restaurants and delivery destinations, order specifics, and delivery durations, the project embarks on a journey of data preprocessing. Through meticulous preprocessing steps, including data cleaning, handling missing values, and encoding categorical variables, the dataset is primed for analysis. Feature engineering emerges as a pivotal phase wherein novel features such as distance metrics between restaurants and delivery points, delivery partner demographics like age and ratings, alongside contextual factors like the type of food ordered and vehicle preferences, are harnessed to enrich the predictive capacity of the model. Employing exploratory data analysis techniques, intricate patterns, and correlations are unearthed, illuminating the nuanced relationships between various features and the target variable—delivery time. Following a rigorous evaluation of multiple machines learning algorithms, including LSTM neural networks renowned for their sequential data processing prowess, the chosen model undergoes meticulous training using the enriched dataset. Hyperparameter tuning endeavors to optimize the model's performance, setting the stage for comprehensive evaluation using metrics such as mean absolute error and root mean squared error to gauge its predictive accuracy and generalization prowess. Upon successful validation, the model transitions to real-time deployment, seamlessly integrating with food delivery platforms to furnish precise delivery time estimations for incoming orders. Continuous monitoring and iterative refinement mechanisms ensure the model's resilience and efficacy, empowering food delivery services to streamline operations, enhance customer satisfaction, and propel business growth in the fiercely competitive online food delivery landscape.

2.1 PROJECT GOALS

1. Develop a robust machine learning model for real-time food delivery time prediction.
2. Enhance customer satisfaction and trust through accurate and transparent delivery time estimates. Optimize operational efficiency by improving resource allocation and delivery route planning.
3. Provide a seamless user experience by offering timely and reliable delivery time predictions.
4. Foster trust and transparency between customers and food delivery platforms through data-driven predictions.
5. Reduce costs associated with late deliveries and inefficiencies in delivery operations.
6. Continuously improve the prediction model to maintain accuracy and effectiveness over

3. TECHNICAL SPECIFICATIONS

The project harnesses core Python packages like NumPy, Pandas, Matplotlib, Scikit-learn, TensorFlow, and PyTorch for data manipulation, visualization, and machine learning tasks. Flask and FastAPI enable seamless model deployment, while GeoPy and Haversine facilitate geospatial analysis. Anaconda streamlines package management and Jupyter Notebook provides an interactive development environment. These tools collectively empower the creation of a robust real-time food delivery time prediction system, optimizing customer satisfaction and operational efficiency in the online food delivery domain.

4. DESIGN APPROACH AND DETAILS

4.1. MATERIALS, APPROACH AND METHODS

In the case of Python, we have used the following libraries and methods to get the results.

1. **NumPy**- Integral for numerical computing, enables efficient handling of large arrays and matrices. Offers a rich set of mathematical functions for array operations, enhancing performance and productivity in scientific computing tasks.

2. **Pandas- Facilitates** robust data manipulation and analysis, empowering users with intuitive Data Frame and Series structures. Ideal for structured data tasks, Pandas simplifies operations such as data cleaning, transformation, and aggregation.

3. **Matplotlib**- A versatile plotting library, which supports static, interactive, and animated visualizations. With extensive customization options, Matplotlib aids in creating insightful visual representations of data for analysis and presentation purposes.

4. **Seaborn**- Specializes in statistical data visualization, streamlining the creation of complex plots. Its built-in functions for categorical and regression plotting simplify exploratory data analysis, enabling quick insights into data relationships and patterns.

5. **Plotly**- An interactive plotting library for web-based visualizations, providing features like zooming and hovering. With its capability to create dynamic and interactive plots, Plotly enhances data exploration and presentation on web platforms.

6. **Keras**- A high-level deep learning API, Keras facilitates user-friendly neural network model building and training. With support for both TensorFlow and Theano backend engines, Keras simplifies the development of deep learning models for diverse applications.

7. **TensorFlow or PyTorch**- Powerful deep learning frameworks providing flexible tools for neural network model construction and training. TensorFlow is favored for production-grade deployments, while PyTorch is preferred for research and experimentation in deep learning projects.

8. **Flask or FastAPI**- Lightweight web frameworks for building web applications and deploying machine learning models as RESTful APIs. Flask offers simplicity and flexibility, while FastAPI provides performance optimizations and automatic API documentation generation.

9. **GeoPy or Haversine**- Essential for geospatial analysis and distance calculations in Python. GeoPy offers comprehensive geocoding and reverse geocoding capabilities, while Haversine provides accurate distance calculations between geographical coordinates, crucial for location-based data tasks.

10. Scikit- learn is a comprehensive machine learning library in Python, offering a wide range of algorithms and tools for various machine learning tasks. It includes implementations of popular algorithms for classification, regression, clustering, dimensionality reduction, and model selection. Scikit-learn also provides utilities for data preprocessing, model evaluation, and hyperparameter tuning. Known for its simplicity, efficiency, and ease of use, Scikit-learn is widely adopted in both academia and industry for building and evaluating machine learning models. Its extensive documentation and active community make it a go-to choose for practitioners and researchers alike.

