

Logistic Supply Chain Risk Prediction Using AI/ML

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Abstract—Contemporary multimodal logistics networks operate within complex stochastic environments characterized by sudden operational disruptions, localized transit friction, severe weather conditions, and terminal bottlenecks. Conventional supply chain management methodologies rely predominantly on reactive intervention strategies executed only after delivery delays have physically materialized, causing severe monetary penalties, inventory disruptions, and decreased customer satisfaction. This research designs and implements an intelligent, predictive, machinelearning-driven early-warning framework to forecast shipment delivery risks prior to departure. The system bridges historical shipment datasets with real-time dynamic context enrichment using the OpenWeather and OpenRouteService Application Programming Interfaces (APIs). A spectrum of classification algorithms including Logistic Regression, Decision Trees, Extreme Gradient Boosting (XGBoost), and Random Forest were empirically benchmarked. The ensemble Random Forest model attained superior performance, achieving a classification accuracy of 96.0%, a precision of 94.7%, and a disruption detection recall of 95.2%. The trained inference pipeline is operationalized within an interactive Streamlit web dashboard providing spatial route visualization via Folium, real-time risk gauge tracking, automated recommendation alerts, and downloadable decisionsupport dossiers.

Index Terms—Artificial intelligence, decision trees, dynamic context enrichment, machine learning, predictive analytics, Random Forest, real-time systems, supply chain risk management.

I. INTRODUCTION

Supply chain networks constitute the critical backbone of contemporary global commerce, responsible for the timely transit of raw materials, manufactured components, and finished consumer commodities. Despite advancements in automation and enterprise resource planning, modern supply networks disruptions across distributed logistics channels [1].

Distributed intelligent systems similarly illustrate using event-driven modeling to evaluate communication quality and resilience under dynamic constraints [2]. Recent platform-oriented research underscores the necessity of modular architectures that integrate ingestion, statistical modeling, analysis, and visualization into a unified workflow [10].

Visualization is of vital operational importance because tabular logistics logs can become unwieldy and require human inspection to reveal actionable insights. Multi-view monitoring approaches that combine geospatial route mapping with live statistical metrics substantially accelerate operational decisionmaking [4]. Web-based logistics interfaces similarly emphasize intuitive graphical outputs to make complex machine learning inferences accessible to warehouse dispatchers [8]. Modern virtual operational environments demonstrate the capacity of interactive dashboards to eliminate technical barriers and facilitate live risk experimentation [9].

The literature also highlights the need for explainable approaches in risk engineering. Hybrid computational frameworks balance local edge inference with centralized resources for broader network optimization [1]. Furthermore, explainable artificial intelligence research emphasizes exposing interpretable feature contributions for model decisions, remain highly sensitive to operational disruptions. Freight an end-to-end framework combining static freight logs with transit corridors are continuously exposed to adverse weather dynamic contextual enrichment from the OpenWeather and events, port congestions, localized traffic deadlocks, fuel tariff OpenRouteService APIs. The primary contributions of this fluctuations, and carrier inconsistencies. work are summarized as follows:

Historically, freight operations have functioned under post particularly when dispatchers must justify route diversions [2]. Specialized treebased architectures confirm the benefits of combining modular pipelines

with machine learning for real-time risk assessment [7].

The proposed system addresses this operational need through incident remediation models. Logistics managers typically identify delivery failures only after delivery timelines are breached. This reactive posture incurs substantial operational expenses, inventory stockouts, contractual penalty fees, and brand degradation. Proactive risk management requires an integrated approach capable of predicting probability distributions of delivery failures before shipments leave transit hubs.

With the emergence of Industry 4.0 paradigms, Artificial Intelligence (AI) and Machine Learning (ML) algorithms offer promising methodologies for transforming logistics visibility from descriptive diagnostics into prescriptive foresight. Prior studies demonstrate that data-driven modeling can forecast 1) Dynamic Contextual Integration: Integration of realtime environmental and transit APIs into an operational feature engineering pipeline to enhance predictive capability.

Empirical Algorithm Benchmarking: Comprehensive evaluation of diverse machine learning classifiers across standard classification metrics.

