Dual-Stage Random Forest Pipeline for Demand Prediction and Delivery Time Estimation in On-Demand Food Dispatching Systems

Prof. Vijayalaxmi S D[1], Veeresh [2]

[1] *Professor, Master of Computer Application, VTU, Kalaburagi , Karnataka ,India*

[2] *Student , Master of Computer Application , VTU, Kalaburagi , Karnatak ,India*

ABSTRACT- *Food delivery services are rapidly expanding, driving the need for intelligent and scalable dispatching systems that ensure timely service and customer satisfaction. Conventional methods often fail to address dynamic factors such as traffic, weather, courier skills, and fluctuating demand. This study introduces a dual-stage machine learning pipeline integrated with reinforcement learning to optimize dispatching. First, a Random Forest Classifier predicts whether an order is on-demand, followed by a Random Forest Regressor estimating delivery time. These predictions are then utilized by a Q-learning agent to select couriers by maximizing efficiency and urgency. A decoupling strategy enhances adaptability and scalability. Implemented via a Flask interface, the system consistently delivers optimized assignments under varying operational and environmental conditions.*

Keywords:Food delivery, Random Forest, delivery time estimation, reinforcement learning, Q-learning, intelligent logistics, dispatch optimization.

1. INTRODUCTION

Online food delivery industry has witnessed exponential growth, fueled by urbanization, widespread smart phone usage, and evolving consumer expectations that prioritize speed and convenience. Platforms such as Zomato, Swiggy, Uber Eats, and DoorDash have reshaped how meals reach customers, creating near-instant and personalized delivery experiences. However, the surge in demand introduces challenges in maintaining operational efficiency, minimizing delivery times, and ensuring cost-effectiveness. A critical component in this ecosystem is the order dispatching system, which determines how new orders are matched with available couriers. Traditional dispatching methods, often based on heuristic rules or static logic, struggle to adapt to dynamic variables like traffic congestion, weather conditions, courier workload, or peak-hour demand. These shortcomings frequently result in inefficient courier assignments, delays, and reduced customer satisfaction.

To overcome these challenges, this study introduces an intelligent dispatching framework that integrates machine learning (ML) and reinforcement learning (RL) for real-time courier allocation. At its core lies a multi-stage pipeline featuring order classification, delivery time estimation, and adaptive dispatching in a modular workflow. The system employs a Random Forest Classifier to determine whether an order is on-demand, enabling priority assignment based on contextual factors such as time of day, traffic, and courier experience. Following this, a Random Forest Regressor estimates delivery time by considering distance, preparation duration, and environmental inputs. Finally, a Q-learning-based RL agent dynamically assigns couriers using a reward-driven mechanism to optimize metrics like reduced delivery delays, balanced workloads, and responsiveness to urgent requests.

Deployed via a Flask-based interface, the solution provides interactive inputs, real-time predictions, and optimized assignments, offering a scalable, data-driven alternative to traditional rule-based dispatching systems.

2. PROBLEM STATEMENT

The rapid expansion of the on-demand food delivery sector highlights a persistent challenge: inefficient and suboptimal assignment of orders to couriers. Existing dispatch systems, often dependent on static rules or manual decision-making, fail to adapt to dynamic conditions such as traffic congestion, weather fluctuations, courier availability, and unpredictable customer demand. These limitations result in longer delivery times, rising operational expenses, and declining customer satisfaction.

Furthermore, the lack of adaptability and scalability in current models restricts their ability to optimize assignments in real time. Hence, there is a pressing need for an intelligent, data-driven dispatching solution to overcome these inefficiencies.

3. OBJECTIVES

The primary objective of this study is to design an intelligent food delivery dispatching system that integrates machine learning and reinforcement learning for optimized performance. The system first classifies orders as either *on-demand* or *not on-demand* using a Random Forest Classifier, based on contextual features such as traffic, weather, and time of day. Next, a Random Forest Regressor accurately predicts delivery times by considering distance, preparation duration, and courier attributes. A Q-learning–based reinforcement learning agent then dynamically selects the most suitable courier to improve efficiency. To enhance scalability and maintainability, a decoupling strategy is employed. Finally, the solution leverages a Kaggle dataset for realistic evaluation and is deployed through an interactive Flask web application.