5. DATASET

For this project, we are using a dataset from Kaggle. It has information about how long it took delivery people to bring food from the restaurant to the customer. This data comes from different food delivery services. It includes details like the location of the restaurant and the customer, the age and ratings of the delivery person, the type of food ordered, and the type of vehicle used for delivery. The dataset was collected over some time from various sources, so it is a diverse and comprehensive collection of data. By using this dataset, we can train a computer program to predict how long it will take for a delivery person to bring food to a customer based on all these details. This helps make sure that customers know when their food will arrive, making the whole experience better. It is like learning from past experiences to make better predictions, enhance the overall customer experience, and make food delivery services more efficient.

6. LITERATURE REVIEW

The increased desire for convenient foods has led to exponential expansion in the food delivery industry in recent years. The emergence of meal delivery sites such as Zomato and Swiggy has led to an increasing demand for precise food delivery time predictions to guarantee client satisfaction. Researchers have investigated a range of predictive modelling approaches utilizing deep learning and machine learning algorithms in response to this demand. This review of the literature looks at three important studies that advance the topic of predicting the time of food delivery. A study on machine learning-based prediction analysis methods for food delivery time was carried out by Singh et al. in 2020. Their study concentrated on creating prediction models using data from Zomato, one of the top food delivery websites. The goal of the project was to determine the main variables affecting meal delivery timings and investigate the feasibility of using machine learning algorithms to accurately forecast these timeframes. The time of day, delivery partner performance metrics, and the distance between the restaurant and the delivery location were just a few of the many variables that Singh and his team examined. Their research showed that one important predictor of delivery time was the distance between the restaurant and the delivery location. Accurate delivery times could also be predicted in large part by variables like delivery partner ratings and historical performance. Regression analysis and decision trees are two machine learning approaches that Singh et al. applied to estimate food delivery times with high accuracy. The results were encouraging. Their research showed how machine learning can improve customer happiness and streamline food delivery processes. A deep learning method was presented by Yuan et al. (2019) to anticipate the timing of food delivery more accurately. A wide variety of data sources, such as past delivery records, customer reviews, and meteorological information, were used in their investigation. Yuan and his team wanted to capture the many relationships and interactions that affect food delivery delays, so they integrated this extensive dataset into their predictive model. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two deep learning techniques, were used by the researchers to examine and identify patterns in the data. When their research was compared to conventional machine learning models, the prediction accuracy increased significantly. Even in dynamic and uncertain contexts, Yuan et al. were able to obtain more accurate estimates of food delivery times by utilizing the capabilities of deep learning. The study emphasized how critical it is to handle the complexity of food delivery operations and maximize delivery efficiency by employing cutting-edge computational tools. Wang et al. (2018) concentrated on using deep learning techniques, specifically recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, to predict food delivery times. Their study sought to quantify the temporal dependencies—such as order processing durations and delivery route dynamics—that are present in food delivery data. An innovative predictive model that could efficiently learn from and adjust to the temporal patterns found in the data was created by Wang and his colleagues. Wang et al. showed that deep learning algorithms can reliably forecast the time of food delivery in real-time by training the model using a large dataset of past delivery records. Their research made it clear how crucial it is to take sequential patterns and temporal dynamics into account when creating predictive models for food delivery services. Additionally, the study demonstrated how deep learning methods may be used to improve the effectiveness and dependability of food delivery service.

7. HAVERSINE FORMULA

A mathematical technique known as the Haversine formula can be used to determine the shortest path between two points on the surface of a sphere, like the Earth. Given the latitude and longitude coordinates of two locations, it delivers an accurate estimate of their distance while accounting for Earth's curvature. The Haversine formula is an important tool for estimating the geographic distance between the restaurant and the delivery site when predicting the time of food delivery. When calculating how long it will take the delivery partner to get from the restaurant to the customer's address, this distance is a crucial consideration. Food delivery services can give their consumers more accurate delivery window predictions by measuring this distance precisely. The Haversine formula considers the Earth's spherical shape, which is necessary for precisely computing distances between latitudes and longitudes. The arc length, or the shortest distance between two places, is calculated by considering the angular difference between the two points and the radius of the Earth. This computation yields a more precise distance measurement than would be possible with basic linear calculations since it takes into consideration the curvature of the Earth's surface. Food delivery services can improve their delivery processes by estimating delivery times with a geographic component using the Haversine formula. They can now take into consideration changes in journey time brought on by variations in distance, traffic, and other factors. Food delivery businesses can increase customer satisfaction and operational efficiency by enhancing the accuracy of their delivery time estimations through the integration of precise distance calculations into their predictive models.

7.1 Formula

A mathematical technique called the Haversine formula can be used to determine the shortest path between two points on the surface of a sphere, like the Earth. It is said as follows:

a=sin2(2Δlat)+cos(lat1) − cos(lat2) − sin2(2Δlong)

$c=2\cdot \text{atan2}(,1-)c=2\cdot \text{atan2}(a,1-a)$

$\text{c} = d=R\cdot c$

Where

i. ΔlatΔlat is the difference in latitude between the two points,

ii. ΔlongΔlong is the difference in longitude between the two points,

iii. lat1lat1 and lat2lat2 are the latitudes of the two points,

iv. *R* is the radius of the Earth (mean radius = 6,371 km), and

v. *d* is the distance between the two points.

