

Designing an AI-Driven Intelligent Vehicle Routing Model for Real-Time Order Picking and Delivery Operations in Food Service Logistics

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Abstract – With the advent of modern food service logistics, intelligent and dynamic routing systems have become necessary to efficiently tackle complex order picking and last-mile delivery scenarios. The design and implementation of a smart AI-enabled vehicle routing model with real-time data integration, IoT connectivity, and communication networks are proposed to maximize delivery efficiency in food service logistics. According to the model, it uses historical order data, weather data, and time features to predict demand patterns using advanced regression methods while duly incorporating the predictions into a vehicle routing heuristic to fulfil orders dynamically. Exploratory data analysis and feature engineering were applied, architecture was proposed, and several machine learning models were checked for prediction, including linear regression, ridge regression, and support vector regression. Although drawbacks are observed with predictive R² scores pointing to model limitations, the proposed integrated framework has shown useful applications in aiding routing decisions through real-time update communications. The study gives a pragmatic perspective on deploying AI- and IoT-enabled communication systems for the optimization of logistics operations for rapidly evolving urban food-service environments.

Keywords: AI-driven logistics; Vehicle routing optimization; Order picking; Food service delivery; Machine learning

I. INTRODUCTION

The rapid growth of the food service logistics sector has created unparalleled challenges in the management of real-time order picking and last-mile delivery operations [1][2]. Consumers have become increasingly demanding when it comes to punctual and reliable deliveries, such that logistics providers need to incorporate intelligent routing systems capable of dynamic adaptation to evolving demand patterns and environmental conditions [3][4]. In most instances, the traditional vehicle routing models do not consider real-time data streams, which restricts their applicability to operational uncertainty [5].

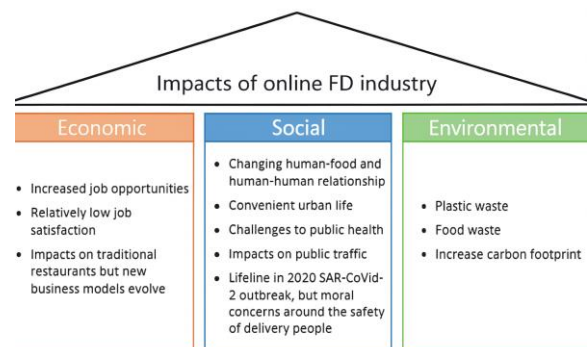


Fig. 1. Impact of Online FD Industry [11]

Food logistics has always been service-oriented, characterized by intense rivalry and poor profit margins, while also responding to fluctuating customer needs as seen in figure 1. With technological advancements in communications and IoT on land, data can be collected, transmitted, and

processed seamlessly across distributed logistics systems [6][7][28]. IoT-empowered sensors, GPS tracking, and wireless communication infrastructure help to track the locations of vehicles continuously, grasp traffic conditions applied weather status, and create enhancements on order statuses, thereby improving routing and scheduling decision-making processes [8][9]. AI-powered predictive analytics combined with IoT-driven communication systems promise huge gains in vehicle-route optimization by coupling forecasting of demands with real-time operational data [10][11].

This research presents an AI-based intelligent vehicle routing algorithm for the food service logistics sector, relying on communication [26] networks and IoT connectivity for dynamic and efficient routing decisions. By coupling machine learning-based demand prediction with heuristic routing algorithm performance assessment within a real-time data framework, the proposed model addresses a critical issue in delivery systems—the need to be responsive and adaptive in an urban setting. [12][13]. These works contribute further to the growing field of smart logistics, connected transport systems, and AI-enabled communications framework, offering working insight to researchers and practitioners in the fields of logistics, transport, and communications system engineering [14][15].

