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Logi Mind Framework: Multi-Dimensional Decision Analytics for Proactive Delay Detection and Operational Optimization

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ABSTRACT

Global logistics networks manage billions of shipments annually, yet over 20% of freight experiences delays, and inefficient routing increases operational costs by nearly 15%. Traditional supply chain systems depend on manual intervention or static decision-making, limiting real-time responsiveness and resource efficiency. This study proposes an advanced predictive analytics framework for intelligent delay detection and operational optimization in logistics. The dataset includes detailed shipment records such as delivery timelines, routing paths, resource allocation, and feasibility indicators. A comprehensive preprocessing pipeline comprising data cleaning, normalization, and transformation is implemented to ensure data quality for multi-output predictive modeling. For benchmarking, baseline models including K-Nearest Neighbor with Classification and Regression Tree (KNN-3CA1RT) and Huber-3CA1RT are evaluated. The proposed model, a hybrid Decision Tree-based 3CA1RT (DT-3CA1RT), integrates three classification components and one regression module. The first classifier detects rerouted shipments, the second assesses resource allocation feasibility, and the third validates overall shipment feasibility. The regression component predicts delivery delays. Experimental results show that DT-3CA1RT outperforms baseline models in delay prediction accuracy while effectively optimizing routing and resource allocation. By automating delay detection and feasibility assessment, the framework provides actionable insights to minimize disruptions and improve supply chain performance. Additionally, the system is deployed as a Flask-based web application, enabling logistics managers to input shipment data, perform real-time predictive analysis, and make informed decisions on delay risks, rerouting, and resource adjustments, thereby enhancing operational efficiency and reliability.

Keywords: logistics networks, freight delay detection, supply chain optimization, routing optimization, resource allocation.

1. INTRODUCTION

In modern logistics, supply chain management (SCM) plays a crucial role in ensuring the efficient and seamless movement of goods from manufacturers to consumers across global boundaries, as illustrated in Figure 1. Optimizing these global supply chains is essential to achieve both cost-effectiveness and time efficiency while maintaining system resilience. With the advent of Industry 4.0, supply chains have become increasingly dynamic and uncertain, limiting the effectiveness of traditional deterministic models in handling such variability [1]. These conventional approaches often fail to account for uncertainties such as fluctuating demand, unexpected disruptions, and variations in lead times, all of which significantly influence overall supply chain performance. To address these limitations, recent research has focused on integrating probabilistic and fuzzy decision-making approaches.

Probabilistic models provide a deeper understanding of uncertainty by considering the likelihood of different events, while fuzzy logic effectively handles imprecise and uncertain inputs, better reflecting

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real-world conditions [2]. Together, these approaches offer enhanced flexibility and robustness compared to deterministic methods. To further strengthen decision-making in SCM, the application of uncertainty theory is recommended. This approach emphasizes incorporating risks into stochastic and fuzzy frameworks to develop more resilient and adaptive systems [3]. Such integration supports improved risk management and enables more informed decision-making, ultimately enhancing overall supply chain performance. As supply chains continue to evolve in complexity, the need for advanced optimization models becomes increasingly critical [4]. In this context, goal programming (GP), originally introduced by Charnes and Cooper over five decades ago, emerges as a powerful multi-objective optimization technique. Its flexibility makes it highly suitable for addressing multiple, often conflicting objectives within complex and dynamic supply chain environments [5].

Figure. 1: Activity Prediction Pipeline using Smart Logistic.

Furthermore, dependent chance constraints (DCC) are incorporated into optimization models to capture the interdependencies among uncertain parameters. By considering the joint distribution of these uncertainties, DCC-based models provide a more comprehensive approach to risk management, leading to more accurate and reliable optimization outcomes that closely align with real-world scenarios.