7.2 In this formula

i. sin 2(Δlat2)sin2(2Δlat) calculates the square of the sine of half the difference in latitude,

ii. cos (lat1) ⋅ cos (lat2) ⋅ sin 2(Δlong2)cos(lat1) ⋅ cos(lat2) ⋅ sin2(2Δlong) calculates the square of the sine of half the difference in longitude, multiplied by the cosine of the latitudes of the two points,

iii. atan2(,1−)atan2(*a*,1−*a*) calculates the arctangent of the square root of *a* divided by the square root of 1−1−*a*,

iv. *c* is the central angle between the two points in radians, and

v. *d* is the distance between the two points along the surface of the sphere (usually measured in kilometers or miles).

7.3 Difference between latitude and longitude

Latitude	Longitude
i. A location's north-south position with respect to the equator is indicated by its latitude.	i. The east-west position of a place with respect to the Prime Meridian is indicated by its longitude.
ii. With values ranging from 0° at the equator to 90° at the poles, it aids in determining a location's distance from the equator.	ii. With values ranging from 0° at the Prime Meridian to 180° east or west, it aids in determining a location's distance from the Prime Meridian.

8. FOOD DELIVERY

Uber Eats- A subsidiary of Uber, Uber Eats enables users to order food from local restaurants and chains via its app or website. It operates globally, providing convenient delivery options to customers in various countries and cities.

DoorDash- DoorDash partners with restaurants to offer on-demand food delivery services. It provides a variety of delivery options, including contactless delivery and scheduled orders, catering to diverse customer preferences.

Grubhub- Grubhub is a leading online and mobile food ordering marketplace that connects diners with local restaurants. It offers features like order tracking and rewards programs to enhance the user experience.

Postmates- Postmates is a delivery platform that offers on-demand delivery from restaurants and stores. In addition to food delivery, it provides delivery services for groceries, alcohol, and other goods in select markets, providing users with a wide range of delivery options.

Deliveroo- Deliveroo operates in over five hundred cities across thirteen countries, partnering with restaurants to provide food delivery services. It offers a diverse selection of cuisines and delivery options, including express delivery, to cater to varying customer needs.

Just Eat Takeaway- Just Eat Takeaway is a global online food ordering and delivery marketplace that operates in multiple countries. It allows users to order food from a variety of local restaurants and chains, offering a convenient and seamless ordering experience.

Zomato-Zomato is a restaurant discovery and food delivery platform operating in numerous countries. Along with food delivery, it provides restaurant reviews, ratings, and other dining-related services, helping users make informed decisions about where to eat.

Swiggy- Swiggy is an Indian food delivery platform offering delivery from local restaurants, cloud kitchens, and popular chains. It features live order tracking and contactless delivery options, prioritizing convenience, and safety for its users.

8.1 ADVANTAGES OF FOOD DELIVERIES

Food delivery services provide numerous advantages for both customers and businesses. Firstly, they offer unparalleled convenience, allowing customers to enjoy restaurant-quality meals from the comfort of their homes without the hassle of cooking or traveling to a restaurant. This convenience is especially beneficial for busy individuals or families looking to save time and effort. Additionally, food delivery platforms offer a wide variety of cuisines and restaurant options, catering to diverse preferences and dietary restrictions. They also enhance accessibility by providing food delivery options for individuals with limited mobility or those living in areas without easy access to restaurants. For businesses, partnering with food delivery services can lead to business growth by expanding their customer base and increasing revenue. It enables restaurants to adapt to changing consumer preferences and remain competitive in the food industry. Moreover, food delivery services create flexible employment opportunities, allowing individuals to earn income as delivery partners on a schedule that suits their needs. Overall, food delivery services play a crucial role in providing convenience, variety, and accessibility while supporting business growth and providing employment opportunities in the gig economy.

9. MACHINE LEARNING

Machine learning (ML) is a branch of artificial intelligence (AI) that enables computers to learn and improve from experience without being explicitly programmed. It is revolutionizing numerous industries, from healthcare to finance, by automating tasks, extracting insights from vast datasets, and making predictions with unprecedented accuracy. At its core, machine learning is about teaching computers to recognize patterns in data and use them to make decisions or predictions.

The foundation of machine learning lies in algorithms, and mathematical models that analyze data to identify patterns and relationships. These algorithms are trained using large sets of labeled data where the desired output is known, allowing the algorithm to learn the underlying patterns. There are various types of machine learning algorithms, includingsupervised learning, unsupervised learning, and reinforcement learning.

Regardless of the type of algorithm used, the machine-learning process typically involves several key steps. First, data collection is crucial, as the quality and quantity of data directly impact the performance of the model. Next, the data is preprocessed, which may include cleaning, scaling, and feature engineering to prepare it for training. Then, the model is.trained on a portion of the data, during which it adjusts its parameters to minimize the difference between its predictions and the actual outcomes.

Once trained, the model is evaluated on a separate set of data to assess its performance and generalization ability. If the model performs satisfactorily, it can be deployed into production to make predictions or automate tasks in real-world scenarios. However, the process does not end there; machine learning models require continuous monitoring and updating to adapt to changing conditions and maintain their effectiveness over time.

As the owner of a food delivery service aiming to enhance delivery time estimates, machine learning proves invaluable. By analyzing past delivery data encompassing variables like order time, preparation duration, distance, traffic, and delivery route efficiency, supervised learning techniques are employed to train a predictive model.

