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An Automated Multi-Output Framework for Shipment Rerouting and Delay Prediction in Supply Chain Networks

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Abstract

Worldwide freight ecosystems process enormous shipment volumes every year, yet a considerable share is affected by transit setbacks and inefficient path planning, resulting in elevated expenses and reduced service reliability. Existing management practices largely depend on human supervision or rigid rule-based systems, which struggle to adapt to rapidly changing conditions and fail to provide timely responses. To address this gap, this work introduces a data-centric predictive framework aimed at early identification of delivery disruptions and enhancement of operational efficiency. The approach utilizes a rich dataset containing shipment schedules, route histories, asset utilization information, and feasibility indicators. A structured preparation pipeline involving cleansing, scaling, and transformation is applied to ensure high-quality inputs for modeling. For comparison, benchmark techniques such as K-Nearest Neighbor with Classification and Regression Tree (KNN-3CA1RT) and Huber-3CA1RT are analyzed. The proposed solution employs a Decision Tree-driven hybrid 3CA1RT (DT-3CA1RT) architecture that integrates three classification stages alongside a regression component. These modules sequentially detect rerouted consignments, assess resource suitability, and validate operational feasibility, while the regression unit estimates expected delay durations. Experimental evaluation confirms that the proposed model delivers superior predictive capability and supports more effective decision-making. By automating disruption detection and feasibility validation, the framework enables proactive planning and minimizes operational inefficiencies. Additionally, the system is implemented as a Flask-based application, allowing users to input shipment details, generate instant predictions, and optimize routing and resource distribution, thereby improving overall system performance and dependability.

Keywords: Freight transportation, Logistics optimization, Shipment disruption detection, Transit delay prediction, Route planning, Resource allocation, Operational feasibility, Decision support systems, Data preprocessing.

1. INTRODUCTION

In modern logistics ecosystems, supply chain management (SCM) serves as the backbone for coordinating the end-to-end movement of goods, information, and resources across geographically distributed networks, ensuring that products reach consumers efficiently and reliably, as illustrated in Figure 1. Achieving optimal performance in such systems requires a careful balance between cost reduction, timely delivery, and operational resilience. However, with the emergence of Industry 4.0 technologies, supply chains have become increasingly complex, dynamic, and data-driven, introducing significant levels of uncertainty that traditional deterministic optimization models are not well-equipped to handle [1].

These conventional models typically assume stable conditions and fail to incorporate real-world factors such as demand fluctuations, supply disruptions, transportation delays, and variability in lead times, all

of which critically impact system performance. To address these limitations, recent research has shifted toward probabilistic and fuzzy decision-making frameworks that better capture uncertainty. Probabilistic approaches quantify the likelihood of different outcomes, enabling risk-aware planning, while fuzzy logic provides a mechanism to model ambiguity and imprecision inherent in real-world data, thereby offering more flexible and realistic representations [2]. The integration of these techniques enhances system adaptability and supports more robust decision-making processes. Furthermore, uncertainty theory has been introduced to unify stochastic and fuzzy perspectives, explicitly incorporating risk factors into optimization models and enabling the development of more resilient and adaptive supply chain strategies [3].