A. Challenges in Order Picking, Delays, and Inefficient Resource Allocation

Effective order pickup and prompt delivery are crucial to the success of food service logistics, particularly in an age when customer expectations are influenced by immediate service and minimum delays [5]. In the dynamic realm of food service logistics, order pickup and prompt delivery are essential duties that encounter many operational impediments. The complexity of real-time order

fulfilment escalates owing to the substantial number of perishable commodities, unpredictable order volumes, and products kept across several temperature-sensitive areas. Static routing techniques often inadequately address real-time variables like as traffic, weather, and fluctuating inventory levels, resulting in delays and diminished service quality. Moreover, traditional allocation algorithms overlook real-time inventory metrics, including expiration dates and backorder status, leading to suboptimal labour and vehicle utilisation. The manual coordination between warehouse workers and delivery people aggravates the problem, leading to disjointed operations. The lack of integrated, AI-driven intelligence in logistics operations impedes the system's capacity to adapt dynamically to changing demand, inventory status, and delivery priorities. Data silos and insufficient system interoperability hinder visibility across the supply chain, obstructing the creation of adaptive, data-driven solutions. The compounding issues highlight the need for an intelligent truck routing system that utilises real-time predictive analytics and automated decision-making to enhance order picking and resource allocation.

B. Role of AI and Machine Learning in Optimizing Logistics Operations

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as revolutionary influences in the logistics and supply chain sector. They provide data-driven decision-making skills that markedly improve the efficiency, reactivity, and flexibility of logistics operations [6]. AI and ML significantly impact contemporary logistics, particularly in the food delivery sector. These technologies provide predictive insights that enhance delivery routes, minimise waste, and elevate client pleasure. This project employs AI and ML to predict item demand, prioritise urgent deliveries, and dynamically allocate

delivery routes based on real-time variables. Machine learning methods, including linear regression, random forest, and decision trees, were used to forecast essential logistical variables such as delivery time and vehicle load efficiency. These forecasts are incorporated into a routing engine to reduce delays and resource inefficiencies. Moreover, AI enables adaptive task scheduling, optimising the utilisation of human and vehicular resources. The system seeks to optimise picking, packaging, and delivery schedules using data-driven decision-making to improve overall operational efficiency. This part emphasises the practical applications of AI and ML methods, which provide the fundamental technical basis of the proposed intelligent logistics system.

The application of AI and ML in logistics processes not only resolves existing problems but also helps build smart systems capable of independent learning, adaptation, and optimization. These tools are critical for building a well-defined and agile logistics network in fast growing sectors like food service delivery [9, 10]. The specific aims of the study:

- To design an AI-based routing model for efficient food delivery.
- To reduce delays through predictive modeling.
- To optimize resource allocation using historical inventory and sales data.

II. KEY CONTRIBUTION OF THE STUDY

This study brings forth several key contributions to the evolution of AI-controlled logistics and smart delivery systems. First, it attempts to provide a new paradigm of AI-based vehicle routing system tailored to tackle the dynamically evolving and time-

critical demands of food service logistics. An added leverage to last-mile delivery operations results from the system's ability to consider predictive modeling and real-time data inputs in its decision-making.

The main innovation is the incorporation of real-time inventory and perishability metadata, such as expiry dates, backorder status, and promotion tags, into routing logic. Based on this information, prioritizing deliveries can be accomplished with concerned urgency or with respect to freshness level, which goes a long way toward minimizing food waste and improving service quality. Complementing this workflow, the research evaluates several machine learning models for sales forecasting, which are then used as input for intelligent order picking and delivery scheduling; this includes Linear Regression, Random Forest, and Decision Tree Regressors.

Alongside these models, the authors create a synthetic multi-dimensional dataset that simulates real-world food logistics operations. Key operational bottlenecks and demand trends are brought to light through a robust exploratory data analysis (EDA), which includes heatmaps and time-series patterns. Furthermore, feature engineering improves the model by introducing logistics-specific variables like "Days to Expiry" and "Stock Turnover Rate," thereby enriching the routing model's contextual awareness.

Each of the predictive models is tested for robustness via R^2 Score, Adjusted R^2 , and RMSE. These results indicate that it is feasible to utilize forecasting, even with simplistic models like Linear Regression (with an RMSE of approximately 23.82) for work purposes. These forecasts, then, are tied into the rule-based AI logic that detours resources, delivery prioritization, and vehicle assignment,

effectively linking predictive analytics with day-to-day operational decision-making.

An end-to-end methodology from data cleansing and feature extraction to predictive modeling and routing logic deployment is described in the article, providing a replicable pipeline for a smart logistics system. Moreover, the framework proposes reducing wastage, optimization of delivery cycles, and increased vehicle utilization toward sustainable urban logistics. Finally, a forward-looking basis is laid in suggesting that integration could be extended to encompass traffic pattern data, weather forecast information, and customer response tracking, thereby augmenting intelligence and adaptability in the delivery process.