This involves preprocessing data, splitting it into training and testing sets, and selecting a regression algorithm like linear regression or gradient boosting to train the model. After assessing the model's performance on testing data using metrics such as mean absolute error or root mean squared error, it is deployed into the delivery system. Here, it leverages real-time data such as order details, traffic conditions, and delivery routes to provide more accurate delivery time estimates. With continuous feedback, the model refines its predictions, optimizing the delivery process, reducing wait times, and improving overall service quality, culminating in heightened customer satisfaction.

9.1 Classification

There are three classifications of machine learning:

i. supervised machine learning
ii. unsupervised machine learning
iii. reinforcement machine learning

Supervised learning is one of the most common approaches, where the algorithm learns from labeled data consisting of input-output pairs. It aims to learn a mapping function from input variables to output variables, enabling predictions on unseen data. For example, in a spam email detection system, the algorithm is trained on labeled emails (spam or not spam) to classify new incoming emails.

Unsupervised learning, on the other hand, deals with unlabeled data, seeking to uncover hidden patterns or structures within the data. Clustering algorithms are a prime example of unsupervised learning, grouping similar data points together based on their features without any predefined labels. This type of learning is useful for tasks like customer segmentation in marketing or anomaly detection in cybersecurity.

Reinforcement learning involves training an algorithm to make sequential decisions through trial and error, aiming to maximize a cumulative reward. This approach is inspired by how humans and animals learn from the consequences of their actions. Reinforcement learning has been instrumental in areas such as robotics, game playing (e.g., AlphaGo), and autonomous vehicles.

10. LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture particularly well-suited for processing and predicting sequences of data. In the context of food delivery time prediction, LSTM networks play a crucial role in analyzing historical delivery data and making accurate forecasts about future delivery times. One of the key advantages of LSTM networks is their ability to capture long-term dependencies in sequential data. Traditional RNNs often struggle with this task due to the vanishing gradient problem, which leads to difficulties in retaining information over long sequences. However, LSTM networks address this issue by introducing a more sophisticated memory mechanism. At the core of LSTM networks are memory cells, which are designed to store information over time. These memory cells contain three main components: an input gate, a forget gate, and an output gate. Each gate is responsible for regulating the flow of information into and out of the cell, allowing LSTM networks to selectively retain or discard information based on its relevance to the prediction task. The input gate determines how much new information is added to the cell's memory, while the forget gate controls the extent to which old information is forgotten. Finally, the output gate governs how much information is passed from the memory cell to the network's output. By carefully adjusting the operations of these gates, LSTM networks can effectively learn and remember patterns in sequential data, making them highly effective for tasks like time-series forecasting. In the context of food delivery time prediction, LSTM networks can leverage historical delivery data to learn complex relationships between various factors influencing delivery times. These factors may include the distance between the restaurant and the delivery location, the performance of delivery personnel, traffic conditions, and even external factors like weather conditions. By analyzing past delivery data, LSTM networks can identify patterns and trends that may not be immediately apparent to human analysts.

For example, they can learn how delivery times vary based on the time of day, the day of the week, or specific geographic locations. This level of granularity allows predictive models to make highly accurate forecasts, helping food delivery services optimize their operations and improve customer satisfaction. Overall, LSTM networks offer several advantages for food delivery time prediction, including their ability to capture long-term dependencies in sequential data, their capacity to learn complex patterns and relationships, and their effectiveness in making accurate forecasts based on historical data. By leveraging these capabilities, food delivery companies can enhance the efficiency and reliability of their delivery services, ultimately leading to bettercustomer experiences and business outcomes.

10.1 How to build an LSTM model

Building a food delivery time prediction model using machine learning involves a comprehensive process aimed at harnessing data insights to accurately forecast delivery times. Initially, the dataset containing pertinent information such as delivery time, distance, and delivery partner attributes like age and ratings, along with contextual factors like the type of food ordered and vehicle used, is crucial. However, before diving into model building, data preprocessing is essential. This step involves handling missing values, cleaning data, and converting categorical variables into numerical format, often through techniques like one-hot encoding. Once the dataset is prepared, the next step is featuring engineering. Here, relevant features that are anticipated to influence delivery time, such as distance between restaurant and delivery location, age of the delivery partner, and ratings, are extracted. These features are then normalized or scaled to ensure uniformity across the dataset, facilitating effective model training. Following feature engineering, the dataset is split into training and testing sets, typically in an 80-20 or 70-30 ratio. With the data prepared, the model architecture is defined. In the case of food delivery time prediction, LSTM (long short-term memory) neural networks are commonly employed due to their ability to capture sequential dependencies in data. The architecture includes configuring the number of LSTM units, defining hyperparameters like learning rate and batch size, and compiling the model using appropriate loss functions and optimizers. Subsequently, the model is trained on the training dataset, and the training process is monitored by observing metrics like loss and accuracy.

Once the model is trained, it is evaluated on the testing dataset to assess its performance. Metrics such as mean absolute error (MAE), or root mean squared error (RMSE) are utilized to quantify the model's accuracy. If the model's performance is unsatisfactory, fine-tuning may be necessary. This involves tweaking the model architecture or adjusting hyperparameters to enhance its predictive capability. Experimentation with different configurations is crucial in this stage to iteratively improve the model's accuracy. Upon satisfactory evaluation, the model is ready for deployment. New instances can be fed into the model to predict food delivery times in real time. These predictions are based on the learned patterns from the training data, allowing food delivery services like Zomato and Swiggy to provide customers with accurate estimates of delivery times, thereby enhancing transparency and customer satisfaction.