2. LITERATURE SURVEY

Fatorachian, H. al [6] presented a predictive analytics framework integrating digital twin technology, IoT-enabled logistics data, and cybernetic feedback loops to improve last-mile delivery accuracy, congestion management, and sustainability in smart cities. Grounded in Systems Theory and Cybernetic Theory, the framework models urban logistics as an interconnected network, where real-time IoT data enable dynamic routing, demand forecasting, and self-regulating logistics operations. By incorporating machine learning-driven predictive analytics, the study demonstrates how AI-powered logistics optimization can enhance urban freight mobility. The cybernetic feedback mechanism further improves adaptive decision-making and operational resilience, allowing logistics networks to respond dynamically to changing urban conditions. Aljohani, A al. [7] proposed an innovative strategy that makes use of machine learning as well as predictive analytics approaches. Traditional supply chain risk management frequently uses post-event analysis as well as historical data, which restricts its ability to address real-time interruptions, on the other hand, promotes a futuristic methodology that uses predictive analytics to foresee possible disruptions. Based on contextual and historical data, machine learning models can be trained to find patterns and correlations as well as anomalies that point to imminent dangers. Organizations can identify risks as they arise and take preventative measures by incorporating these models into a real-time monitoring system.

Pasupuleti, V al. [8] depicted the advanced machine learning (ML) techniques to enhance logistics and inventory management. Using historical data from a multinational retail corporation, including sales, inventory levels, order fulfillment rates, and operational costs, they applied a variety of ML algorithms, including regression, classification, clustering, and time series analysis. result the application of these ML models resulted in significant improvements across key operational areas. They achieved a 15% increase in demand forecasting accuracy, a 10% reduction in overstock and stockouts, and a 95% accuracy in predicting order fulfillment timelines. Chen, W al. [9] identified and analysed prominent challenges within sustainable logistics, such as reducing carbon emissions, minimizing waste generation, and optimizing transportation routes while considering ecological factors. They also explored emerging trends in AI-driven logistics optimization, such as the integration of real-time data analytics, blockchain technology, and autonomous systems, which hold immense potential for enhancing efficiency and sustainability.

Khatib, E.J al. [10] proposed such scenarios and challenges and proposed 5G technology as a global unified connectivity solution and also proposed a system for exploiting the application-specific optimization capabilities of 5G networks to better cater for the needs of Smart Logistics. An application traffic modelling process is proposed, along with a proactive approach to network optimization that can improve the Quality of Service and reduce connectivity costs. Kashem, M.A al. [11] aimed to model AI's and blockchain's role in supply chain optimization by conducting a systematic literature review) and the SALSA mechanism. In addition, this paradigm-shifting approach will provide fairer views and options for managing forecasting, planning, monitoring, and reporting across the entire supply chain. The emphasis remains on real-time accuracy, easy access, and optimization of operational indicators such as sales, visibility, and end-to-end supply chain operations always and from any location. It will be an eye-opening experience to enable stakeholders and partners to communicate information collaboratively, consistently, and efficiently.

Woschank, M al. [12] analysed the scientific literature on artificial intelligence, machine learning, and deep learning in the context of Smart Logistics management in industrial enterprises. Furthermore, based on the results of the systematic literature review, the authors present a conceptual framework, which provides fruitful implications based on recent research findings and insights to be used for directing and starting future research initiatives in the field of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in Smart Logistics. Riad, M al. [13] proposed a conceptual framework for strengthening supply chain resilience through AI integration. The framework leverages AI technologies to improve key aspects of supply chain resilience, including risk management, operational efficiency, and real-time visibility. Result/Conclusions: Additionally, it underscored the importance of collaborative relationships with supply chain partners, enabled by AI-powered data-sharing and communication tools that foster trust and coordination within the network. Originality/Value: This comprehensive framework offered a strategic approach to integrating AI into supply chain management, highlighting its potential to significantly enhance resilience, operational efficiency, and sustainability, thereby empowering organizations to navigate the complexities of modern supply chains more effectively.

Mohsen, B.M al. [14] depicted an innovative framework that integrates artificial intelligence (AI), autonomous vehicles (AVs), and Internet of Things (IoT) technologies to address these challenges. The framework leveraged real-time data from IoT-enabled infrastructure to optimize route planning,