III. LITERATURE SURVEY

The objectives focus on the formulation of an efficient AI-based intelligent vehicle routing [24] model for real-time order processing and dish delivery within food service logistics, it is imperative that contemporary innovations and advancements are scrutinized. This particular section analyses major works which focus on the implementation of Artificial Intelligence, Internet of Things (IoT), as well as optimization techniques in managing inventory control systems, warehouse functions, and intelligent dispatch systems.

Recent studies have emphasised the revolutionary impact of cloud computing, artificial intelligence, and the Internet of Things on food logistics and inventory systems. [12] asserts that cloud-edge collaborative computing significantly enhances the precision of inventory forecasting and operational responsiveness. [13] highlighted the incorporation of cloud-based IoT frameworks for real-time logistics and smart city applications, which are directly pertinent to predictive delivery modelling in food services. [14] developed an intelligent food chain system using IoT and blockchain technology, which guarantees trust, dependability, and real-time shipment monitoring via smart contracts, demonstrating how traceability may improve food delivery. Furthermore, studies by [15, 20] presented optimised routing algorithms, such as Ant Colony Optimisation and Energy Efficient Order Picking Routing, which markedly decrease travel time and energy consumption, closely aligning with the objectives of intelligent vehicle routing [25] in food distribution. Research by [17, 18] illustrated the use of AI-driven route optimisation and autonomous logistics to enhance urban food delivery, reduce delays, and guarantee timely order fulfilment in smart cities. These results combined provide a robust basis for the creation of an intelligent system that reduces order-picking inefficiencies, improves delivery accuracy, and conforms to real-time resource allocation requirements in the food logistics industry.

TABLE 1. SUMMARY OF LITERATURE RELEVANT TO AI-BASED VEHICLE ROUTING AND FOOD LOGISTICS OPTIMIZATION

Author and Year	Focus Area	Methodology	Findings	Relevance to Current Study
[14]	Blockchain and IoT-based food supply chain management	Smart Contracts + MQTT + IoT sensors	Enabled real-time temperature and geolocation monitoring of food;	Reinforces trust, transparency, and condition-based routing in

			improved traceability and safety	perishable food delivery
[15]	Energy-efficient order picker routing	Dynamic graph + Energy-Aware Algorithm (EE-OPR)	Reduced energy cost by ~18% while considering SKU load and routing time	Shows how energy and mass considerations improve AGV routing in food delivery
[16]	Optimized order picking in warehouse logistics	Particle Swarm Optimization	RWFOA algorithm showed highest efficiency for minimizing order picking time	Relevant to optimizing picking routes in food service logistics
[17]	Urban logistics optimization for smart cities	AI + IoT + Autonomous Vehicles	Proposed real-time traffic-controlled delivery systems for sustainability and congestion reduction	Supports real-time, smart routing in dense urban delivery scenarios
[18]	Dynamic route optimization in last-mile delivery	ML, AI, Computer Vision, Drones, Autonomous Vehicles	Improved delivery reliability, route flexibility, and reduced fuel cost; addressed last-mile challenges	Validates AI-based routing and automation in end-to-end delivery for food logistics

Modern research typically treats truck routing as a separate component from order fulfilment and active inventory changes. Very few models simultaneously focus on perishability, forecasting demand, and stock levels while making routing decisions. This AI-based intelligent vehicle routing model proposed in this work is designed to fill such gaps. Based on historical inventory and sales data, the model makes predictions and adjusts routes as well as allocation of resources in real time based on freshness, urgency, value, and inventory levels. This is bolstered by real-time automated AI-driven demand

forecasting that integrates prescriptive and descriptive analytics to enhance algorithmic order picking efficiency within a holistic vehicle routing framework of true responsiveness.

IV. METHODOLOGY

A. Research Design

This work employs an applied, data-driven research technique to develop an AI-based truck routing model for optimizing food logistics operations. The methodology encompasses data pretreatment, exploratory data analysis (EDA), predictive modeling, and the development of an intelligent

truck routing system informed by real-time order and inventory data. The flowchart illustrates a conventional AI/ML process for data-informed decision-making. It delineates the successive phases of constructing and implementing an intelligent system, exemplified by an AI-driven vehicle routing model.