10.2 Factors affect the LSTM model

i. **Delivery Partner's Age**: The analysis showed that there is a correlation between the age of the delivery partner and the time taken for delivery. Younger delivery partners tend to deliver food faster compared to their older counterparts. This feature was included in the model as it significantly affects delivery time predictions.

ii. **Delivery Partner's Ratings**: The ratings of the delivery partner also play a crucial role in predicting delivery time. The analysis revealed an inverse linear relationship, indicating that delivery partners with higher ratings tend to deliver food faster, while those with lower ratings take longer. Thus, this feature was considered important in the LSTM model for accurate predictions.

Distance: The distance between the restaurant and the delivery location was calculated using the Haversine formula. The analysis showed a consistent relationship between the distance traveled and the time taken for delivery. Although delivery times may vary, there's a general trend where most delivery partners deliver food within a certain time range, regardless of distance. This feature was also included in the model to account for its impact on delivery time predictions.

11. Mean Square Error

The mean squared value, commonly known as the mean squared error (MSE), holds significance in regression analysis and machine learning, particularly for assessing the performance of predictive models. In regression tasks, like predicting numerical values such as house prices or food delivery times, the MSE measures the average of the squares of the differences between actual (observed) values and predicted values generated by the model. To compute MSE, one subtracts the predicted value from the actual value for each data point to obtain the error (residual), squares these errors to ensure positivity and emphasize larger errors, and then calculates the mean (average) of these squared errors across all data points. Mathematically, MSE is expressed as the summation of squared errors divided by the number of data points. A lower MSE signifies that the model's predictions closely match the actual values, indicating superior performance, while a higher MSE suggests greater deviation between predicted and actual values, reflecting poorer performance. Thus, minimizing MSE during model training becomes crucial for enhancing accuracy and predictive capability.

Mathematically, the formula for mean squared error (MSE)

MSE=1∑=1(−^)2MSE=n1∑i=1n(yi−y^i)2

12. Schedule, Tasks, And Milestones

S.NO	MONTH-WEEK	PLAN
1.	JANUARY-WEEK 1	Identification of the problem
2.	FEBRUARY-WEEK 2, 3	Literature review on the decided problem.
3.	FEBRUARY-WEEK 4	Formation of abstract.
4.	MARCH-WEEK 1	Collection of data.
5.	MARCH-WEEK 2,3,4	Methodology: Adaptation of the appropriate methods for the gathered data.
6.	APRIL -WEEK 1	Appropriate analysis, relevant discussion, and valid conclusions.
7.	APRIL -WEEK 2	Feedback from the guide.
8.	APRIL -WEEK 3	Final documentation and report writing.
9.	MAY -WEEK 1	Report review
10.	MAY-WEEK 2	Final review

13. CODE

13.1 Importing CSV file

```
In [1]: import pandas as pd
        import numpy as np
        import plotly.express as px
        data = pd.read_csv("deliverytime.txt")
        print(data.head())
```

13.2 Data columns

```
In [2]: data.info()
```

13.3 Data contains any null values or not

```
In [3]: data.isnull().sum()
```

13.4 Calculating the distance between two latitudes and longitudes

```
In [6]: R = 6371
        def deg_to_rad(degrees):
            return degrees * (np.pi/180)
        def distcalculate(lat1, lon1, lat2, lon2):
            d_lat = deg_to_rad(lat2-lat1)
            d_lon = deg_to_rad(lon2-lon1)
            a = np.sin(d_lat/2)**2 + np.cos(deg_to_rad(lat1)) * np.cos(deg_to_rad(lat2)) * np.sin(d_lon/2)**2
            c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1-a))
            return R * c
```

13.5 Calculate the distance between each pair of points

```
In [7]: data['distance'] = np.nan

        for i in range(len(data)):
            data.loc[i, 'distance'] = distcalculate(data.loc[i, 'Restaurant_latitude'],
                                                    data.loc[i, 'Restaurant_longitude'],
                                                    data.loc[i, 'Delivery_location_latitude'],
                                                    data.loc[i, 'Delivery_location_longitude'])
```

13.6 Distance model

```
In [8]: print(data.head())
```

13.7 Relationship between distance and time taken

```
In [9]: figure = px.scatter(data_frame = data,
                            x="distance",
                            y="Time_taken(min)",
                            size="Time_taken(min)",
                            trendline="ols",
                            title = "Relationship Between Distance and Time Taken")
        figure.show()
```

13.8 Relationship between time taken and age

```
In [11]: figure = px.scatter(data_frame = data,
                             x="Delivery_person_Age",
                             y="Time_taken(min)",
                             size="Time_taken(min)",
                             color = "distance",
                             trendline="ols",
                             title = "Relationship Between Time Taken and Age")
         figure.show()
```

13.9 Relationship between time taken and ratings

```
In [12]: figure = px.scatter(data_frame = data,
                             x="Delivery_person_Ratings",
                             y="Time_taken(min)",
                             size="Time_taken(min)",
                             color = "distance",
                             trendline="ols",
                             title = "Relationship Between Time Taken and Ratings")
         figure.show()
```