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enhance traffic signal control, and enable predictive demand management for delivery services. By incorporating AI-driven analytics, the proposed approach aims to improve traffic flow, reduce congestion, and minimize the carbon footprint of urban logistics, contributing to the development of more sustainable and efficient smart cities. This work highlights the potential for combining these technologies to transform urban logistics, offering a novel approach to enhancing delivery operations in densely populated areas. Rajabzadeh, M al. [15] employed rigorous grounded theory coding procedures, supported by the analytical capabilities of maxqda software. The culmination of the meta-synthesis endeavour culminates in the conceptual representation of IoT adoption within the agricultural logistics domain. This representation is underpinned by the identification of three overarching macro categories/constructs, namely IoT Technology Adoption, encompassing facets such as IoT implementation requisites, ancillary technologies essential for IoT integration, impediments encountered in IoT implementation, and the multifaceted factors that influence IoT adoption; IoT-Driven Logistics Management, encompassing IoT-based warehousing practices, governance-related considerations, and the environmental parameters entailed in IoT-enabled logistics; and the Prospective Gains Encompassing IoT Deployment, incorporating the financial, economic, operational, and sociocultural ramifications ensuing from IoT integration.

3. PROPOSED SYSTEM

The modern logistics industry faces increasing pressure to improve operational efficiency, reduce delays, and optimize resource utilization. Traditional systems that depend on manual tracking and static rule-based processes are no longer capable of handling the rising volume of shipments or the growing complexity of supply chain networks. To address these challenges, this framework presents a modular predictive analytics system that embeds data-driven intelligence into smart logistics operations, as illustrated in the comprehensive architectural workflow in Figure 2. The system is designed to handle both descriptive analytics through an automated Exploratory Data Analysis (EDA) suite and predictive analytics through a multi-target machine learning pipeline, all accessible via a structured Flask web interface.

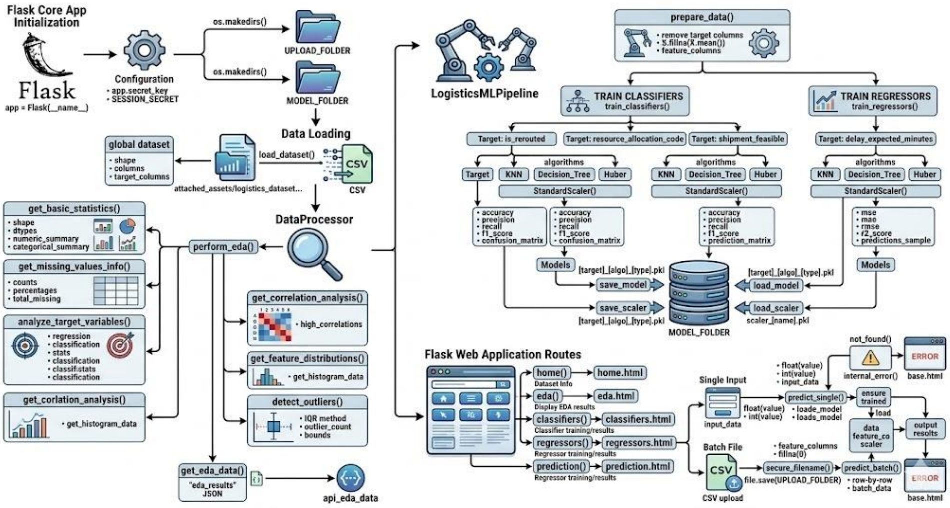

Figure. 2: Proposed System Architecture for Smart Logistics.

System Initialization and Data Ingestion

The framework begins with the Flask Core App Initialization, where the server environment is configured with security keys and essential directory structures. The system automatically executes os.makedirs() to ensure the existence of the UPLOAD_FOLDER (for batch processing) and the MODEL_FOLDER (for model persistence). Following initialization, the Data Loading module ingests the logistics dataset from attached_assets/ in a structured CSV format, capturing critical metadata such as dataset shape, column definitions, and target variables.

Automated Exploratory Data Analysis (EDA)

Once loaded, the dataset is passed to the DataProcessor module. The perform_eda() function orchestrates a multi-dimensional analysis of the shipment data, including:

- **Statistical Profiling:** Generating basic statistics and feature distributions.
- **Data Integrity:** Identifying missing values and detecting outliers using the Interquartile Range (IQR) method.
- **Relational Analysis:** Computing correlation matrices to identify high-dependency features.
- **Target Analysis:** Evaluating distribution patterns for both regression and classification targets.

Data Preprocessing and Feature Engineering

The Logistics ML Pipeline initiates the prepare_data() sequence to transform raw data into a machine-readable format. This involves isolating feature columns from target columns and handling missing data using mean imputation ($\bar{X}_{mean}$). To ensure algorithmic convergence, a StandardScaler is applied to normalize numerical features, ensuring all variables contribute proportionately to the model's decision-making process.

