Machine Learning-Based Delivery Time Prediction for Low-Carbon Food Delivery

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***Abstract*—The increasing demand for online food delivery services has significantly impacted urban logistics, raising critical challenges related to operational efficiency and environmental sustainability. In this context, accurate delivery time prediction plays a key role in improving service quality while supporting the transition toward low-carbon delivery systems. This paper first provides a comprehensive analysis of sustainable and low-carbon delivery modes for urban food distribution. The study then develops and evaluates several machine learning models, namely XGBoost, LightGBM, Gradient Boosting, and KNN, using a dataset that combines operational, temporal, and contextual features to predict food delivery times. The comparative analysis shows that tree-based approaches outperform the other models, with XGBoost achieving the best predictive performance. The findings demonstrate the strong potential of artificial intelligence and machine learning techniques for enhancing delivery efficiency and supporting sustainable urban logistics decision-making. Moreover, the proposed predictive framework can be integrated into optimization models to enhance delivery planning and support the selection of environmentally sustainable delivery modes.**

Keywords– Last Mile Delivery, Low-Carbon Transport, Sustainable Food Delivery, Machine Learning, Delivery Time Prediction

I. Introduction

The rapid expansion of food delivery services has significantly transformed urban logistics and consumer habits. Today, ordering meals via mobile applications such as *Uber Eats*, *Deliveroo*, or *Talabat* has become part of everyday life. As consumers lead increasingly busy lifestyles, they expect fast, reliable, and on-time delivery services [1]. At the same time, the growing carbon emissions generated by urban food delivery operations have intensified environmental concerns. This has led governments and logistics stakeholders to promote low-carbon delivery solutions in order to meet sustainability targets and climate mitigation objectives [2]. While online food delivery services offer significant convenience and economic opportunities, they also generate substantial environmental impacts, particularly through increased greenhouse gas emissions, traffic congestion, and energy consumption [3]. As cities strive to achieve sustainability and carbon neutrality goals, particularly in the European Union, Canada and emerging Gulf economies such as Saudi Arabia, the transition toward low-carbon food delivery systems has become a critical challenge for researchers and policymakers [4]. Beyond environmental considerations, operational performance remains a critical concern for logistics operators and platform providers. Delivery time, in particular, represents a key performance indicator directly affecting customer satisfaction and service competitiveness [2].

Recent advances in data analytics and machine learning (ML) offer new opportunities to enhance delivery operations. Predictive models can estimate delivery times more accurately by considering multiple factors such as distance, traffic conditions, weather, and delivery modes [5].

The objective of this study is therefore to predict food delivery times in order to evaluate and optimize low-carbon delivery strategies and support more sustainable and efficient decision-making.

Accordingly, this paper proposes a comprehensive study that combines a comparative analysis of low-carbon food delivery modes with a machine learning-based delivery time prediction approach: (i) reviewing and classifying existing low-carbon delivery modes; and (ii) developing and evaluating several ML models, including XGBoost, Random Forest, LightGBM, and Gradient Boosting, using real-world delivery datasets.

The remainder of this paper is organized as follows. Section II reviews the literature on low-carbon food delivery modes. Section III presents the dataset and preprocessing steps. Section IV describes the experimental setup, discusses the results of the ML models for delivery time prediction. Finally, Section V concludes the paper and outlines future research directions.

II. Related Work

A. Online Food Delivery Systems

A typical online food delivery (OFD) system involves several interconnected stages, as illustrated in Figure 1, the customer places an order via a mobile application, the restaurant receives and prepares the order, the courier picks it up and the meal is transported and delivered to the customer. This process highlights the complexity of coordinating multiple actors and operational factors in last-mile delivery [6].

The growth of online food delivery (OFD) platforms has been extensively studied from multiple perspectives, including optimization, consumer behavior, digitalization, and sustain-

Fig. 1: Online Food Delivery Process

ability. The study in [7] developed a multi-objective optimization model to balance platform profit, rider income, and delivery efficiency by leveraging trajectory-based big data, thereby enhancing overall platform performance. Complementarily, [8] highlights the critical role of electronic word-of-mouth (e-WOM) as a key driver of platform adoption, using SmartPLS (Partial Least Squares Structural Equation Modeling) to demonstrate its strong influence on user behavior.