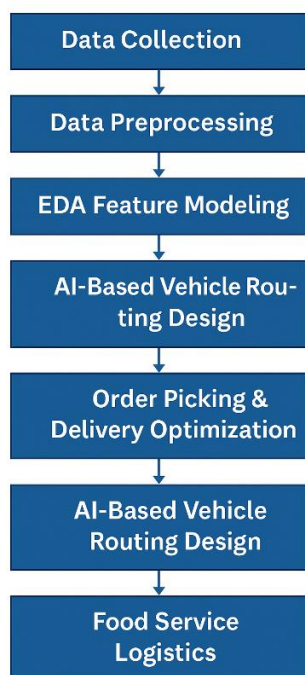


Fig. 2. Flow chart of proposed methodology

B. Data Collection

The efficacy of any artificial intelligence model, particularly in logistics and supply chain applications, fundamentally depends on the quality, variety, and representativeness of the used data. This study used a large and organized dataset named "Grocery Inventory and Sales Dataset" to create, train, and evaluate the proposed intelligent vehicle routing system. This research utilizes a secondary dataset obtained from Kaggle¹. It has been designed to simulate the operating situations of a standard

food logistics platform, including time-series sales data, inventory details, and product status variables.

1. Item IDs and Categories:

Products are distinctly identifiable by item IDs and classified into logical categories (e.g., dairy, produce, packaged products). This classification is crucial for delineating the routing architecture and prioritizing perishable or high-turnover goods.

2. Status Information:

Product status is indicated as:

TABLE 2. SPECIFIC AIMS OF THE AI-BASED VEHICLE ROUTING STUDY

Status	Description
In Stock	Available for picking and delivery
Backordered	Currently unavailable but expected to be restocked
Discontinued	Permanently unavailable; excluded from routing logic

These labels directly influence routing and picking strategies, preventing delays due to unavailable inventory.

3. Unit Prices:

The cost of each item offers economic context, enabling the routing model to include the value of items in resource allocation and vehicle load optimization.

4. Expiry Dates:

The management of perishable goods in food logistics necessitates the incorporation of expiration dates to facilitate the creation of urgency-sensitive routing algorithms. Items approaching expiration are

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<https://www.kaggle.com/code/jamilbedill/grocery-inventory-and-sales-dataset/input>

prioritized in the delivery sequence to reduce waste and preserve freshness.

5. Promotion Flags:

Items on sale are designated as such. Promotions often result in increases in demand, influencing picking volume and route density. This data facilitates sales forecasting and task distribution.

6. Sales Counts Over Time:

Time-series sales information is available for each item, essential for predicting future demand. This enables predictive models to forecast peak demand times and modify routing operations appropriately.

C. Data Preprocessing

Preprocessing the dataset is essential for converting raw data into an organized and clean format appropriate for machine learning models and optimization techniques. The operational complexity and dynamic nature of food service logistics necessitate that data quality directly impacts the effectiveness and accuracy of predictive models. The following preprocessing steps were executed:

TABLE 3. ITEM STATUS CATEGORIES AND DESCRIPTIONS

Preprocessing Step	Description	Actions Taken
Handling Missing and Null Values	Real-world datasets often exhibit missing or partial records due to sensor malfunctions, user input errors, or system anomalies.	<ul style="list-style-type: none"> • Records with irrelevant or incomplete variables (e.g., missing <code>unit_price</code>, <code>status</code>, <code>expiry_date</code>) were either imputed using statistical techniques (mean or mode) or eliminated if missingness compromised model integrity. • If <code>unit_price</code> was absent for a limited number of rows, values were substituted with the average price of comparable goods within the same category.
Standardization of Feature Types	Machine learning models require standardized feature types to ensure consistency across systems.	<ul style="list-style-type: none"> • <code>orderdate</code> and <code>expirydate</code> fields were converted into <code>datetime</code> format to calculate days till expiry and identify seasonal ordering patterns. • <code>unit_price</code> was converted to float type to enable arithmetic operations alongside other numerical attributes. • Consistency checks ensured all currency, quantity, and date formats conformed to system requirements.