Hybrid Model Training and Persistence

The framework employs a parallel training architecture to handle diverse logistics tasks:

- **Classification Branch:** Trains KNN, Decision Tree, and Huber-based SGD classifiers to predict categorical outcomes: is_rerouted, resource_allocation_code, and shipment_feasible. Performance is validated using Accuracy, Precision, Recall, and F1-Score.
- **Regression Branch:** Trains corresponding regressors to estimate the continuous variable delay_expected_minutes, evaluated through Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 scores.

Web Application Routing and User Interface

The Flask Web Application serves as the interaction layer, managing the flow between the backend logic and the frontend templates. Defined routes such as /eda, /classifiers, and /regressors allow users to trigger training and view performance metrics. The application includes robust error handling through internal_error() and not_found() controllers to ensure system stability during high-load operations.

Multi-Modal Prediction Services

The final stage of the workflow provides actionable intelligence through two distinct prediction paths:

1. **Single Input Prediction:** Users manually enter shipment parameters through a web form. The predict_single() function loads the relevant .pkl files, scales the input, and returns real-time predictions.

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2. **Batch Prediction:** Users upload a CSV file containing multiple shipment records. The system utilizes secure_filename() for safe storage in the UPLOAD_FOLDER, then processes the data row-by-row via predict_batch() to generate comprehensive logistics forecasts.

4. RESULTS ANALYSIS

The results section presents the key findings of the study in a clear and organized manner. It summarizes the data collected and highlights important patterns, trends, or relationships observed during the analysis. The findings are usually supported with tables, graphs, or charts to improve understanding and accuracy. This section focuses only on what was discovered, without interpreting the meaning of the results. It helps readers quickly grasp the outcomes of the research and provides a foundation for further discussion. The results section plays a crucial role in conveying the evidence gathered during the study.

Figure 3 illustrates the comparative performance of KNN, DT, and Huber classifiers for the shipment_feasible prediction task. The DT model achieves perfect classification performance with an accuracy, precision, recall, and F1-score of 1.000, indicating complete separation between feasible and non-feasible shipments. The KNN classifier also demonstrates strong performance, recording an accuracy of 0.962 with balanced precision, recall, and F1-score values of 0.962, reflecting reliable feasibility assessment with minimal misclassification. In contrast, the Huber classifier yields lower effectiveness, achieving an accuracy of 0.786, precision of 0.791, recall of 0.786, and F1-score of 0.788, suggesting limitations in capturing binary feasibility patterns. The confusion matrices further confirm these findings, where the DT exhibits zero false positives and false negatives, while KNN and Huber show higher misclassification rates. These results validate the suitability of tree-based models for accurate shipment feasibility evaluation, which is critical for preventing resource waste and operational inefficiencies in logistics systems.

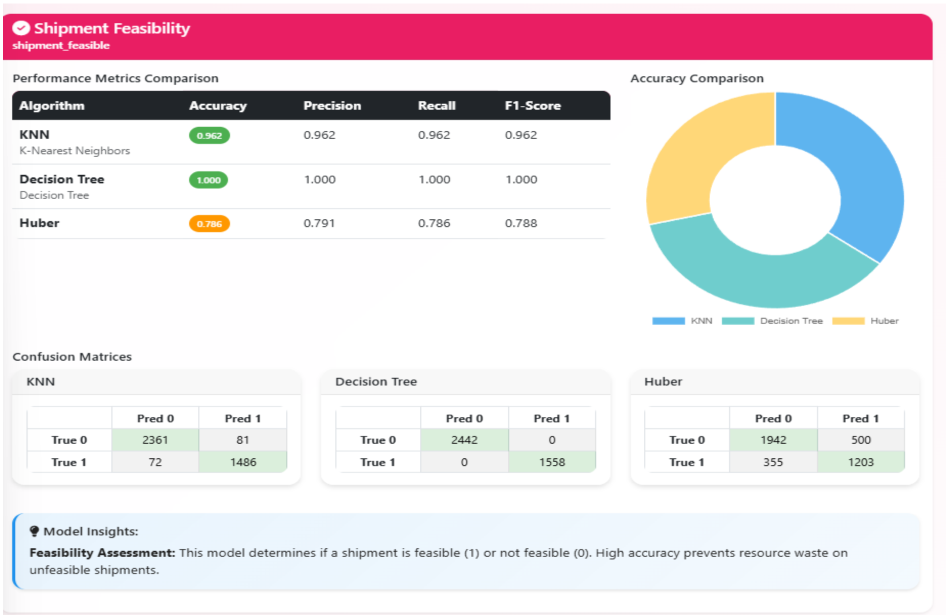

Figure 3: Classification Models Performance Outcome on Shipment Feasibility Target.

