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AI-Powered Supply Chain Disruption Detection and Decision Support System

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***Abstract* - Supply chain disruptions have become a major challenge for modern logistics systems due to supplier failures, transportation delays, fluctuating customer demands, and various operational risks. Traditional forecasting and rule-based approaches often struggle to handle the complexity and dynamic nature of supply chain operations. To address these challenges, this paper presents an AI-powered Supply Chain Disruption Detection and Decision Support System designed to improve disruption prediction, demand forecasting, shipment monitoring, and supplier performance analysis using advanced machine learning techniques.**

The proposed system utilizes historical supply chain data, including shipment records, inventory information, supplier performance metrics, and operational parameters, to train and evaluate multiple machine learning models such as Random Forest, XGBoost, LightGBM, and CatBoost. Advanced feature engineering techniques and hyperparameter optimization using Optuna were applied to enhance prediction accuracy and model performance. Among the evaluated models, LightGBM achieved the best forecasting and disruption prediction performance.

To improve transparency and interpretability, the system incorporates SHAP-based Explainable Artificial Intelligence (XAI) techniques, which help identify the most influential operational factors contributing to supply chain disruptions. The complete framework is implemented as a web-based application featuring interactive dashboards, real-time monitoring, analytics visualization, and automated reporting capabilities. Experimental results demonstrate that the proposed system significantly improves forecasting accuracy, disruption detection, and decision-making efficiency, making it a suitable solution for intelligent and smart supply chain management applications.

Keywords: Supply Chain Disruption Prediction, Machine Learning, Demand Forecasting, SHAP Explainability, LightGBM, Decision Support System, Logistics Analytics, Supplier Risk Analysis, AI-Based Supply Chain Management.

I. INTRODUCTION

Today's supply chains have become highly complex due to the involvement of multiple stakeholders, geographically distributed operations, and continuously changing market conditions.

Factors such as globalization, rapidly growing customer expectations, supplier uncertainties, transportation delays, and operational risks have made supply chain management increasingly challenging for organizations. As a result, businesses are under constant pressure to improve efficiency, reduce disruptions, and make faster and more informed decisions.

To address these challenges, the effective use of advanced analytics and intelligent technologies has become essential in modern supply chain operations. This research focuses on the application of machine learning and data analytics techniques to improve supply chain visibility, disruption prediction, and operational decision-making. The proposed system is designed as an intelligent analytics platform that combines machine learning algorithms with interactive visualizations to support supply chain optimization and monitoring. By analyzing large-scale real-world logistics and operational datasets, the system generates valuable insights that help organizations improve efficiency, reduce risks, and enhance overall supply chain performance.

The backend of the proposed system is developed using Python and is responsible for data acquisition, preprocessing, transformation, and predictive analytics. Multiple machine learning modules are integrated into the system to perform tasks such as demand forecasting, disruption prediction, supplier risk analysis, and shipment delay estimation. Advanced predictive models and time-series analysis

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techniques are used to analyze historical supply chain data and generate accurate forecasts and operational insights. These machine learning services are integrated into the platform through RESTful APIs, enabling smooth communication between different system components.

The frontend of the application is developed using modern JavaScript technologies to provide a responsive, interactive, and user-friendly environment for supply chain managers and analysts.

The system offers customizable dashboards and visualization panels that allow users to monitor key performance indicators (KPIs), analyze predictive insights, and perform scenario-based analysis. In addition, executive dashboards provide high-level operational summaries and business intelligence for strategic decision-making, while detailed analytical panels enable users to examine specific aspects of supply chain operations in greater depth.

Overall, the proposed system aims to provide an intelligent, scalable, and efficient solution for modern supply chain management by integrating machine learning, real-time analytics, predictive forecasting, and interactive visualization into a unified decision support platform.

II. LITERATURE SURVEY

Recent advancements in supply chain analytics have significantly improved the ability of organizations to predict disruptions, optimize operations, and enhance decision-making through the use of machine learning, deep learning, and hybrid optimization techniques. Researchers have proposed various intelligent models to improve forecasting accuracy, operational efficiency, and supply chain resilience under uncertain conditions.

Farshid Abdi (2024) introduced a Hybrid Wavelet-MLP model combined with Multi-Objective Optimization for supply chain demand forecasting. In this approach, the Wavelet Transform is used for feature extraction, while the Multi-Layer Perceptron (MLP) model performs forecasting operations. Multi-objective optimization algorithms were further applied to improve prediction accuracy and performance under uncertain operational conditions. Although the proposed method achieved promising forecasting results, the model was computationally intensive and difficult to implement in large-scale real-world environments.

Neuro-fuzzy systems have also contributed significantly to supply chain resilience research. Murad Samhouri (2023) proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) for improving disruption management and supply chain resilience. The ANFIS model combines the learning capability of neural networks with the uncertainty-handling ability of fuzzy logic, enabling flexible decision-making in complex operational scenarios. However, the model requires extensive fine-tuning and parameter optimization to achieve stable performance.

Shipment delay prediction has become another important area of research in supply chain analytics. Ramakrishna Garimella (2023) developed a hybrid prediction model integrating XGBoost and Bi-LSTM algorithms for shipment delay forecasting. In this model, XGBoost captures non-linear relationships within structured operational data, while Bi-LSTM learns sequential dependencies from time-series logistics information.