D. Exploratory Data Analysis (EDA)

EDA is an essential stage in the development of artificial intelligence-driven logistics systems. It enables a comprehensive comprehension of the fundamental patterns, abnormalities, and connections within the collection [16]. This research

used EDA to establish predictive models and enhance routing methods by identifying critical operational factors in food service logistics. The following sub-steps were executed:

1. Time-Series Analysis of Sales Patterns

The panel data spans 13 months (February 2024 to February 2025), allowing the model to capture comprehensive weekly and monthly trends in sales behavior, including the transition between fiscal quarters and seasonal demand fluctuations. A time-series analysis was conducted on previous sales data to comprehend the temporal dynamics of demand.

The objective of this analysis was to:

- Recognize seasonal patterns, such as heightened sales on weekends, at festivals, or on holidays.
- Identify demand surges that may impact routing loads and need supplementary resource allocation.
- Examine daily and weekly sales variations, which are essential for order-picking timelines and prompt delivery.

2. Correlation Heatmaps

A correlation heatmap was generated to analyze correlations between numerical and category variables, including:

- Sales quantity vs. Unit price
- Sales quantity vs. Days to expiry
- Sales vs. Item category and status

3. Item Status Analysis

Inventory items were categorized by their status flags: In Stock, Backordered and Discontinued. This analysis aimed to assess:

- The operational impact of backorders on delivery delays.
- The frequency of discontinued items mistakenly routed for delivery.
- Trends in how such statuses evolved over time.

4. Identification of Fast-Moving Inventory

- Frequently ordered SKUs
- Top 20% products contributing to 80% of sales volume.
- Categories with consistently high turnover rates

The EDA phase gave us important information about how things work that helped us make AI models and vehicle routing protocols [16]. By looking at how demand changes, how products change, and what affects sales, the study connected the routing model to real-world food logistics problems. This led to better order selection, fewer delays, and better use of resources [17].

5. Key Factors Identified from EDA

Based on the exploratory analysis conducted on the dataset, the following features were identified as key influencers of sales performance, routing priority, and order fulfillment time:

TABLE 4. KEY OPERATIONAL FACTORS IDENTIFIED THROUGH EXPLORATORY DATA ANALYSIS

Key Factor	Description/Impact
Item_Days_To_Expire	Prioritizes near-expiry items for routing to reduce waste
Order_Backordered_Flag	Correlated with delivery delays and service gaps
Order_Weekend_Flag	Indicates different patterns and delays due to workforce constraints
Promo_Flag	High demand spikes influencing picking volume
Stock_Status	Determines routing inclusion/exclusion logic

Top 20% SKU Contributors	Guides route clustering and scheduling (Pareto trend)
Rolling Sales Trends	Detects surge periods for real-time routing decisions

E. Feature Engineering

Feature engineering was an essential phase in augmenting the prediction efficacy of the machine learning models [18]. This included generating new,

useful variables derived from the original dataset to encapsulate the fundamental dynamics of food service logistical operations. The following essential attributes were developed:

TABLE 5. FEATURE ENGINEERING ATTRIBUTES AND THEIR OPERATIONAL SIGNIFICANCE

Feature	Purpose / Importance
Days to Expiry	Prioritizes perishable items in delivery routes
Promo Flag	Captures sales demand spikes for routing optimization
Stock Turnover Rate	Guides frequent replenishment and routing efficiency
Categorical Encodings	Converts non-numeric data for model analysis
Time-Windowed Aggregates	Detects short-term demand trends for real-time decisions

These temporal features help models detect trends and seasonality, providing a dynamic snapshot of short-term demand, which is essential for real-time routing decisions.