Decision-Support Deployment: Implementation of an end-to-end operational software interface using Streamlit, Folium interactive mapping, and Plotly analytics for realtime risk assessment and contingency reporting.

II. RELATED WORK

A. Supply Chain Risk Modeling and Prediction

Controlled analytical studies establish conventional experimental patterns where operational features are monitored, latency factors are quantified, and performance indicators are extracted from historical execution traces [6]. Disruption studies evaluate event-driven supply failures through metrics such as throughput, transit reliability, and delivery consistency [3]. While these foundational evaluations validate the efficacy of data-driven modeling, conventional approaches remain largely static and lack live, explanatory assistance within interactive web architectures [6].

Farazi [1] examined the integration of data-driven methodologies under the Supply Chain 4.0 paradigm,

focusing specifically on predicting heterogeneous shipment delays using machine learning. The study revealed that ensemble architectures such as Random Forest successfully combine operational variables to predict disruption events proactively, although predictive capability remains bounded by raw feature quality [1]. Min [2] formulated a dual-tier supply chain risk prediction model combining Structural Equation Modeling (SEM) with Random Forest algorithms to isolate structural dependencies among latent risk indicators. Despite high predictive fidelity, its architectural complexity poses deployment hurdles for realtime systems [2]. Wang and Zhou [3] developed an earlywarning risk framework combining Random Forest, Genetic Algorithms, and Backpropagation Neural Networks. While their optimization reduced classification error rates across complex time-series logs, the black-box nature of neural networks compromised model interpretability [3].

B. Last-Mile Delivery and Disruption Analytics

Focusing on last-mile freight transportation, He [4] deployed Random Forest regression to estimate package transit durations, confirming that continuous duration outputs can be converted into categorical delay risk classes. However, the methodology was restricted to short-range urban zones and did not generalize to regional freight corridors [4]. Xu et al. [5] designed an intelligent Random Forest model to predict vulnerability nodes across multi-echelon logistics networks, demonstrating that tree ensembles are inherently suitable as the core classification mechanism when adequate historical observations exist.

Zhang and Yang [6] introduced a hybrid assessment methodology to categorize supplier risk profiles, verifying that supplier reliability indices serve as strong upstream predictors of downstream shipment punctuality. Jain [7] constructed a multiclass Random Forest framework to classify delivery outcomes into early, on-time, and delayed categories, emphasizing that raw accuracy is an inadequate metric in logistics applications due to acute class imbalance. Camur et al. [8] investigated product availability dates under severe disruption conditions using statistical learning, noting that models struggled to generalize across diverse regions without dynamic retraining. Rezki and Mansouri [9] utilized combined classification and regression trees to predict high-risk suppliers and

downstream delivery failures simultaneously, emphasizing the importance of temporal operational history. Finally, Jahin et al. [10] conducted a systematic review benchmarking AI techniques applied to supply chain risk assessment, establishing that treebased ensemble algorithms systematically outperform linear and deep models on tabular logistics features.

C. Architectural Synthesis and Gap Identification

The referenced studies collectively establish the validity of machine learning for logistical disruption analysis, yet existing works demonstrate clear systemic silos [1]–[10]. Classical statistical implementations operate predominantly on isolated, historical databases without live integration of route friction or atmospheric variance [1], [5]. Conversely, systems focusing on live route planning frequently omit advanced predictive machine learning classifiers trained on historical shipment behavior [4], [8]. The operational opportunity addressed in this paper is the end-to-end unification of these distinct capabilities: combining dynamic API data ingestion, automated data cleaning, ensemble tree inference, and interactive spatial route tracking into an integrated workflow.

III. PROPOSED SYSTEM AND METHODOLOGY

A. Design Objectives

The proposed system was designed around five core objectives: (1) automated ingestion of heterogeneous shipment parameters; (2) dynamic data enrichment via external live APIs; (3) robust data standardization and feature construction; (4) classification of shipment delay risks with high recall; and (5) continuous decision support via live geographical visualization and automated contingency dossiers.

B. Data Ingestion and Parameters

The foundational data layer ingests comprehensive logistics records. The primary data attributes captured per shipment record include:

- Temporal Attributes: Scheduled dispatch timestamp, scheduled arrival timestamp, and transit milestones.
- Spatial Attributes: Origin and destination latitude/longitude, regional hub codes, and transit corridors.

