PREMIER UNIVERSITY, CHATTOGRAM

Department of Computer Science & Engineering

Project Proposal Report

On

"Food Delivery Time Prediction"

SUBMITTED BY

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1 Introduction

In today's world, online food delivery services are becoming increasingly popular. Customers want their food delivered quickly and accurately. However, many food delivery companies struggle to provide precise delivery times due to various unpredictable factors such as traffic, weather, and the time it takes for restaurants to prepare food. Currently, most food delivery platforms use simple methods to estimate delivery times, such as historical data and average delivery times. These methods do not consider real-time changes and can often lead to inaccurate predictions, resulting in unhappy customers and inefficiencies in the delivery process. This project presents a solution that utilizes the power of machine learning to more precisely determine food preparation time. By analyzing historical data comprising a variety of factors, the machine learning model can discover intricate patterns and correlations in order to generate precise time estimates. [1] In 'Domino's' like stores, when a customer places an order online through their app, the food delivery process unfolds in four discrete steps:

1. Assign the order to the nearest outlet.
2. A delivery vehicle is assigned.
3. The delivery vehicle drives to the restaurant to pick up the next order.
4. Preparation and packaging of the food by the restaurant.
5. Dropping off the order at the customer's location. [1]

Our project aims to solve this problem by developing a system that uses artificial intelligence (AI) to predict food delivery times more accurately. By using these advanced technologies, we can analyze a wide range of factors in real-time, including current traffic conditions, weather patterns, and restaurant preparation times. This will allow us to provide more precise delivery time estimates, leading to improved customer satisfaction and better resource management for food delivery services.

2 Background and Present State of the System

There are few contributions regarding accurate food delivery time prediction systems. Among other systems, it has become necessary to find a robust solution that can help reduce delivery time variability, provide real-time predictions, and enhance the efficiency of the entire delivery process. This system should accurately account for various factors such as traffic, weather, and restaurant preparation times, ultimately leading to improved customer satisfaction and operational efficiency for food delivery services. Hirschberg, C., A. Rajko, and M. W. Thomas Schumacher (2016) implements the changing market for food delivery. They has investigated two types of online platforms have risen to fill that void. The first type is the "aggregators," which emerged roughly 15 years ago; the second is the "new delivery" players, which appeared in 2013. Both allow consumers to compare menus, scan and post reviews, and place orders from a variety of restaurants with a single click. The aggregators, which are part of the traditional-delivery category, simply take orders from customers and route them to restaurants, which handle the delivery themselves. In contrast, the new-delivery players build their own logistics networks, providing delivery for restaurants that don't have their own drivers.[2] Luhtala, R. (2023). Quantifying the effects of external predictors on food delivery platform order volumes (Master's thesis).[3]

Coelho et al. (2016) describe a solution to optimize lunch breaks in furniture delivery tours but take the duration of the time windows for assembly as a fixed and predetermined value. [4] In the field of logistics, the planning of service times is often only a part of the larger vehicle routing problem (VRP), which is based on the traveling salesman problem (TSP). There exist many different variants of this problem when it comes to how services or deliveries are executed at geographically separated locations. The classic problem of reaching a number of nodes by the shortest possible way was well described by Laporte (1992). [5] A variation of this basic version is the consideration of time windows which specify when the traveler or the vehicle has to arrive at a specific node (Ahn and Shin 1991). [6] This is related to the situation discussed in this paper, as the vehicle routing problem with time windows (VRPTW) considers the duration that a vehicle has to stand at a stop. Calculating the duration of this stop time is generally considered a different problem. Other noticeable variants of the vehicle routing problem include the consideration of multi-vehicle problems [7], mixed pickup and delivery [8] or nodes which need to be visited in specific orders [9]. The problem of having variable-timed stops at each node was described by Vo¨ssing (2017) in an attempt to show why many companies still rely on human dispatcher knowledge for tour planning and time estimations.[10] The variations in the required time are complex and require a case-by-case analysis of the underlying reasons and data. Extrapolation from one problem domain to another is often not possible, because the problems have been simplified too much to be able to implement them in the real world [11].