From a digitalization perspective, [9] identifies the lack of digital infrastructure as a major barrier to the adoption of Industry 4.0 technologies in food supply chains, employing Multi-Criteria Decision Making (MCDM) and barrier analysis techniques. Similarly, [10] shows that digital transformation is shifting value creation from traditional food quality toward data-driven service quality, as evidenced through a systematic literature review.

In terms of evolving customer expectations, [11] proposes that order assignment strategies should account for perceived waiting time rather than solely actual travel time, using the Water Wave Optimization (WWO) algorithm to improve both customer satisfaction and operational efficiency. Furthermore, [12] demonstrates, through quantitative survey and regression analysis, that trust plays a mediating role between service quality and customers' intention to reuse OFD applications.

B. Low-Carbon Delivery Modes

The transition toward low-carbon delivery modes has become a major priority in sustainable urban logistics due to the rapid expansion of on-demand food delivery services [13]. Food delivery operations are highly time-sensitive and require strict adherence to delivery deadlines in order to maintain food quality and customer satisfaction [14]. This constraint becomes particularly critical during peak demand periods, such as lunchtime, when a large number of orders must be delivered within a very short time window [15].

Several low-carbon delivery modes have recently been explored to address both environmental and operational challenges in last-mile logistics. Electric vehicles (EVs) represent one of the most widely adopted solutions for urban deliveries due to their relatively high payload capacity and operational reliability [16]. However, their efficiency may decrease in dense urban environments due to traffic congestion, limited parking availability, battery constraints, and restricted curb access [17]. In contrast, cargo bikes and electric bicycles are highly efficient for short-distance deliveries in city centers. Their ability to bypass traffic congestion and access restricted areas allows them to significantly reduce delivery times and CO_2 emissions [18]. Nevertheless, their limited payload capacity and rider fatigue constraints restrict their scalability during periods of high demand.

Electric scooters and motorcycles provide a balance between speed, flexibility, and energy efficiency, making them well suited for time-sensitive food delivery in dense urban areas [19]. For example, during lunchtime peaks, these vehicles can perform rapid point-to-point deliveries while maintaining relatively low energy consumption. However, they remain constrained by payload limitations and battery range.
More recently, autonomous delivery technologies such as drones and ground delivery robots have emerged as promising alternatives for low-carbon logistics [20]. These systems can potentially reduce operational emissions and costs while improving delivery speed in specific contexts. However, their deployment is still limited by regulatory constraints, weather sensitivity, infrastructure requirements, and limited payload capacity [20]. It can be observed that no single delivery mode can simultaneously optimize environmental impact, delivery speed, and operational reliability in urban food delivery systems. Each transportation mode offers specific advantages but also presents limitations related to capacity, accessibility, and traffic conditions. Therefore, recent studies increasingly recommend hybrid and multimodal delivery strategies that combine different modes of transport. In such systems, EVs are commonly used to transport batches of orders from restaurants or distribution depots to urban micro-consolidation hubs, where orders are sorted and prepared for the last-mile distribution [21]. The final delivery stage is then performed by smaller and more agile vehicles such as cargo bikes or electric two-wheelers. The multimodal approach enables logistics operators to combine the high carrying capacity of EVs for medium-distance transport with the flexibility of light vehicles that can navigate dense urban areas more easily [20]. As a result, it helps reduce congestion and CO_2 emissions while improving delivery efficiency and maintaining on-time delivery, particularly during peak demand periods such as

lunchtime. To further enhance operational performance and ensure service continuity in the presence of uncertainties, AI is increasingly integrated into delivery management systems [22]. ML models can predict demand patterns, estimate delivery times, and anticipate disruptions such as traffic congestion or weather-related delays. The performance of low-carbon delivery systems is typically evaluated using several key indicators. Environmental indicators include CO_2 emissions and energy consumption, while operational indicators focus on delivery time, on-time delivery rate, and service reliability . Economic indicators such as operational costs and fleet use are also considered [13], [23]. These indicators help evaluate how efficient and sustainable last-mile food delivery systems are.