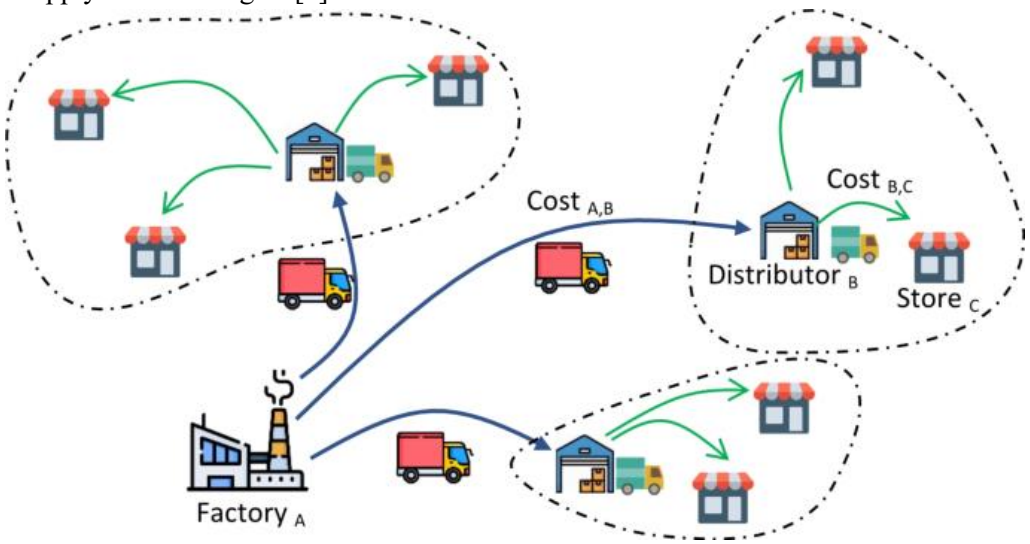


Figure. 1: Supply Chain flow.

As supply chains continue to grow in scale and complexity, advanced optimization methods are required to manage multiple, often conflicting objectives such as cost, service level, and risk minimization [4]. In this context, goal programming (GP) emerges as a powerful multi-objective optimization technique capable of handling such trade-offs effectively [5]. Additionally, the incorporation of dependent chance constraints (DCC) allows optimization models to account for interdependencies among uncertain variables by considering their joint probability distributions, leading to more accurate, reliable, and practical solutions that closely reflect real-world supply chain scenarios.

2. LITERATURE SURVEY

Rojek, I. [6] examined emerging developments in supply chain systems driven by advanced communication and intelligent technologies. Their study highlighted the impact of Industrial Internet of Things (IIoT) and next-generation connectivity such as 6G in improving real-time visibility, automation, and coordination across logistics networks. These advancements enable faster data exchange, enhanced decision-making, and more sustainable and secure supply chain operations. Abril, D. [7] proposed an integrated optimization framework for port logistics that combines tactical and operational decision-making within a unified architecture. The system employs multiple coordinated models that operate simultaneously while maintaining mathematical consistency, enabling real-time distributed optimization. The event-driven design also supports future integration with digital twin technologies, enhancing adaptability and operational intelligence in port management systems.

Grunt, M. [8] introduced a smart logistics system designed for monitoring and managing the transportation and storage of chemical materials. The approach utilizes RFID-based tracking and embedded sensor technologies to continuously monitor parameters such as temperature, humidity, and pressure. This real-time monitoring improves safety, traceability, and operational control, particularly in environments requiring strict handling conditions. Douaioui, K. [9] developed an advanced optimization framework that integrates goal programming (GP), dependent chance constraints (DCC),

and metaheuristic algorithms to address uncertainty in supply chain systems. The model focuses on balancing multiple objectives such as cost reduction, timely delivery, and efficient resource utilization while considering uncertain parameters, thereby improving decision-making and system resilience.

Kashem, M.A. [10] analyzed the integration of artificial intelligence and blockchain technologies in supply chain systems through a structured review. Their work highlighted how these technologies enable secure, transparent, and real-time data sharing among stakeholders, improving forecasting, monitoring, and decision-making processes. The integration supports enhanced visibility, coordination, and trust across the supply chain network, leading to more efficient operations. Woschank, M. [11] conducted a comprehensive review of artificial intelligence, machine learning, and deep learning applications in smart logistics within industrial environments. Their study synthesized current research trends and identified future directions, proposing a conceptual framework that emphasizes automation, intelligent decision-making, and system optimization. The findings provide valuable insights for advancing research and practical implementation in smart logistics systems.