Related works on food delivery time prediction have limitations and significant scope for development. Most existing systems use basic algorithms and historical data, but they do not adequately address real-time factors such as traffic, weather, and restaurant preparation times. Additionally, while machine learning has been applied to delivery time predictions, there is still a lack of comprehensive solutions that integrate all relevant data sources effectively. Handling the dynamic nature of real-time data, such as sudden traffic changes or unexpected delays in food preparation, remains a challenging task. Developing a system that can accurately process and analyze this data in real-time to provide precise delivery time predictions is essential for improving customer satisfaction and operational efficiency in food delivery services.

3 Objectives

The proposed work will be done to reach the following objectives:

- To design a model that can predict food delivery time accurately.
- To reduce customer waiting times by providing accurate delivery time estimates.
- To see the impact of delivery time predictions on customer satisfaction.
- To create a simple and easy-to-use platform or model where both restaurants and customers can check estimated delivery times.
- To analyze and utilize historical delivery data to improve prediction accuracy.

4 Literature Review

There is a growing interest in food delivery time prediction.In the past years,customers and restaurants people do not accurately precdict the delivery time.,but an ai based model can easily predict the time by using previous famous dataset.There are some algorithm that can help the model to learn data sets and then it will give some result basen on the training set that the model learn before.

To predict the food delivery time in real time, we need to calculate the distance between the food preparation point and the point of food consumption. After finding the distance between the restaurant and the delivery locations, we need to find relationships between the time taken by delivery partners to deliver the food in the past for the same distance.[12]

There are some key factors that influence delivery time:

I. Real-time traffic data significantly impacts delivery time predictions. Models often incorporate traffic data to adjust predictions dynamically.[13]

II. Weather can affect delivery times by influencing both the speed of delivery and the volume of orders.[13]

III. The number of orders and their distribution within a delivery area are critical factors. Higher order volumes can lead to delays due to longer preparation times and increased delivery stops.[14]

IV. The variability in preparation times across different restaurants is a significant factor. Some models integrate historical preparation time data to enhance prediction accuracy.[1]

V. The experience and efficiency of delivery drivers, along with optimal routing algorithms, are important considerations.[4]

Machine learning has proven to be a valuable tool in predicting food delivery times, offering substantial improvements over traditional methods. Ongoing advancements in ML algorithms and the integration of real-time data sources are expected to further enhance the accuracy and reliability of delivery time predictions.[15]