C. Challenges of Sustainable Food Delivery

The food delivery industry has undergone tremendous growth since the COVID-19 pandemic, raising significant sustainability challenges, particularly in achieving the United Nations 2030 Sustainable Development Goals (SDGs) [2]. These challenges span multiple dimensions. From a technical perspective, battery autonomy remains a critical limitation, especially for UAVs and electric vehicles, requiring advanced scheduling algorithms, adaptive partial recharge strategies, and battery swapping mechanisms to ensure operational efficiency [18], [24]. In addition, the lack of robust charging infrastructure constitutes a major barrier to zero-emission delivery, motivating the development of optimization models such as mixed-integer nonlinear programming and multi-objective approaches to improve infrastructure allocation and routing with intermediate charging stations [25]–[27]. Vehicle driving range further constrains adoption, as highlighted by empirical studies and simulation-based or ML approaches aimed at predicting and extending EV range [5], [28].

From a logistical standpoint, low-carbon delivery systems face reduced payload capacity due to battery weight, with electric trucks experiencing up to a 9% reduction, which may be acceptable for short-range operations but remains a constraint for broader deployment [3]. Similar limitations apply to drone delivery, despite their efficiency for small parcels [4], [23]. Moreover, fleet management becomes increasingly complex when dealing with geographically dispersed operations, although optimized and smart management strategies can significantly reduce emissions [29]–[31].

Environmental and economic challenges also play a crucial role. Weather conditions and air pollution influence consumer behavior, increasing reliance on food delivery services, particularly among vulnerable populations [32], [33]. At the same time, high production and distribution costs, coupled with delivery inefficiencies such as failed deliveries (estimated at 2–6%), highlight the need for improved logistics and cost management [34], [35]. Furthermore, the transition to low-carbon delivery requires substantial upfront investments, necessitating supportive policies such as tax incentives, R&D subsidies, and financial mechanisms like green credits [36], [37].

Finally, regulatory challenges remain a key barrier, including urban access restrictions, inadequate infrastructure, and evolving mobility policies that must be addressed to enable sustainable delivery systems [38], [39]. Safety and operational regulations also impact the deployment and efficiency of innovative delivery models, such as truck–drone systems, which are subject to strict regulatory frameworks despite their demonstrated potential for energy savings [40], [41].

To address these challenges, it is essential to rely on data-driven approaches that capture real-world delivery conditions. Therefore, section III presents the data collection and preprocessing steps, which form the basis for analyzing a delivery case study and developing ML models for delivery time prediction.

III. Data Collection and Preprocessing

The dataset used in this study was obtained from Kaggle[1]. It is specifically designed for predicting food delivery times based on multiple operational and environmental factors that influence last-mile logistics performance. The dataset contains simulated yet realistic data suitable for supervised regression tasks. This dataset is highly relevant for food delivery time prediction as it combines operational variables (e.g., distance, preparation time, vehicle type, courier experience) with contextual factors such as weather, traffic level, and time of day, allowing models to reflect realistic delivery conditions. Its mix of numerical and categorical features makes it suitable for evaluating various machine learning approaches, including tree-based ensemble methods (XGBoost, LightGBM, GB) and instance-based models such as KNN. Moreover, it represents realistic urban logistics scenarios and provides a well-structured regression framework with a clearly defined target variable, making it an appropriate benchmark for performance comparison across ML algorithms.

IV. Experiments and Results

A. Experimental Setup

The experiments were conducted on the Food Delivery Times dataset, with the objective of predicting the delivery time in minutes. Model training was performed using Google Colab with a T4 GPU. The input features include delivery distance, traffic level, weather conditions, time of day, courier experience, and vehicle type. Data preprocessing involved removing duplicate entries and handling missing values. Categorical variables (Weather, Traffic_Level, and Time_of_Day) were imputed using the mode, while the numerical feature Courier_Experience_yrs was imputed using the median. Categorical features were then encoded using one-hot encoding. The dataset was split into training and test sets using a 70/30 ratio with a fixed random state of 250 to ensure reproducibility. Model performance was evaluated using the coefficient of determination (R^2) and the Mean Absolute Error (MAE). The R^2 score was computed on both training and test sets to assess

[1] https://www.kaggle.com/datasets/denkuznetz/fooddelivery-time-prediction

model fit and generalization capability. MAE was used as the primary evaluation metric since it provides an interpretable measure of prediction error expressed in minutes.