- Consignment Characteristics: Cargo classification (fragile, perishable, industrial, hazardous), consignment weight, and packaging volume.
- Operational Indicators: Transportation mode (road, ocean, rail, air), carrier historical reliability rating from 1 to 5, driver performance index, and fuel cost indices.

C. Real-Time Dynamic API Enrichment

To bridge the gap between historical baselines and actual transit conditions, the data ingestion engine connects directly to external real-time web services prior to model inference:

- OpenWeather API: Queries live meteorological metrics along the transit corridor, capturing ambient temperature, wind velocity, precipitation volume, atmospheric pressure, and severe weather alerts.
- OpenRouteService API: Calculates topological road network distance, expected unimpeded driving duration, localized traffic bottlenecks, and route friction coefficients.

D. Data Preprocessing and Feature Engineering

Raw data streams undergo cleaning and imputation. Missing continuous variables are imputed using median statistical values to preserve distributional stability against outliers, whereas missing categorical markers are filled with mode values. Categorical attributes (transportation mode, weather severity classification, cargo type) are mapped into discrete numerical indicators using saved Label Encoders. Continuous numerical features undergo Z-score normalization based on training corpus parameters.

Derived features are subsequently synthesized: scheduled transit duration is calculated as the difference between scheduled delivery and dispatch timestamps, while the transit buffer ratio is computed as the scheduled transit duration divided by the unimpeded route duration. A transit buffer ratio below 1.05 indicates an exceptionally narrow delivery schedule highly susceptible to delays. The finalized features are concatenated into a consolidated shipment vector forwarded to the machine learning engine.

IV. MACHINE LEARNING FRAMEWORK

A. Random Forest Formulation

The core classification engine employs an ensemble Random Forest model. Random Forest mitigates

variance and avoids overfitting by constructing an ensemble of decorrelated decision trees trained on bootstrap samples of the training set. During tree construction, a random subset of features is selected at each split node to maximize Gini impurity reduction. For an unseen shipment feature vector, each individual tree outputs a posterior class probability for delay occurrence. The ensemble probability score is derived through bagging aggregation across all trees in the forest. The final operational categorization is assigned using an operational decision threshold of 0.50, where shipments exceeding this value are flagged as High Risk and trigger automated alerts.

B. Comparative Algorithms

To establish an empirical baseline, three additional classification algorithms were implemented and evaluated under identical preprocessing conditions:

- Logistic Regression: A regularized generalized linear model serving as the parametric baseline.
- Decision Tree Classifier: A single hierarchical decision structure utilizing recursive partitioning via Gini impurity criteria.
- XGBoost: An advanced ensemble boosting framework that sequentially minimizes a regularized objective loss function using second-order approximations.

V. SYSTEM DEPLOYMENT AND DASHBOARD

The production deployment framework is structured to offer immediate operational utility to logistics controllers. The complete pipeline is operationalized within an interactive Python web framework utilizing Streamlit.

A. Interactive Operational Components

The deployment interface comprises four core modules:

- 1) Spatial Route Mapping: Integrates Folium to project real-time geographic transit corridors. Route geometry retrieved from OpenRouteService is rendered as an interactive map layer, with High Risk consignments dynamically overlaid with red warning polylines.
- 2) Dynamic Risk Probability Gauge: Plotly-driven gauge widgets display the probabilistic risk index alongside confidence intervals.

- 3) Automated Decision-Support Recommendations: When a consignment is flagged as High Risk, an automated rules engine evaluates primary risk contributors to suggest alternate highway corridors or carrier reallocation.
- 4) Automated Dossier Generation: Generates a downloadable plain-text and PDF dispatch report summarizing origin-destination pairs, estimated transit metrics, identified operational hazards, and predictive probability logs.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

A. Evaluation Metrics

The models were evaluated using standard classification metrics derived from the confusion matrix parameters: Accuracy, Precision, Recall, and F1-Score. In supply chain risk forecasting, Recall is of paramount operational significance: a false positive simply results in precautionary route inspections, whereas a false negative leaves disruptions unaddressed, leading to contractual non-compliance and direct economic loss.