4. METHODOLOGY USED

1)Data Collection and Preparation:Data Collection: The foundation of this system is built on a real-world dataset sourced from Kaggle, which captures key aspects of food delivery operations such as distance, weather, traffic levels, time of day, vehicle types, preparation times, and courier experience. To address edge cases and improve representation, synthetic data was generated, particularly for courier profiles and performance metrics. The dataset spans several months, covering seasonal patterns, peak hours, and diverse conditions to ensure model robustness.

2)Data Preprocessing: The preprocessing stage involved cleaning missing values, outliers, and inconsistent entries. Categorical variables (e.g., weather, traffic, vehicle type, and time slots) were encoded into numerical formats, while features like distance and preparation time were normalized and standardized. Additional steps included validation checks, duplicate removal, and the creation of derived features to strengthen predictive accuracy.

3)Feature Extraction: Relevant attributes were selected using domain knowledge, including distance, courier experience, traffic level, and weather. Advanced feature engineering introduced rush-hour indicators, weather–traffic interactions, and distance–vehicle compatibility metrics. Redundant variables were filtered through correlation analysis and importance ranking to retain only the most predictive features.

4)Model Selection and Training: A dual-stage strategy was employed. A Random Forest Classifier was chosen for order classification, and a Random Forest Regressor for delivery time estimation, due to their ability to handle non-linear interactions. Training involved stratified sampling, grid search hyperparameter tuning, and time-based validation. The Q-learning agent was trained iteratively in a simulated environment with optimized learning rate, discount factor, and exploration parameters.

5)Model Evaluation: The classifier was evaluated using precision, recall, F1-score, and ROC-AUC, while regression performance was assessed with RMSE, MAE, and MAPE. The Q-learning agent's efficiency was measured through cumulative rewards and comparisons with baseline strategies.

6)Integration with Flask: A user-friendly Flask web application integrated all models, offering interactive order inputs, real-time predictions, and courier assignments. Modular design, joblib-based model loading, persistent RL agent learning, database storage, and visualization dashboards were incorporated. Security measures such as password hashing, session management, and admin access ensured reliable deployment.

5. LITERATURE SURVEY

Article[1]"A Matching Algorithm with Reinforcement Learning and Decoupling Strategy for Order Dispatching in On-Demand Food Delivery" by *Jingfang Chen, Ling Wang, Zixiao Pan, Yuting Wu, Jie Zheng, Xuetao Ding* in 2024:This paper presents a modular framework for order dispatching in food delivery that combines supervised learning predictions with reinforcement learning for courier matching. The authors emphasize a decoupling strategy where classification and regression tasks are separated from dispatch decisions, ensuring scalability and flexibility for upgrades. A Q-learning agent is trained to maximize a custom reward function balancing delivery efficiency and order priority. Simulation experiments on realistic datasets demonstrate improved order acceptance rates, shorter delays, and more reliable courier utilization compared to heuristic policies. The work highlights how modular AI-driven approaches can outperform traditional static systems in dynamic environments.

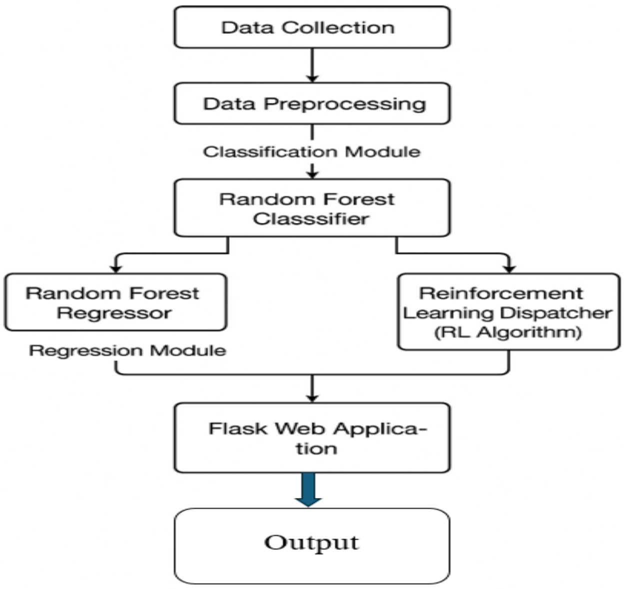
Article[2]"Order Dispatching Via GNN-Based Optimization Algorithm for On-Demand Food Delivery" by *Jing-Fang Chen, Ling Wang, Yile Liang, Yang Yu, Jie Feng, Jiuxia Zhao, Xuetao Ding* in **2024 (IEEE T-ITS)**:This study integrates Graph Neural Networks (GNNs) with optimization heuristics to enhance order dispatching efficiency in food delivery platforms. GNNs are employed to capture the complex interactions between riders and orders, filtering feasible matches, while heuristic rules finalize assignments. By narrowing the search space with learned scores, the system balances speed and quality in real-time decision-making. Experiments on large-scale real-world datasets show that the method reduces delivery delays and improves customer satisfaction compared with greedy or rule-based methods. The approach demonstrates the benefits of combining graph learning with optimization in large, dynamic operational networks.