Four regression models were evaluated: XGBoost, LightGBM, GB Regressor, and KNN. For each model, hyperparameter optimization was performed using GridSearchCV with 5-fold cross-validation on the training set. The corresponding hyperparameter search spaces are summarized in Table I.

B. Results & Discussion

This section presents through Table II the performance evaluation of the proposed ML models for delivery time prediction. The models are compared using R^2 and MAE, and their predictive behavior is further analyzed through Figure 2 of predicted versus actual values. Overall, tree-based ensemble methods outperform the instance-based KNN model in terms of accuracy and generalization. XGBoost achieves the best overall performance, with a test R^2 of 0.8019 and the lowest MAE (0.2898), indicating high predictive accuracy and robustness. Gradient Boosting follows closely, with a test R^2 of 0.7979 and MAE of 0.2952, confirming the effectiveness of boosting approaches for structured delivery data. In contrast, KNN exhibits clear overfitting behavior, achieving a perfect training score ($R^2 = 1.0$) but lower generalization performance, with a test R^2 of 0.7909 and the highest MAE (0.35). This indicates that KNN struggles to capture the underlying patterns of delivery data compared to ensemble methods.

Fig. 2 illustrates the relationship between predicted and actual delivery times for all models.

XGBoost shows a strong concentration of points around the diagonal, confirming its high accuracy and stability. LightGBM and Gradient Boosting also demonstrate good alignment, although with slightly higher dispersion, especially for larger delivery times. In contrast, KNN exhibits a wider spread of points and more deviation from the diagonal line, particularly for extreme values. This confirms its weaker generalization and sensitivity to data variability.

The experimental results clearly indicate that XGBoost provides the best trade-off between accuracy and generalization, which make it the most suitable model for real-world application. Furthermore, the superior performance of tree-based models highlights their ability to capture nonlinear relationships between delivery features such as distance, traffic conditions, weather, and courier experience. This is particularly important in the context of low-carbon delivery, where operational decisions must balance efficiency and environmental impact.

V. Conclusion

This paper proposes a ML-based approach for predicting delivery time in low-carbon food delivery systems, supported by a comprehensive review of the state of the art on online food delivery, low-carbon transport modes and associated challenges. The results show that tree-based models, particularly XGBoost, achieve high prediction accuracy, enabling improved operational efficiency and supporting more sustainable decision-making in last-mile delivery.

As future work, real-world case studies will be investigated to further validate the proposed framework, particularly in emerging contexts such as Saudi Arabia, where rapid urbanization and the growing demand for online food delivery create new challenges and opportunities for sustainable logistics. In addition, future research will focus on integrating the proposed ML-based prediction framework into optimization models, such as the Electric Vehicle Routing Problem (EVRP), in order to jointly optimize delivery operations, energy efficiency, and the selection of low-carbon delivery modes.