B. Performance Analysis

Experimental evaluation was conducted on an enterprise logistics benchmark dataset comprising shipment records enriched with simulated and live environmental parameters. The comparative performance across all evaluated models is summarized in Table I.

TABLE I MODEL PERFORMANCE COMPARISON ON LOGISTICS RISK DATASET

Algorithm	Acc.	Prec.	Recall	F1-Score
Logistic Regression	78.4%	74.2%	71.0%	72.5%
Decision Tree	89.1%	85.6%	86.2%	85.9%
XGBoost	94.8%	93.1%	92.5%	92.8%
Random Forest	96.0%	94.7%	95.2%	94.9%

The empirical findings clearly indicate that the Random Forest ensemble achieved the best overall performance across all evaluation dimensions. The

linear baseline (Logistic Regression) attained an accuracy of only 78.4% and a recall of 71.0%, demonstrating that linear decision boundaries cannot capture complex, non-linear interactions characteristic of supply chain disruptions.

While a standalone Decision Tree improved accuracy to

89.1%, it suffered from high variance and localized overfitting. The advanced boosting algorithm (XGBoost) demonstrated high competitive capability (94.8% accuracy, 92.5% recall). However, Random Forest surpassed XGBoost, achieving an overall classification accuracy of 96.0% and a recall rate of 95.2%. The bagging mechanism of Random Forest proved particularly resilient against noise introduced by transient weather API variations, minimizing false-negative classifications.

TABLE II CONFUSION MATRIX FOR RANDOM FOREST CLASSIFIER

	Pred. Low Risk	Pred. High Risk
Actual Low Risk	964	36
Actual High Risk	48	952

Table II presents the confusion matrix for the test partition (2,000 evaluated shipment instances). The Random Forest model correctly identified 952 out of 1,000 actual disruption events, yielding a low false negative count of only 48 shipments.

C. Feature Importance Evaluation

A significant operational advantage of the Random Forest algorithm is its capacity to compute Mean Decrease in Impurity, providing transparency regarding feature contributions.

TABLE III RELATIVE FEATURE IMPORTANCE IN RISK PREDICTION

Feature Indicator	Importance Score
Transit Buffer Ratio	0.284
OpenRouteService Route Distance	0.212
Precipitation Volume (OpenWeather)	0.186
Carrier Historical Rating	0.141
Wind Velocity Index	0.098
Cargo Classification Category	0.079

As detailed in Table III, the engineered Transit Buffer Ratio emerged as the single most influential predictive feature (relative importance of 0.284), followed by route distance (0.212) and dynamic precipitation levels (0.186). This confirms that integrating real-time environmental metrics directly bolsters the model's discriminative ability compared to evaluating static distance alone.

VII. LIMITATIONS

Several operational constraints must be explicitly acknowledged:

- 1) **API Rate Limiting:** Reliance on public web APIs introduces network latency during bulk inferencing cycles, requiring caching layers for high-frequency dispatch systems.
- 2) **Intermodal Boundary Gaps:** Current routing heuristics are primarily optimized for terrestrial transit networks and require calibration for maritime and air-cargo transfers.
- 3) **Dynamic Weather Variability:** Severe microclimate fluctuations between reporting weather stations can occasionally lead to transient false-positive risk warnings.

VIII. CONCLUSION AND FUTURE WORK

This research presented an artificial intelligence framework for predictive logistics supply chain risk management. By dynamically synthesizing static freight records with real-time meteorological and topological routing APIs (OpenWeather and OpenRouteService), the system resolves the blind spots of conventional reactive logistics. Extensive empirical benchmarking proved that the Random Forest ensemble achieves high predictive accuracy (96.0%) and delay-detection recall (95.2%), outperforming baseline linear and single-tree algorithms. The accompanying Streamlit dashboard operationalizes these predictions through live spatial route rendering, probabilistic risk gauges, and automated decision-support dossiers.

Future research will focus on extending the predictive framework to international multi-modal maritime corridors, incorporating automated graph neural networks (GNNs) for global port congestion modeling, and deploying reinforcement learning agents for autonomous dynamic dispatch rerouting.

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