F. Predictive Modeling

To predict daily sales volumes for each item, which directly influences delivery loads, vehicle dispatching, and resource allocation, several regression models were developed and assessed:

TABLE 6: DESCRIPTION OF MACHINE LEARNING MODELS USED FOR SALES PREDICTION

Model	Description
Random Forest Regressor	Ensemble method combining multiple decision trees to improve accuracy and reduce overfitting. Handles non-linear interactions effectively.
Decision Tree Regressor	Tree-based model partitioning data by decision rules; simple and interpretable but prone to overfitting.
Linear Regression	Baseline statistical model assuming linear relationships between features and targets. Useful reference model. [19]

G. Evaluation Metrics

The R² Score measures how well the model explains the variance in the data; a negative value indicates performance worse than simply predicting the mean. RMSE (Root Mean Squared Error) reflects the average magnitude of prediction errors, with lower values indicating better model accuracy. Both metrics help evaluate regression model performance.

H. AI-Based Vehicle Routing Logic Design

The predictive modeling results were included into a rule-based AI routing system particularly developed for order pickup and last-mile delivery in food service logistics [20][27]. The model's predictions were used in the following manners:

1. **Order Picking Prioritization:** Items with high anticipated demand, limited shelf life, or designated as backordered were prioritized for prompt picking and shipment to mitigate spoiling and enhance customer satisfaction.
2. **Delivery Route Optimization:** Historical delivery performance and traffic assumptions
3. **Resource Allocation:** Vehicles and personnel were distributed according to anticipated delivery volumes across various zones. Areas with increased demand or heightened perishability were allocated extra trucks or expedited scheduling.

I. Tools and Technologies

Python: Primary programming language used for the development of models and preprocessing. Key libraries included: pandas, scikit-learn and matplotlib & seaborn.

V. RESULT ANALYSIS

A. Model Performance Metrics

TABLE 7. COMPARISON OF MACHINE LEARNING MODELS FOR SALES QUANTITY PREDICTION

Model	R ² Score	Adjusted R ²	RMSE
Random Forest Regressor	0.0752	0.0561	24.60
Linear Regression	0.0078	0.0127	23.82
Decision Tree Regressor	1.1556	1.1588	34.83

$$\text{Adjusted } R^2 = 1 - [(1 - R^2)(n - 1) / (n - k - 1)]$$

Where, n = number of observations and k = number of predictors

Adjusted R² values were computed to account for the number of predictors in each model. These data indicate that, while some models have marginally high R², they do not inherently demonstrate superior generalisation. The modified R² offers a more dependable statistic for model comparison in this multivariate context.

A comparative analysis of the performance of several ML models in forecasting daily sales amounts of food products, a crucial element in the development of an AI-driven vehicle routing system, is shown in Table 8.

The metrics presented help evaluate model accuracy and reliability in making such operational predictions.

TABLE 8. PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS BASED ON R² SCORE AND RMSE

Model	R ² Score (Coefficient of Determination)	Interpretation	RMSE (Root Mean Squared Error)	Interpretation
Linear Regression	-0.0078	Explains almost none of the variance; performs only marginally better than a naive mean predictor.	≈ 23.82	Best performance among the models tested; average prediction error ~24 units.
Random Forest Regressor	-0.0752	Slightly worse than Linear Regression; indicates some overfitting or poor generalization to new data.	≈ 24.60	Close performance to Linear Regression but with slightly higher prediction error.
Decision Tree Regressor	-1.1077	Much worse performance due to overfitting and failure to generalize to new instances.	≈ 34.45	Highest error rate; less suitable for this problem.