5 Outline Methodology

5.1 Architecture

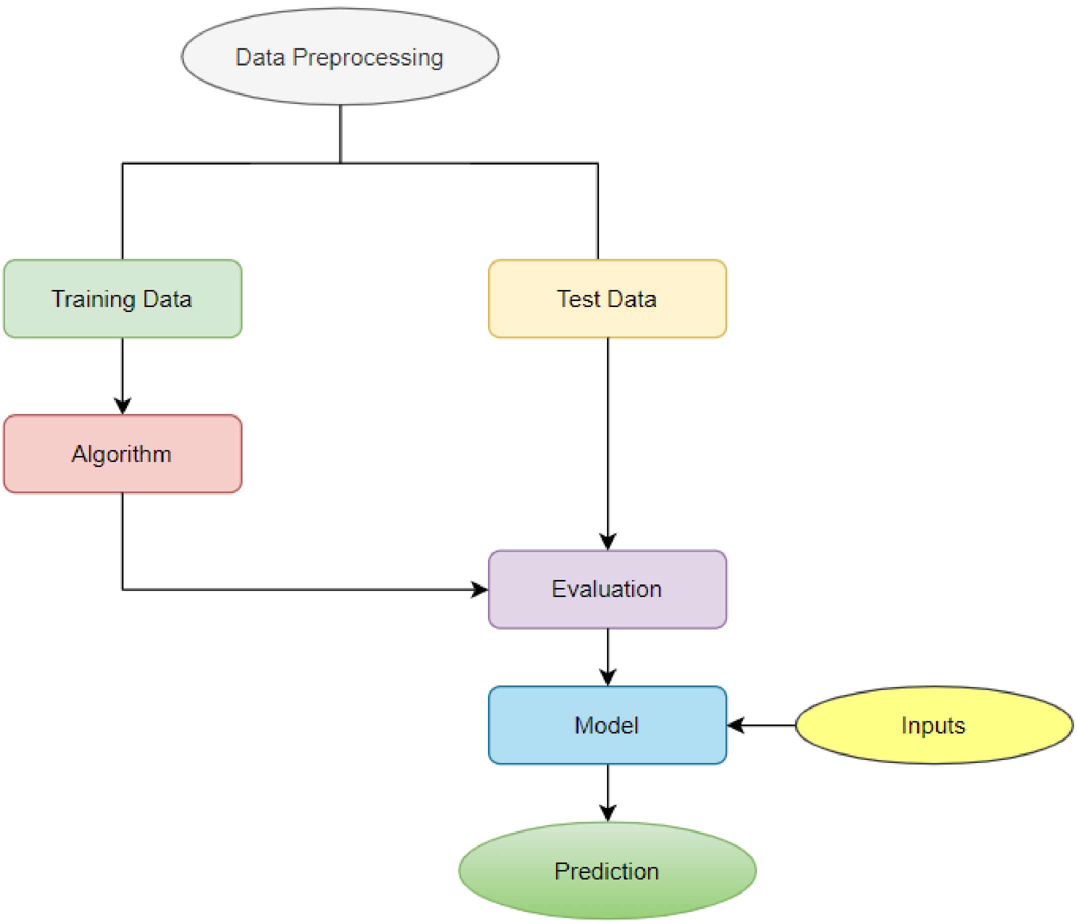

Figure: System Architecture

5.2 Extraction Module

The first step in our methodology is the extraction module, which focuses on gathering and preprocessing the data required for accurate delivery time predictions. This involves collecting both historical and real-time data. Historical data includes information on order times, delivery distances, and actual delivery times, while real-time data encompasses current traffic conditions, weather, and restaurant preparation times. This data collection process is crucial as it provides the raw input needed for our machine learning model. Once the data is collected, it undergoes a thorough preprocessing stage to ensure its quality and consistency. Data cleaning is performed to remove any errors or inconsistencies, and normalization is applied to maintain uniformity across the dataset. One key task during this phase is calculating the distances between the restaurant and the delivery location using the Haversine formula [16], which utilizes latitude and longitude coordinates to determine the most accurate distance. Additionally, feature engineering is conducted to create relevant variables, such as the time of day, day of the week, and specific traffic patterns, which can significantly impact delivery times.

5.3 Query Module

Following the extraction and preprocessing of data, the query module processes new orders and retrieves relevant data for real-time prediction. When a new order is placed, essential features such as the delivery partner's age, partner's rating, and the distance between the restaurant and the customer are extracted. This step ensures that the most pertinent information is considered for each delivery prediction. The query module then searches the preprocessed dataset to find similar historical orders and their associated delivery times. This process leverages the power of historical data to inform real-time predictions, ensuring that the model can draw from past experiences to make more accurate estimates. The extracted data serves as the input for the prediction model, forming the foundation for generating precise delivery time estimates.

5.4 Score Generation Module

The score generation module is at the heart of our predictive methodology, responsible for generating the actual delivery time predictions based on the processed data[15]. The first step involves importing the necessary libraries, such as Pandas, NumPy etc which provide the tools required for data manipulation, analysis etc.

Next, the dataset is loaded from a reliable source, like a GitHub repository, and read into the system. The dataset undergoes preprocessing, where any missing values are checked and addressed. Distances between the restaurant and delivery location are calculated using the Haversine formula, and these distances are added as a new column in the dataset. This enriched dataset is then analyzed to understand the relationships between delivery time and various features, such as distance, delivery partner's age, and rating. Visualization tools like Plotly are used to create scatter plots and other visual representations, revealing trends and correlations within the data.

With the data prepared and analyzed, the next step is model training. The dataset is split into training and testing sets to evaluate the model's performance.

After training, the model is ready for predictions. It will be tested with sample input data, such as the delivery partner's age, rating, and distance, to predict delivery times. The model's performance is validated to ensure its accuracy and reliability.