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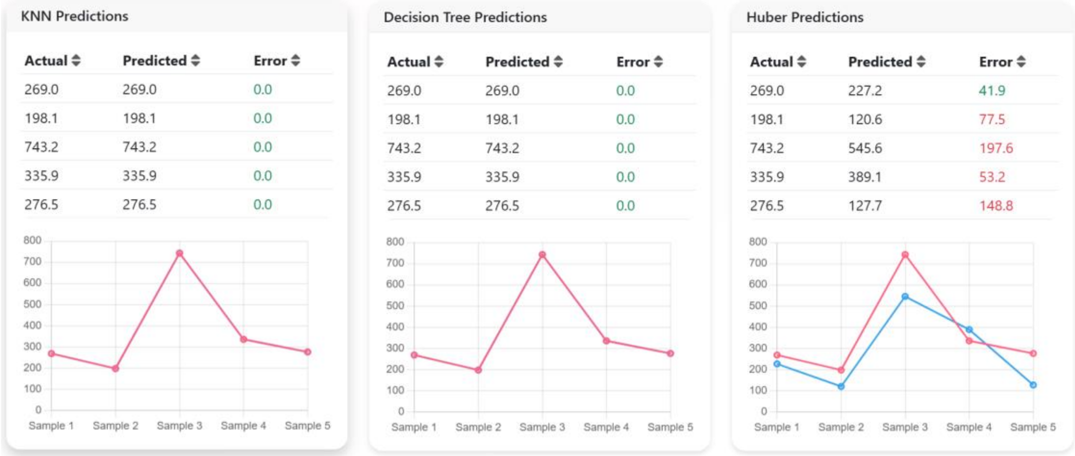
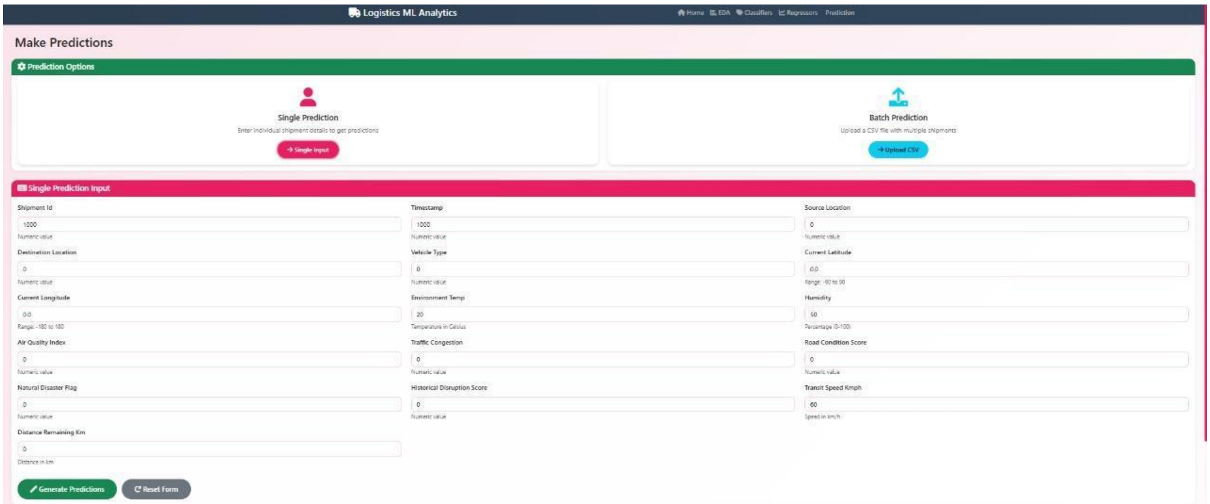
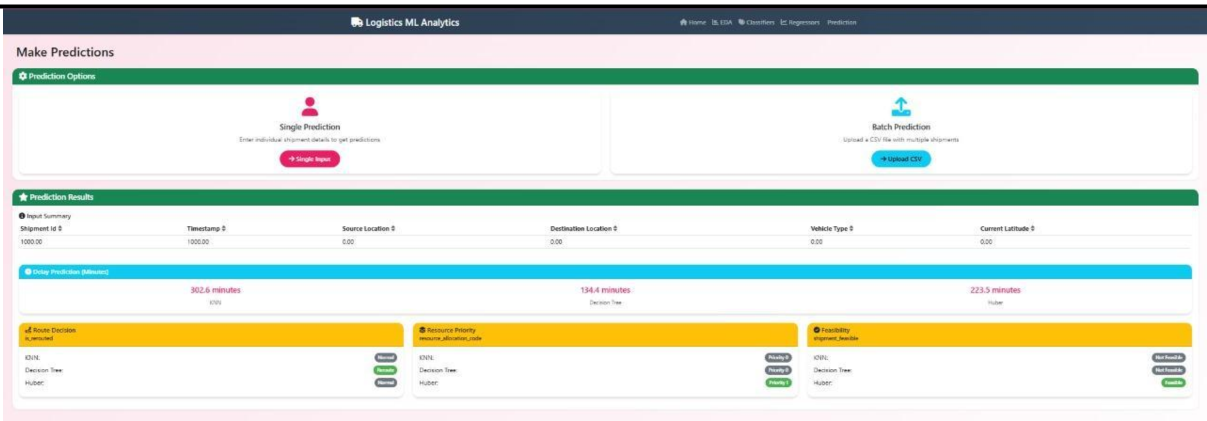