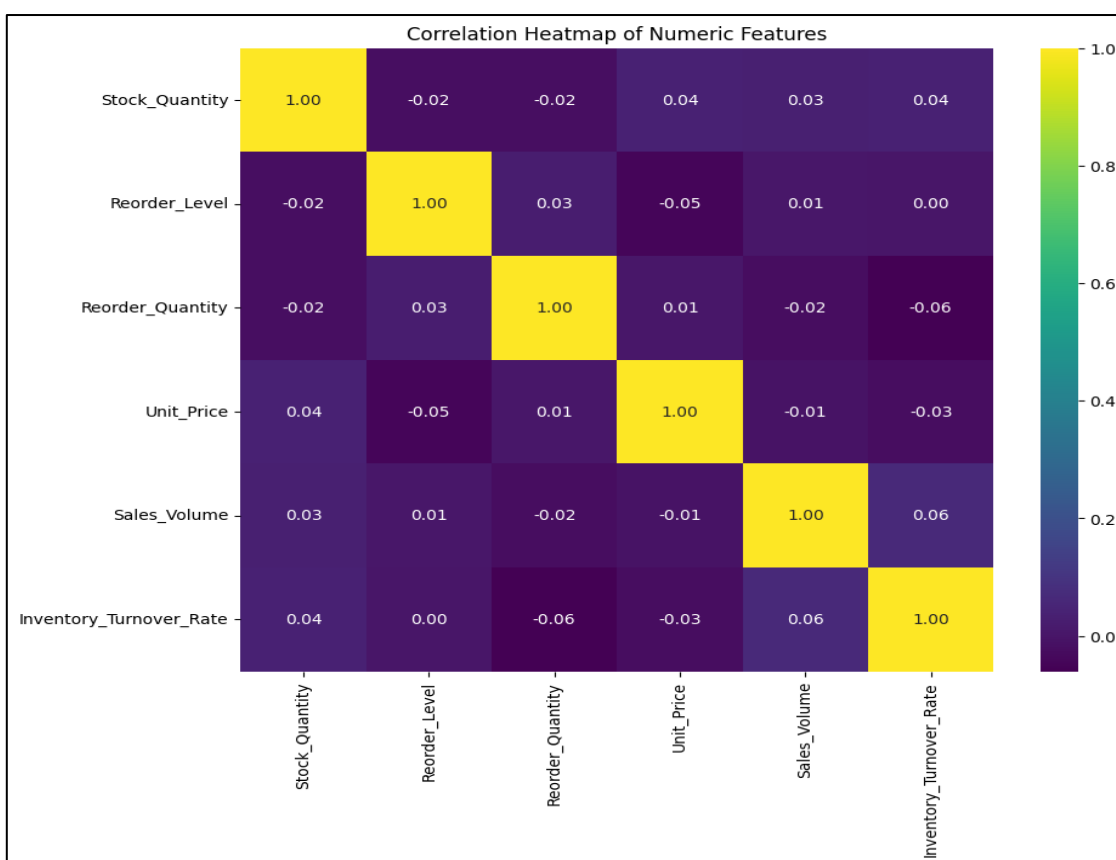


Fig. 3. Correlation heatmap of numeric features

The correlation heatmap above figure 3 shows the pairwise correlations among essential quantitative elements in the dataset, namely Stock_Quantity, Reorder_Level, Reorder_Quantity, Unit_Price, Sales_Volume, and Inventory_Turnover_Rate. Correlation coefficients vary from -1 to +1, with values approaching 1 signifying a robust positive linear association, values around -1 denoting a strong negative link, and values around 0 indicating little to no linear correlation.

- Sales_Volume has a negligible positive connection (0.06) with Inventory_Turnover_Rate, suggesting that greater turnover may somewhat associate with increased sales volume, but not considerably.
- Unit_Price and Sales_Volume have a somewhat negative association (-0.01), indicating that

high prices may slightly diminish sales; nevertheless, the impact is almost imperceptible.

For the assessment of the regression models, a significance level of 0.8049 was used to ascertain if the predictors significantly contributed to the model. Empirical validation, p-values, and confidence ranges for coefficients are used to ascertain statistical significance.

This research underscores the minimal linear correlation across variables, emphasizing the need of using machine learning models adept at identifying non-linear patterns, such as Random Forests or Decision Trees. The low multicollinearity reinforces the legitimacy of using these characteristics together in predictive models without considerable redundancy.