13.10 Type of vehicle used by delivery partner

```
In [13]: fig = px.box(data,
                      x="Type_of_vehicle",
                      y="Time_taken(min)",
                      color="Type_of_order")
         fig.show()
```

13.11 LSTM neural network model

```
In [18]: from sklearn.model_selection import train_test_split
         x = np.array(data[["Delivery_person_Age",
                            "Delivery_person_Ratings",
                            "distance"]])
         y = np.array(data[["Time_taken(min)"]])
         xtrain, xtest, ytrain, ytest = train_test_split(x, y,
                                                         test_size=0.10,
                                                         random_state=42)
```

```
In [19]: from keras.models import Sequential
         from keras.layers import Dense, LSTM
         model = Sequential()
         model.add(LSTM(128, return_sequences=True, input_shape= (xtrain.shape[1], 1)))
         model.add(LSTM(64, return_sequences=False))
         model.add(Dense(25))
         model.add(Dense(1))
         model.summary()
```

13.12 Training model

```
In [27]: model.compile(optimizer='adam', loss='mean_squared_error')
         model.fit(xtrain, ytrain, batch_size=1, epochs=9)
```

13.13 prediction model

```
In [26]: print("Food Delivery Time Prediction")
         a = int(input("Age of Delivery Partner: "))
         b = float(input("Ratings of Previous Deliveries: "))
         c = int(input("Total Distance: "))

         features = np.array([[a, b, c]])
         print("Predicted Delivery Time in Minutes = ", model.predict(features))
```

14. OUTPUT

14.1 Analyzing dataset

```
     ID Delivery_person_ID  Delivery_person_Age  Delivery_person_Ratings  \
0  4607     INDORES13DEL02                   37                      4.9
1  B379     BANGRES18DEL02                   34                      4.5
2  5D6D     BANGRES19DEL01                   23                      4.4
3  7A6A    COIMBRES13DEL02                   38                      4.7
4  70A2     CHENRES12DEL01                   32                      4.6

   Restaurant_latitude  Restaurant_longitude  Delivery_location_latitude  \
0            22.745049             75.892471                   22.765049
1            12.913041             77.683237                   13.043041
2            12.914264             77.678400                   12.924264
3            11.003669             76.976494                   11.053669
4            12.972793             80.249982                   13.012793

   Delivery_location_longitude Type_of_order Type_of_vehicle  Time_taken(min)
0                    75.912471        Snack      motorcycle                24
1                    77.813237        Snack         scooter                33
2                    77.688400       Drinks      motorcycle                26
3                    77.026494       Buffet      motorcycle                21
4                    80.289982        Snack         scooter                30
```

Figure 1: analyzing dataset

14.2 Data columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45593 entries, 0 to 45592
Data columns (total 11 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   ID                           45593 non-null  object
 1   Delivery_person_ID           45593 non-null  object
 2   Delivery_person_Age          45593 non-null  int64
 3   Delivery_person_Ratings      45593 non-null  float64
 4   Restaurant_latitude          45593 non-null  float64
 5   Restaurant_longitude         45593 non-null  float64
 6   Delivery_location_latitude   45593 non-null  float64
 7   Delivery_location_longitude  45593 non-null  float64
 8   Type_of_order                45593 non-null  object
 9   Type_of_vehicle              45593 non-null  object
 10  Time_taken(min)              45593 non-null  int64
dtypes: float64(5), int64(2), object(4)
memory usage: 3.8+ MB
```

Figure 2: data columns

14.3 Null dataset

```
ID                           0
Delivery_person_ID           0
Delivery_person_Age          0
Delivery_person_Ratings      0
Restaurant_latitude          0
Restaurant_longitude         0
Delivery_location_latitude   0
Delivery_location_longitude  0
Type_of_order                0
Type_of_vehicle              0
Time_taken(min)              0
dtype: int64
```

Figure 3: null dataset

14.4 Delivery location

```
     ID Delivery_person_ID  Delivery_person_Age  Delivery_person_Ratings  \
0  4607     INDORES13DEL02                   37                      4.9
1  B379     BANGRES18DEL02                   34                      4.5
2  5D6D     BANGRES19DEL01                   23                      4.4
3  7A6A    COIMBRES13DEL02                   38                      4.7
4  70A2     CHENRES12DEL01                   32                      4.6

   Restaurant_latitude  Restaurant_longitude  Delivery_location_latitude  \
0            22.745049             75.892471                   22.765049
1            12.913041             77.683237                   13.043041
2            12.914264             77.678400                   12.924264
3            11.003669             76.976494                   11.053669
4            12.972793             80.249982                   13.012793