Figure. 4: Prediction Mapping Comparison of Regression Models.

Figure 4 illustrates a sample-wise comparison between actual delay values and predicted outputs generated by KNN, DT, and Huber regression models on the test dataset. The KNN and DT regressors demonstrate near-perfect alignment with actual delay values, producing zero or negligible prediction errors across all shown samples, which is visually evident from the overlapping actual and predicted curves. In particular, the DT model consistently predicts exact delay values for samples such as 269.0, 198.1, 743.2, 353.9, and 276.5 minutes, resulting in zero error for each instance. In contrast, the Huber regressor exhibits substantial deviations, with errors ranging from approximately 41.9 to 197.6 minutes, indicating poor generalization to nonlinear delay patterns. These observations further validate the quantitative results reported earlier and confirm the robustness and reliability of tree-based regression for precise delay estimation in smart logistics systems.



(a)



(b)

Figure. 5. Predictive Analytics on Logistics ML Analytics Platform. (a) Input. (b) Outcomes.

Figure 5 (a) shows the Make Predictions interface with options for Single Prediction, where users can input details like shipment_id and environmental conditions to get a delay prediction, and Batch Prediction, allowing CSV file uploads for multiple predictions. Figure 5 (b) displays Prediction Results, showing a sample output with a predicted delay of 202.1 minutes using KNN, 154.4 minutes using DT, and 223.1 minutes using Huber, along with classification results for is_rerouted, resource_allocation_code, and shipment_feasible.

Figure 6(a) presents a snapshot of the batch input dataset used for large-scale prediction, comprising multiple shipment records with heterogeneous attributes. Each row corresponds to a shipment instance characterized by temporal (shipment_timestamp), spatial (source_location, destination_location, current_latitude, current_longitude), vehicle-related (vehicle_type, transit_speed), environmental (environment_temp, humidity, air_quality_index), and operational factors (traffic_congestion, road_condition, natural_disaster, historical_delay, distance_remaining). Sample values illustrate the diversity of conditions, such as shipment timestamps ranging from 860 to 3174, environmental temperatures between approximately -31.8°C and 40.2°C, humidity levels from 37.7% to 94.4%, and air quality indices spanning 55.97 to 135.05, ensuring that the model is evaluated under realistic and varied logistics scenarios.