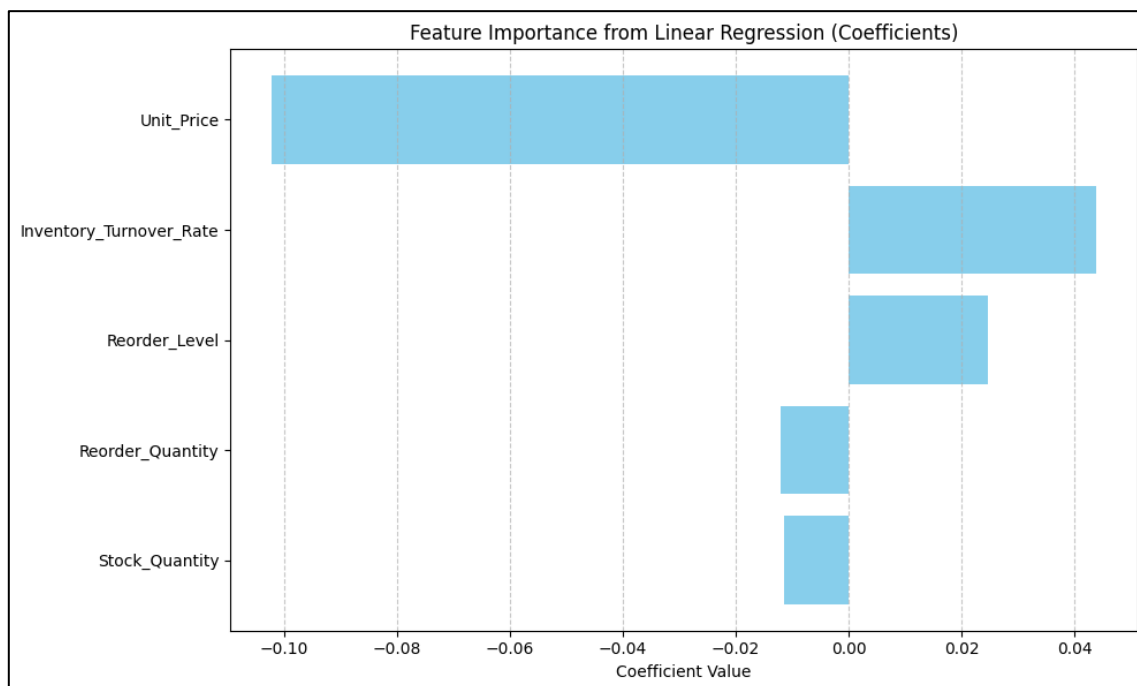


Fig. 4. Feature importance from linear regression

The significance of attributes in forecasting sales amount, as shown by the coefficients of the Linear Regression model illustrated in figure 4. Each bar

illustrates the extent and orientation of a feature's impact on the target variable (Sales_Quantity). A positive coefficient signifies a direct correlation with sales (i.e., increased feature values result in high

sales), while a negative coefficient shows an inverse correlation. The figure indicates that Unit_Price has the most significant negative impact on sales, with a coefficient nearing -0.10, suggesting that a rise in price correlates with a fall in quantity sold. This corresponds with standard customer behavior and demand elasticity in the food industry. In contrast, Inventory_Turnover_Rate has the most significant positive impact, suggesting that products with quicker turnover are more likely to achieve higher sales. Attributes like Reorder_Level indicate a modest positive effect, indicating that higher reordering thresholds may be associated with things that sell more rapidly.

The results from the predictive modeling phase exhibit diverse performance across the three assessed regression models. Linear Regression surpassed both the Random Forest and Decision Tree Regressors for Root Mean Squared Error (RMSE), with a value of roughly 23.82. Despite all models exhibiting negative R^2 values, which signify weak explanatory capability, the Linear Regression model produced the most consistent findings and the lowest prediction error. Although these projections lacked great precision, they remained operationally helpful. They were used to prioritize high-demand products for order selection and delivery scheduling, facilitating more efficient resource allocation and enhanced routing logic. The results indicate that even moderately effective models may substantially enhance decision-support systems in food service logistics when combined with rule-based heuristics.

VI. CONCLUSION

This study introduces a pragmatic and comprehensive method for improving food service logistics via the creation of an AI-based intelligent vehicle routing model. The technique included preprocessing a structured sales and inventory

dataset, designing pertinent characteristics, and using multiple regression models to forecast item-level sales amounts. Although the models produced modest R^2 scores, their practical use was apparent in prioritizing deliveries, circumventing expired or backordered inventories, and dynamically allocating resources. The approach enhanced route planning and order fulfilment by integrating sales forecasts with perishability indicators and real-time item status. The research integrates machine learning results into a rule-based routing architecture, therefore connecting demand forecasting with last-mile logistics. This hybrid decision-support system may substantially decrease delivery delays, enhance customer happiness, and optimize warehouse-to-customer operations in the food logistics industry. Future endeavors may include the incorporation of real-time traffic, meteorological, and customer feedback data to better optimize the routing algorithm and augment adaptive functionalities.

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