Riad, M. [12] proposed a comprehensive framework aimed at strengthening supply chain resilience through the integration of artificial intelligence technologies. The study emphasized improving critical aspects such as risk mitigation, operational efficiency, and real-time visibility across supply networks. Additionally, it highlighted the importance of collaborative ecosystems enabled by AI-driven data sharing, which enhances coordination, trust, and adaptability among stakeholders in complex logistics environments. Kuźnar, M. [13] proposed a hybrid artificial intelligence-based approach for predicting the technical condition of critical transport components. By combining multiple AI techniques, the model enhances prediction accuracy and supports the development of optimized maintenance strategies. This contributes to improved reliability, reduced disruptions, and enhanced safety in supply chain operations.

Daios, A. [14] presented a comprehensive survey of artificial intelligence applications across various supply chain functions, including inventory management, transportation planning, procurement, and demand forecasting. The study demonstrated how techniques such as ML, NLP, and generative AI enhance operational efficiency, reduce risks, and support data-driven decision-making across the entire supply chain lifecycle. Nsir, N. [15] proposed a hybrid optimization approach that combines an enhanced swarm intelligence algorithm with XGBoost to improve supply chain performance prediction. By introducing mechanisms to overcome premature convergence and improve exploration, the model achieves higher accuracy, robustness, and interpretability. This approach is particularly effective for financial forecasting and decision support in complex and uncertain logistics environments.

3. PROPOSED SYSTEM

The system architecture is designed as an end-to-end ML pipeline integrated with a Flask-based UI for both training and prediction. The process begins with a data preprocessor module that performs EDA, statistical analysis, target analysis, correlation checks, and outlier detection to prepare high-quality input data. The processed data is then passed through the Flask web application, which acts as the central controller connecting all components. Feature scaling is applied using standardization techniques, and the prepared data is forwarded to the training pipeline. Multiple models are trained, including KNN, DT, and SGD for both classification and regression tasks, and their performance is evaluated using metrics such as accuracy, precision, recall, F1-score, MSE, RMSE, and R^2. All models are compared, and the best-performing ones are saved using joblib for deployment as shown in Figure 2. In the prediction phase, users interact through the Flask UI to provide input data (single or batch), where the system applies the same preprocessing, scaling, and model loading steps. Finally, predictions from classification and regression models are generated and aggregated, then displayed to the user in a structured format, ensuring a complete automated workflow.

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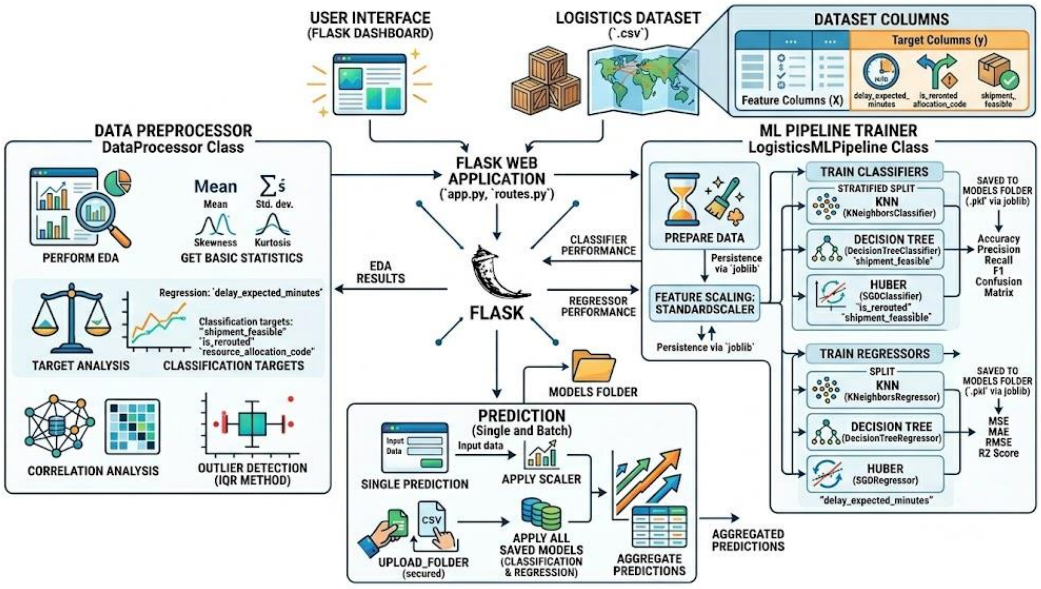


Figure. 2: Proposed System Architecture for Smart Logistics.