shipment_	timestamp	source_loc	destinatio	vehicle_ty	current_la	current_lo	environme	humidity	air_quality	traffic_cor	road_cond	natural_di	historical_	transit_sp	distance_rem
3174	217	10	6	1	49.58456	-112.905	43.87565	75.05032	23.82824	0.299457	8	0	0.555737	70.7244	89.07599
860	2321	15	7	4	-28.843	-8.41333	1.818453	37.73685	86.41265	0.230487	8	0	0.267489	77.0697	130.9925
1294	0	13	4	3	-31.7726	80.97337	39.1922	70.16826	168.536	0.433175	7	0	0.102437	30.58979	161.7522
1130	1434	7	14	3	-31.8341	138.5724	39.7161	88.89408	82.63936	0.627629	7	0	0.467606	25.62109	483.9866
1095	668	14	8	4	-52.3763	13.95331	6.091383	70.11485	127.3419	0.525399	7	0	0.330649	47.31919	41.92093
3092	2615	14	5	1	6.384103	-87.6939	-2.94045	62.85939	115.3045	0.595127	6	0	0.473997	68.40242	33.93783
1638	2610	8	11	5	-28.6471	148.8383	21.61328	43.26427	27.09457	0.341249	3	1	0.128237	44.01992	121.8647
2169	366	15	5	4	40.20057	84.19711	9.720437	94.38192	55.97409	0.36748	10	0	0.593963	78.93835	102.4258

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(a)

Index	Delay Prediction (min)	Route Decision	Resource Priority	Feasibility
0	234.3 / 234.3 / 256.4	Normal Normal Normal	Priority 1 Priority 1 Priority 0	Feasible Feasible Feasible
1	149.1 / 149.1 / 204.9	Normal Normal Normal	Priority 1 Priority 1 Priority 1	Feasible Feasible Feasible
2	319.5 / 319.5 / 285.4	Normal Normal Normal	Priority 1 Priority 1 Priority 1	Not Feasible Not Feasible Feasible
3	667.2 / 667.2 / 480.0	Normal Normal Normal	Priority 0 Priority 0 Priority 1	Not Feasible Not Feasible Not Feasible
4	287.5 / 279.5 / 261.3	Normal Normal Normal	Priority 0 Priority 0 Priority 1	Not Feasible Not Feasible Not Feasible
5	232.0 / 240.9 / 288.4	Normal Normal Normal	Priority 1 Priority 1 Priority 0	Not Feasible Not Feasible Not Feasible
6	669.0 / 669.0 / 731.4	Normal Normal Normal	Priority 0 Priority 0 Priority 1	Not Feasible Not Feasible Not Feasible
7	250.6 / 250.6 / 232.8	Reroute Reroute Normal	Priority 1 Priority 1 Priority 1	Not Feasible Not Feasible Feasible
8	290.8 / 299.0 / 112.3	Normal Normal Normal	Priority 0 Priority 0 Priority 1	Not Feasible Not Feasible Feasible
9	184.6 / 184.6 / 245.0	Normal Normal Normal	Priority 2 Priority 2 Priority 1	Feasible Feasible Not Feasible

(b)

Figure 9.12. Batch Prediction Analysis. (a) Input Dataset. (b) Outcomes.

Figure 6(b) shows the corresponding batch prediction outcomes generated by the proposed DT-3CA1RT framework for ten shipment instances. The delay prediction column reports estimated delays in minutes (e.g., 234.3, 149.1, 319.5, 667.2, and 669.0 minutes), demonstrating the model's ability to handle both moderate and extreme delay cases. Route decision results indicate mostly Normal routing, with selective Reroute decisions (e.g., at index 7) under high-risk conditions. Resource allocation priorities are dynamically assigned across Priority 0, Priority 1, and Priority 2, reflecting adaptive resource management. Feasibility predictions distinguish feasible and non-feasible shipments, where several instances are correctly flagged as Not Feasible due to adverse combined conditions. These outcomes collectively validate the framework's capability to deliver integrated, real-time logistics decisions at scale.

4.1 Comparative Analysis

Table 1 compares the classification performance of KNN, Huber, and DT classifiers for the route optimization (is_rerouted) target. The DT classifier achieves near-perfect performance with an accuracy, precision, recall, and F1-score of 0.999, indicating its strong capability to capture nonlinear routing patterns. The KNN classifier also performs well with balanced metrics of 0.966, reflecting reliable neighborhood-based decision-making. In contrast, the Huber classifier shows noticeably lower effectiveness, with an accuracy of 0.781 and F1-score of 0.685, highlighting its limitation in handling discrete routing decisions compared to tree-based approaches.