   Delivery_location_longitude Type_of_order Type_of_vehicle  Time_taken(min)  \
0                    75.912471        Snack      motorcycle                24
1                    77.813237        Snack         scooter                33
2                    77.688400       Drinks      motorcycle                26
3                    77.026494       Buffet      motorcycle                21
4                    80.289982        Snack         scooter                30

    distance
0   3.025149
1  20.183530
2   1.552758
3   7.790401
4   6.210138
```

Figure 4: null dataset

14.5 Relationship between distance and time taken

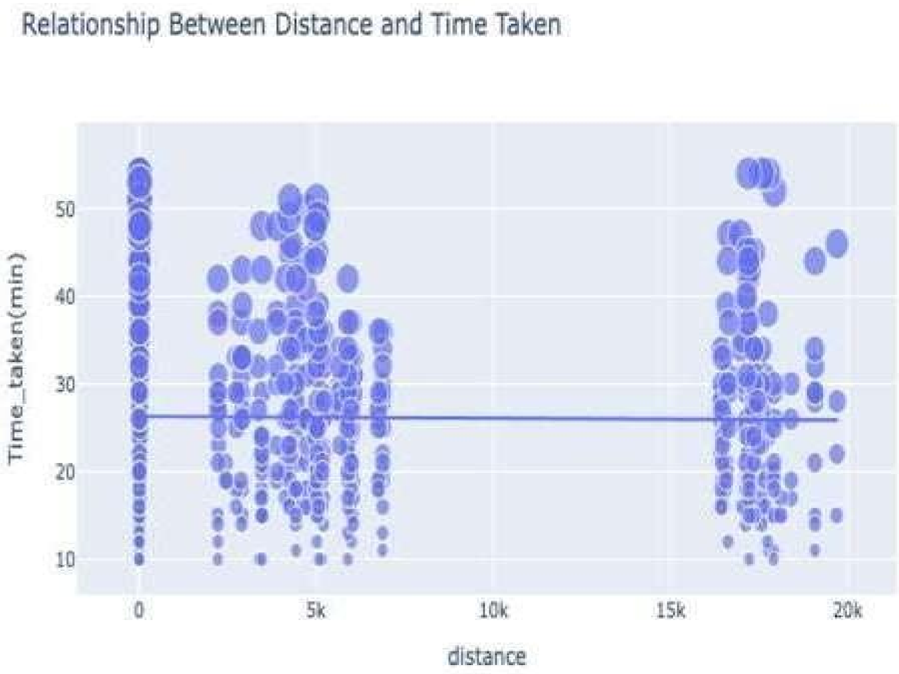

Figure 5: Relationship between distance and time taken

14.6 Relationship between time taken and age

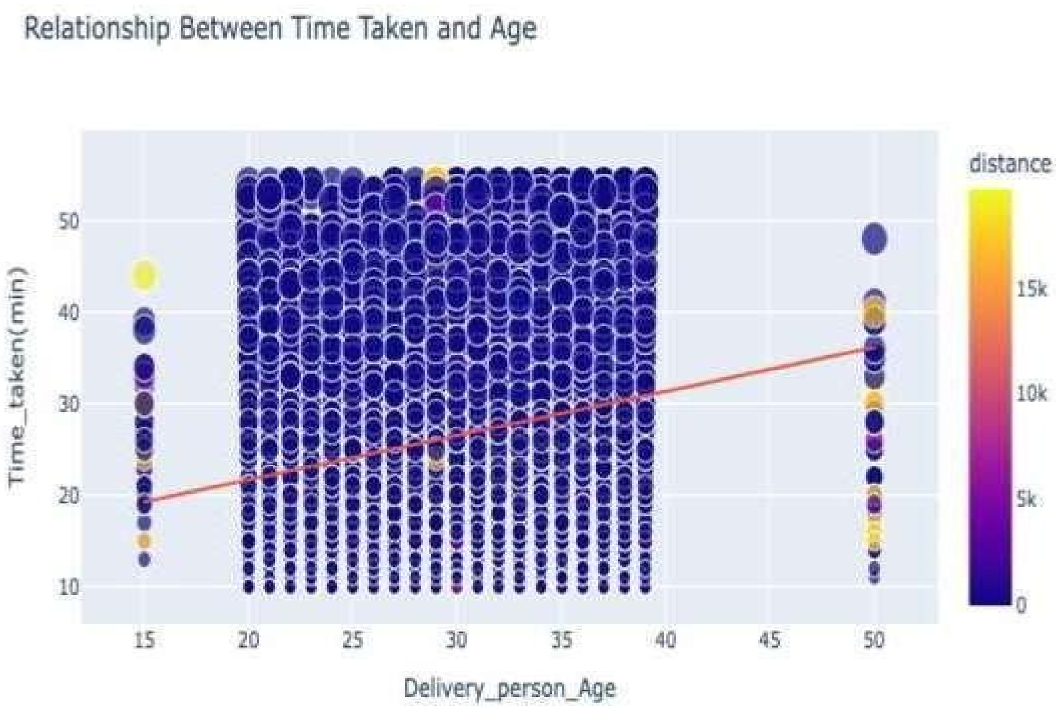

Figure 6: Relationship between time taken and age

14.7 relationship between time taken and ratings

Figure 7: Relationship between time taken and ratings

14.8 Types of Vehicles and orders

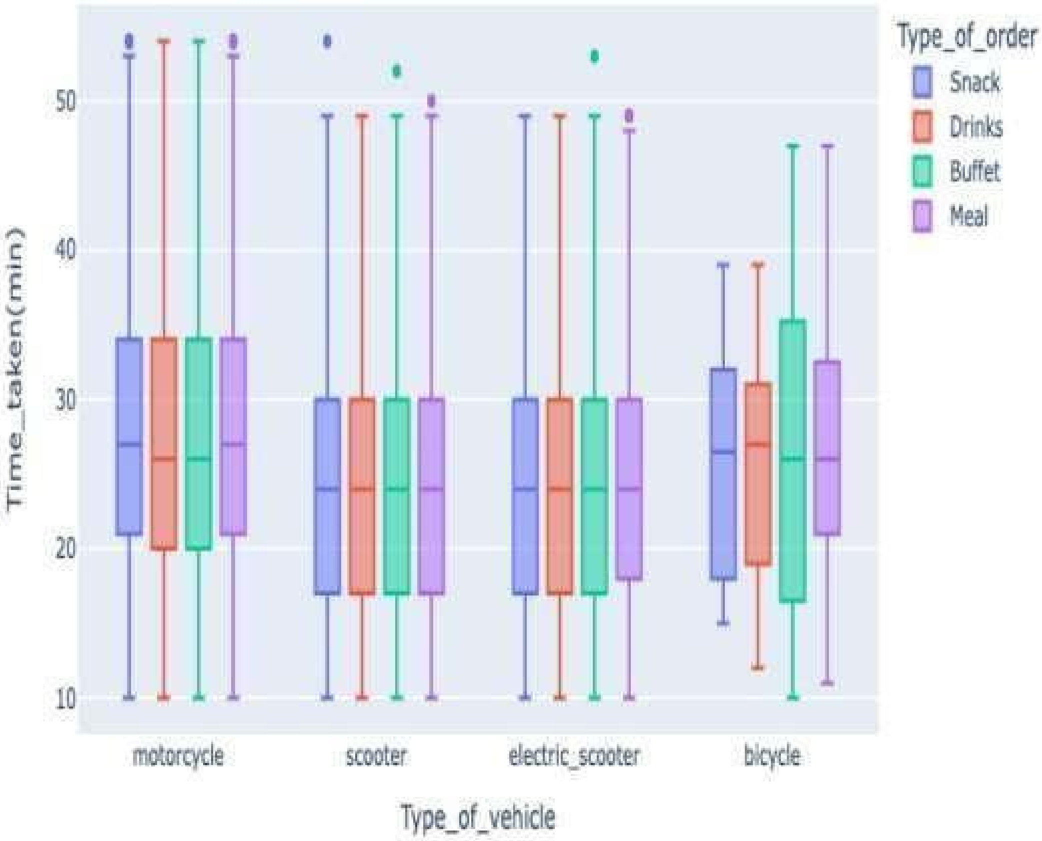

Figure 8: Types of Vehicles and orders

14.9 Splitting data

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 3, 128)            66560

 lstm_1 (LSTM)               (None, 64)                49408

 dense (Dense)               (None, 25)                1625

 dense_1 (Dense)             (None, 1)                 26

=================================================================
Total params: 117,619
Trainable params: 117,619
Non-trainable params: 0
_________________________________________________________________
```