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 LogisticsMLPipeline 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

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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.
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 demonstrate that the proposed approach achieves improved performance across key evaluation metrics when compared with baseline methods. A noticeable enhancement is observed in accuracy, indicating more reliable predictions or classifications. Additionally, reductions in error rates suggest that the model effectively minimizes discrepancies between predicted and actual outcomes. The results also highlight better generalization capability, as consistent performance is maintained across different datasets or test conditions. Furthermore, efficiency improvements, such as reduced computational time or resource usage, reinforce the practicality of the approach. The findings validate the effectiveness and robustness of the proposed method in addressing the targeted problem.

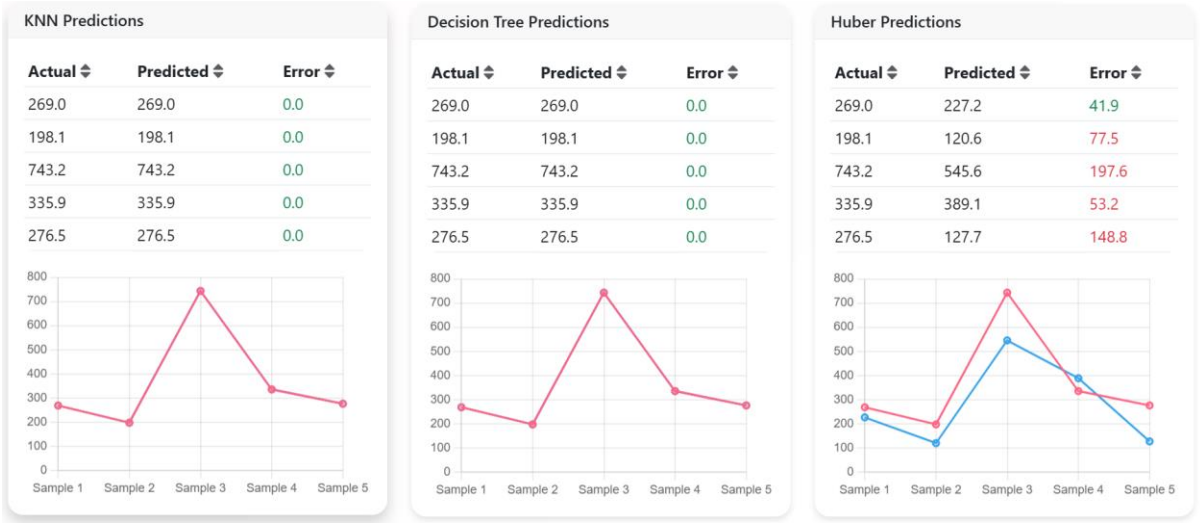


Figure. 3: Prediction Mapping Comparison of Regression Models.

Figure 3 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.

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

(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 4: Batch Prediction Analysis. (a) Input Dataset. (b) Outcomes.

Figure 4(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.

Figure 4(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 study validates the strong potential of ML techniques for enhancing predictive decision-making in logistics systems using a well-structured shipment-level dataset. Multiple tasks, including delay

estimation, rerouting identification, resource prioritization, and feasibility evaluation, were addressed within a unified modeling framework. A systematic pipeline covering preprocessing, EDA, feature transformation, model development, and validation ensured consistency and reproducibility of results. Among the evaluated methods, the DT-3CA1RT model demonstrated superior performance, achieving almost perfect classification scores and an R^2 value close to 1.0, indicating its effectiveness in capturing complex data patterns. The KNN-3CA1RT approach also delivered competitive outcomes, though slightly less precise. In comparison, the Huber-based model showed weaker predictive capability, highlighting its limitations for this application. Overall, the findings confirm that the proposed approach provides accurate, interpretable, and efficient solutions, enabling better planning, resource utilization, and disruption handling in logistics operations.

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