Table. 1: Classification Performance Comparison for Route optimization Target.

Algorithm	Accuracy	Precision	Recall	F1-Score
KNN Classifier	0.966	0.966	0.966	0.966
Huber Classifier	0.781	0.610	0.781	0.685
DT Classifier	0.999	0.999	0.999	0.999

Table 2 presents the performance comparison for predicting the resource_allocation_priority across three priority classes. The DT classifier again demonstrates superior performance, achieving 0.998 accuracy, precision, recall, and F1-score, confirming its robustness in multi-class logistics decision problems. The KNN classifier attains moderate performance with all metrics at 0.938, indicating reasonable priority classification with some confusion among classes. The Huber classifier performs poorly, with an accuracy of 0.484 and F1-score of 0.406, making it unsuitable for priority-based discrete allocation tasks in logistics environments.

Table. 2: Classification Performance Comparison for Resource Allocation Priority Target.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN Classifier	0.938	0.938	0.938	0.938
Huber Classifier	0.484	0.417	0.484	0.406
DT Classifier	0.998	0.998	0.998	0.998

Table 3 evaluates the classifiers for the shipment_feasibility target. The DT classifier achieves perfect classification performance (1.000 across all metrics), signifying complete separation between feasible and non-feasible shipments. The KNN classifier follows closely with consistent metrics of 0.962, indicating strong predictive reliability. However, the Huber classifier records lower performance with an accuracy of 0.786 and F1-score of 0.788, suggesting difficulty in modeling feasibility constraints that depend on complex interactions among shipment attributes.

Table. 3: Classification Performance Comparison for Shipment Feasibility Target.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN Classifier	0.962	0.962	0.962	0.962
DT Classifier	1.000	1.000	1.000	1.000
Huber Classifier	0.786	0.791	0.786	0.788

Table 4 compares regression models for predicting shipment delay in minutes. The DT regressor significantly outperforms other models, achieving an exceptionally low MSE of 42.54, RMSE of 6.54, MAE of 0.28, and a very high R^2 score of 0.999, indicating near-perfect delay estimation. The KNN regressor provides reasonable performance with an R^2 score of 0.960, but exhibits higher error values (RMSE = 34.54, MAE = 12.12). In contrast, the Huber regressor shows poor predictive capability, with a high RMSE of 105.17, MAE of 80.66, and a low R^2 score of 0.625, making it unsuitable for accurate delay modeling in complex logistics scenarios.

Table. 4: Regression Performance Comparison for Delay Target.

Algorithm	MSE	RMSE	MAE	R^2 Score
KNN Regressor	1193.00	34.54	12.12	0.960
Huber Regressor	11060.12	105.17	80.66	0.625
DT Regressor	42.54	6.54	0.28	0.999

5. CONCLUSION

The research demonstrates the effective application of machine learning models for predictive analytics in logistics operations. By leveraging a clean and diverse dataset containing shipment-level operational features, the study focused on both regression and classification tasks relevant to logistics: shipment delay prediction, rerouting detection, resource allocation prioritization, and feasibility assessment. Through the development of a structured pipeline, encompassing preprocessing, exploratory data analysis, feature scaling, model training, and evaluation, the research ensured a robust and reproducible methodology. The experimental results revealed that the DT-3CA1RT algorithm consistently outperformed other models across both classification and regression tasks. It achieved near-perfect accuracy in classification (0.998-1.000) and a remarkably high R^2 score of 0.999 for regression, underscoring its ability to capture nonlinear relationships and feature interactions within the dataset. The KNN-3CA1RT emerged as a reliable alternative, delivering strong but slightly less precise results. In contrast, the Huber model showed significant limitations, with relatively low accuracy in classification and weak fit in regression, indicating its unsuitability for logistics-based predictive modeling in this context. So, the findings establish the DT-3CA1RT as the most suitable predictive algorithm for logistics operations, offering high interpretability, consistency, and computational efficiency. These strengths are critical in logistics, where decisions must often be transparent, reliable, and explainable for operational managers and stakeholders. The results also highlight that integrating machine learning into logistics workflows can significantly improve shipment planning, resource allocation, and disruption management.

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