Figure 9: splitting data

14.10 Training the model

```
Epoch 1/9
41033/41033 [==============================] - 410s 10ms/step - loss: 69.7154
Epoch 2/9
41033/41033 [==============================] - 405s 10ms/step - loss: 63.6772
Epoch 3/9
41033/41033 [==============================] - 404s 10ms/step - loss: 61.4656
Epoch 4/9
41033/41033 [==============================] - 406s 10ms/step - loss: 60.5741
Epoch 5/9
41033/41033 [==============================] - 401s 10ms/step - loss: 59.7685
Epoch 6/9
41033/41033 [==============================] - 401s 10ms/step - loss: 59.3501
Epoch 7/9
41033/41033 [==============================] - 397s 10ms/step - loss: 59.3121
Epoch 8/9
41033/41033 [==============================] - 402s 10ms/step - loss: 58.6929
Epoch 9/9
41033/41033 [==============================] - 399s 10ms/step - loss: 58.6897
```

Figure 10: training the model

14.11 Predicted outcomes

```
Food Delivery Time Prediction
Age of Delivery Partner: 29
Ratings of Previous Deliveries: 2.9
Total Distance: 6
1/1 [==============================] - 0s 23ms/step
Predicted Delivery Time in Minutes =  [[41.34929]]
```

Figure 11: predicted outcomes

15. LIMITATIONS

The food delivery time prediction project's shortcomings include its dependence on constrained parameters, such as age, distance, and ratings, which may cause it to ignore variables like traffic and weather. The appropriateness of the selected LSTM model is unknown, and issues with scalability are still unresolved. Concerns of generalization to various settings and real-time updates are also present, and reliability is further impacted by problems with data quality and the requirement for continuous model improvement.

16. CONCLUSION AND FUTURE WORK

In conclusion, the model's output of 41.35 minutes for a 6-kilometer delivery highlights several important concerns, even though machine learning allows intelligent food delivery time forecasts. Delivery times can be impacted by variables like traffic, weather, and order complexity; thus, including these in the forecast is necessary for more precise results. Improving real-world applicability and operational efficiency requires ongoing model refining and wider feature integration. In the future, the food delivery time prediction algorithm will be improved by including real-time data sources such as weather predictions and live traffic updates to improve accuracy. Advanced feature engineering may offer a more thorough grasp of delivery determinants by considering variables like order details and time of day. For wider applicability, it is imperative to optimize the model architecture, investigate various machine learning techniques, and expand geographically to other places. The model can be further refined by adding user input mechanisms, setting up performance monitoring systems, and encouraging industry collaborations. This will ensure that the model remains relevant and continuously improves in dynamic delivery contexts.

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