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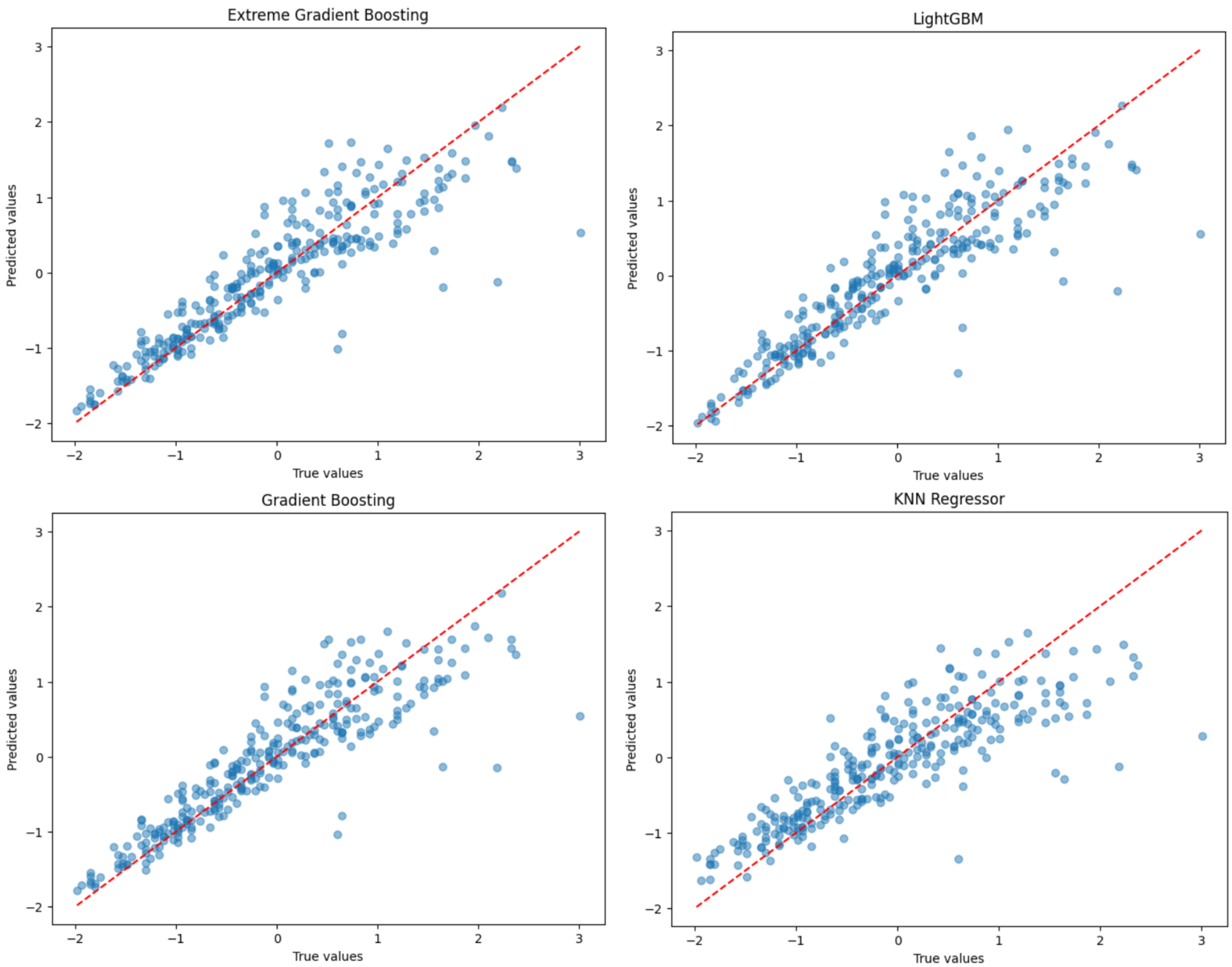

Fig. 2: Actual vs. predicted delivery times: (a) XGBoost, (b) LightGBM, (c) Gradient Boosting, (d) KNN.

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TABLE I: Hyperparameter Search Space for Each ML Model

Model	Hyperparameter	Values
XGBoost	$n\_estimators$	$\{50, 100, 200\}$
	$learning\_rate$	$\{0.1, 0.2\}$
	max_depth	$\{3, 5, 10\}$
	$subsample$	$\{0.8, 1.0\}$
	min_child_weight	$\{1, 3, 5\}$
LightGBM	$n\_estimators$	$\{50, 100, 200\}$
	$learning\_rate$	$\{0.05, 0.1, 0.2\}$
	max_depth	$\{3, 5, 10\}$
	num_leaves	$\{31, 50, 100\}$
	$subsample$	$\{0.8, 1.0\}$
	min_child_weight	$\{1, 3, 5\}$
GB	$n\_estimators$	$\{50, 100, 200\}$
	$learning\_rate$	$\{0.05, 0.1, 0.2\}$
	max_depth	$\{3, 5, 10\}$
	$subsample$	$\{0.8, 1.0\}$
	$min\_samples\_split$	$\{2, 5, 10\}$
KNN	$n\_neighbors$	$\{3, 5, 7, 10\}$
	$weights$	{uniform, distance}
	p	$\{1, 2\}$
	$algorithm$	{auto, ball_tree, kd_tree, brute}

TABLE II: Model Performance Comparison

Model	Train R^2	Test R^2	MAE
XGBoost	0.8091	0.8019	0.2898
LightGBM	0.8268	0.7909	0.3003
GB	0.8162	0.7979	0.2952
KNN	1.0000	0.7909	0.3500

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