6 Conclusion

To conclude,it can be said that the food delivery time prediction project aims to guess correct time of delivering food.By using this project any customer or restaurants owners can easily see the delivery time.By looking at past deliveries and considering things like traffic,weather,delivery man's age,vehicle type,delivery man's rating, the system tries to give accurate estimates.That's means this helps both customers and restaurants know when to expect their orders.Through this model customer or restaurants owmner can check who can give order within less time.Food delivery company can be benefited by improving efficiency and potentially reduce cost and time further.This also aimed to identify the most effective machine learning models for predicting food delivery times and to understand the key factors influencing these times.[14]

Bibliography

[1] M. Kumar, "Prediction of kitchen preparation time in food delivery," Ph.D. dissertation, INDIAN INSTITUTE OF TECHNOLOGY DELHI, 2023.

[2] C. Hirschberg, A. Rajko, T. Schumacher, and M. Wrulich, "The changing market for food delivery," 2016.

[3] R. Luhtala *et al.*, "Quantifying the effects of external predictors on food delivery platform order volumes," M.S. thesis, 2023.

[4] L. C. Coelho, J.-P. Gagliardi, J. Renaud, and A. Ruiz, "Solving the vehicle routing problem with lunch break arising in the furniture delivery industry," *Journal of the Operational Research Society*, vol. 67, pp. 743–751, 2016.

[5] G. Laporte, "The traveling salesman problem: An overview of exact and approximate algorithms," *European Journal of Operational Research*, vol. 59, no. 2, pp. 231–247, 1992.

[6] B.-H. Ahn and J.-Y. Shin, "Vehicle-routeing with time windows and time-varying congestion," *Journal of the Operational Research Society*, vol. 42, no. 5, pp. 393–400, 1991.

[7] G. J. Beaujon and M. A. Turnquist, "A model for fleet sizing and vehicle allocation," *Transportation Science*, vol. 25, no. 1, pp. 19–45, 1991.

[8] D. O. Casco, B. L. Golden, E. A. Wasil, *et al.*, "Vehicle routing with backhauls: Models, algorithms and case studies," *Vehicle routing: methods and studies*, no. 16, pp. 127–147, 1988.

[9] J. Desrosiers, Y. Dumas, M. M. Solomon, and F. Soumis, "Time constrained routing and scheduling," *Handbooks in operations research and management science*, vol. 8, pp. 35–139, 1995.

[10] M. Vössing, "Towards managing complexity and uncertainty in field service technician planning," in *2017 IEEE 19th Conference on Business Informatics (CBI)*, IEEE, vol. 1, 2017, pp. 312–319.

[11] K. Sörensen, M. Sevaux, and P. Schittekat, ""multiple neighbourhood" search in commercial vrp packages: Evolving towards self-adaptive methods," *Adaptive and multilevel metaheuristics*, pp. 239–253, 2008.

[12] H. Şahin and D. İçen, "Application of random forest algorithm for the prediction of online food delivery service delay," *Turkish Journal of Forecasting*, vol. 5, no. 1, pp. 1–11, 2021.

[13] C. Gao, F. Zhang, G. Wu, *et al.*, "A deep learning method for route and time prediction in food delivery service," in *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 2021, pp. 2879–2889.

[14] E. Yalçinkaya and O. A. Hızıroğlu, "A comparative analysis of machine learning models for time prediction in food delivery operations," *Artificial Intelligence Theory and Applications*, vol. 4, no. 1, pp. 43–56, 2024.

[15] A. Crivellari, E. Beinat, S. Caetano, A. Seydoux, and T. Cardoso, "Multi-target cnn-lstm regressor for predicting urban distribution of short-term food delivery demand," *Journal of Business Research*, vol. 144, pp. 844–853, 2022.

[16] J. Renfree, "Distance calculation using haversine formula," *Consultado en http://www. mathworks. com/matlabcentral/fileexchange/27785-distance-calculation-usinghaversine formula Rice, MT, Paez, FI, Mulhollen, AP, Shore, BM, Caldwell, R., & Caldwell, D.(2012). Crowdsourced Geospatial Data. A report on the emerging phenomena of crowdsourced and user-generated geospatial data*, p. 147, 2010.

[1] [2] [3] [4] [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] [16] [15] [14]