Article[3]"Courier Routing and Assignment for Food Delivery Service Using Reinforcement Learning" by *Aysun Bozanta, Mucahit Cevik, Can Kavaklıoğlu, Eray Mert Kavuk, Ayşe Tosun, Sibel B. Sonuç, Bilgin Kosucu, Ayşe Başar* in **2022**:This paper addresses courier routing and order assignment as a Markov Decision Process, highlighting the dynamic and uncertain nature of online food delivery. The authors implement Q-learning and Double DQN algorithms to train agents in a realistic simulator that models traffic, order arrivals, and courier workloads. Their findings show that reinforcement learning policies outperform heuristic approaches in terms of delivery time and courier utilization. The study also explores the effects of varying courier fleet sizes and order demand intensities on system performance. Overall, the paper demonstrates the adaptability of reinforcement learning in handling dynamic dispatch scenarios.

Article[4]"A Deep Reinforcement Learning Approach for the Meal Delivery Problem" by *Hadi Jahanshahi, Aysun Bozanta, Mucahit Cevik, Eray M. Kavuk, Ayşe Tosun, Sibel B. Sonuç, Bilgin Kosucu, Ayşe Başar* in **2022 (Knowledge-Based Systems)**:This research applies deep reinforcement learning to the complex problem of meal delivery where both routing and dispatch decisions must adapt to dynamic orders and uncertain preparation times. The authors propose a deep Q-network framework that enables couriers to learn efficient decision-making policies through simulated environments. Results indicate that deep RL significantly reduces delivery delays and increases courier productivity compared with rule-based methods. The study also addresses issues such as reward design, hyperparameter tuning, and scaling for larger cities. The work provides strong evidence of how deep learning can improve dispatch outcomes in logistics.

Article[5]"Online Food Ordering Delivery Strategies Based on Deep Reinforcement Learning" by *Guangyu Zou, Jiafu Tang, Levent Yilmaz, Xiangyu Kong* in **2022 (Applied Intelligence)**:This paper models the food delivery dispatching process as an MDP and applies a Double Deep Q-Network (DDQN) approach to optimize courier selection. Using the SUMO traffic simulator, the authors replicate real-world conditions such as congestion and travel variability to train and test the system. Their experiments show that RL-based strategies consistently outperform static dispatching methods by reducing late deliveries and improving assignment efficiency. The study also discusses how batching strategies, exploration techniques, and state-space design influence dispatch quality. It highlights the potential of deep reinforcement learning to revolutionize order dispatching.

Article[6]"Meal Delivery Routing Problem with Stochastic Meal Preparation Times and Customer Locations" by *Surendra Reddy Kancharla, Tom Van Woensel, S. Travis Waller, Satish V. Ukkusuri* in **2024 (Springer, Networks and Spatial Economics)**:This work introduces a stochastic formulation of the Meal Delivery Routing Problem that accounts for uncertain preparation times and varying customer demand. The authors employ a rolling horizon framework supported by Sample Average Approximation and Adaptive Large Neighborhood Search to generate robust routing solutions. Their approach outperforms deterministic routing methods by reducing delivery delays and improving profitability. By modeling uncertainty explicitly, the paper provides valuable insights into managing variability in real-world food delivery. It also emphasizes scalability and flexibility, making it highly relevant to on-demand service



platforms.

Figure1:System Architecture of Food Delivery Dispatch

6. SYSTEM DESIGN

The proposed food delivery dispatch system is designed with a layered architecture that integrates data processing, predictive modeling, and intelligent dispatch optimization. At the initial stage, raw inputs such as delivery distance, traffic, weather conditions, vehicle type, and courier experience are preprocessed and encoded into structured formats using label encoders. These refined features are then directed to two distinct machine learning models: a Random Forest Classifier, which identifies whether an order is urgent or regular, and a Random Forest Regressor, which predicts the estimated delivery time. The predictions are subsequently utilized by a Reinforcement Learning-based Dispatcher employing Q-learning to allocate the most appropriate courier, considering factors like experience and vehicle suitability. Finally, the system is deployed through a Flask web interface, enabling users to submit order details and receive optimized, real-time dispatch solutions.

7. SCREENSHOTS

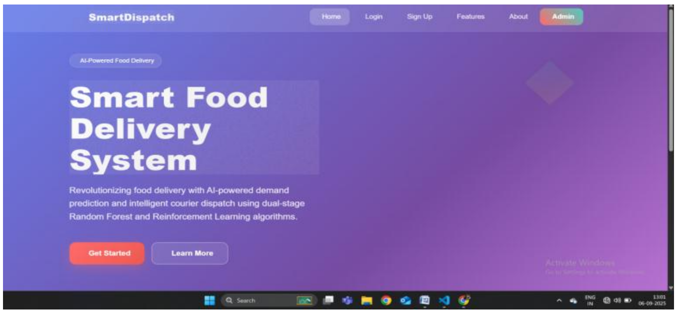


Figure 6: Home page

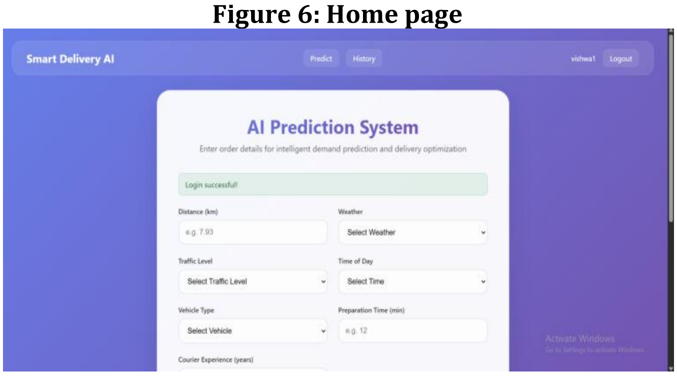


Figure 7: Food order details

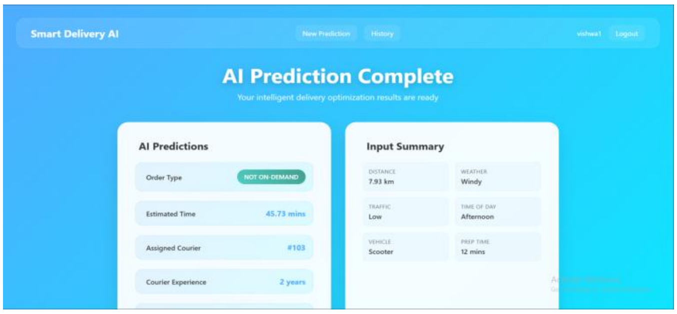


Figure 8: Predicated Result

8. CONCLUSION & FUTURE SCOPE

In this paper, a robust and intelligent order dispatching framework for on-demand food delivery has been presented, integrating machine learning and reinforcement learning techniques to address existing inefficiencies in logistics. The approach begins with a Random Forest Classifier to distinguish on-demand orders, followed by a Random Forest Regressor to predict delivery times using key features such as distance, traffic, weather, and courier experience. Trained on a realistic Kaggle dataset and deployed through a Flask-based web application, the system allows users to input order details and instantly view predictions and courier assignments, demonstrating real-time adaptability and practicality. Compared to traditional rule-based systems, this intelligent model-driven solution significantly enhances decision-making accuracy, operational performance, and scalability.

For future work, several enhancements can strengthen the system's effectiveness. Incorporating real-time data streams such as live traffic, weather updates, and GPS tracking of couriers would improve responsiveness and accuracy. Employing advanced techniques like Deep Reinforcement Learning (DRL) and graph-based optimization could enable handling of more complex dispatching scenarios. Additionally, features such as multi-order batching, customer and courier feedback loops, mobile application integration, and cloud-based deployment would increase scalability and accessibility, making the solution more suitable for large-scale, city-wide food delivery networks.

9. REFERENCES

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