The hybrid approach demonstrated high prediction accuracy, but its computational complexity and training cost were relatively high.

Deep learning models, particularly Transformer-based architectures, have also shown strong potential in optimizing supply chain efficiency. Lixing Bo (2022) proposed a Transformer-based predictive analytics framework combined with Particle Swarm Optimization (PSO) for improving sales forecasting and inventory optimization. The proposed system improved operational efficiency and reduced costs; however, the complexity of Transformer models increased implementation and maintenance challenges.

Another important contribution in this domain was presented by Javed K. Sayyad (2022), who applied the CatBoost algorithm for predictive modeling in e-commerce supply chains. CatBoost demonstrated strong performance when handling categorical supply chain data and produced accurate forecasting results. Nevertheless, the model required large datasets and considerable computational resources for effective training.

In addition to hybrid and deep learning approaches, ensemble machine learning techniques such as Decision Trees, Random Forest, and Gradient Boosting have been widely used for supply chain risk analysis and operational decision-making. Kassem Danachi (2024) highlighted that these ensemble methods improve prediction reliability and operational analytics; however, challenges related to data dependency, scalability, and privacy remain important concerns.

Research focusing on supply chain collaboration and disruption management has also gained attention. Mustafa Saidi (2023) conducted a systematic review on collaborative resource sharing in supply chains and emphasized its importance in improving resilience and recovery capabilities during disruptions. However, the study reported limited

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empirical validation in practical environments. Similarly, Kai Kang (2023) investigated dual-channel supply chain disruptions using mathematical modeling techniques to analyze operational risks and disruption impacts. Although the study provided valuable insights into disruption management, it relied on several assumptions that limited real-world applicability.

Furthermore, benchmarking studies comparing different machine learning models have become increasingly important in evaluating supply chain prediction systems. N. Müller (2025) analyzed the performance of various predictive models for supply chain disruption forecasting and concluded that hybrid machine learning models, deep learning approaches, and optimization-based systems significantly improve prediction accuracy, flexibility, and operational robustness. Despite these advantages, existing methods still face challenges related to computational complexity, scalability, interpretability, and real-world deployment.

Overall, the existing literature demonstrates that machine learning, deep learning, and intelligent optimization techniques are transforming modern supply chain analytics and disruption prediction systems.

Although these approaches offer substantial improvements in forecasting accuracy, operational efficiency, and resilience, further research is still required to improve scalability, interpretability, computational efficiency, and practical applicability in large-scale supply chain environments.

III. RELATED WORK

Prediction of disruptions in supply chain operations and the development of intelligent logistics management systems have gained significant attention from researchers and industries due to the increasing complexity of modern supply chains. The rapid growth of logistics data related to shipments, suppliers, inventories, transportation, and operational activities has encouraged the adoption of advanced predictive analytics and intelligent decision-making systems. Modern supply chains generate large volumes of both structured and unstructured data, making accurate prediction, monitoring, and analysis essential for efficient operations.

Traditional supply chain management systems commonly provide functionalities such as inventory tracking, shipment monitoring, demand forecasting, and supplier management. These systems are widely used across industries including logistics, manufacturing, retail, and transportation for operational planning and resource management. Although they help organizations manage day-to-day logistics activities effectively, most traditional systems rely heavily on statistical forecasting methods, rule-based approaches, and historical trend analysis. As a result, they often struggle to capture complex non-linear relationships among factors such as fluctuating customer demand, supplier failures, transportation delays, weather conditions, and other operational risks.

Conventional forecasting techniques such as linear regression, moving average models, and inventory planning methods are suitable for basic operational planning, but they are not sufficient for handling large-scale and dynamic logistics datasets involving multiple operational variables. This limitation has created a strong need for machine learning and artificial intelligence techniques that can identify hidden patterns, learn from historical operational data, and provide more accurate predictions for supply chain management.

Several researchers have explored the application of advanced machine learning models in supply chain optimization and disruption prediction. Abdi et al. proposed a machine learning-based demand forecasting framework that demonstrated the importance of predictive analytics in improving supply chain efficiency. Similarly, Samhouri et al. investigated Adaptive Neuro-Fuzzy Inference Systems (ANFIS) for improving supply chain resilience and disruption management in uncertain operational environments. Other studies focused on ensemble and hybrid learning techniques for operational analytics. Garimella et al. introduced a hybrid XGBoost and Bi-LSTM model for shipment delay prediction and logistics optimization, while Sayyad et al. explored the use of CatBoost algorithms for predictive analytics in e-commerce supply chain systems.

Recent advancements in Explainable Artificial Intelligence (XAI) have further improved the transparency and interpretability of machine learning-based supply chain systems. SHAP (SHapley Additive exPlanations) has emerged as one of the most effective frameworks for interpreting predictions generated by tree-based machine learning models. Researchers have applied SHAP analysis to identify important operational factors such as supplier reliability, transportation delays, route complexity, inventory utilization, and demand fluctuations that significantly influence disruption prediction and forecasting performance.

Another important research direction involves the development of intelligent decision support systems and web-based supply chain analytics platforms. Several studies have attempted to integrate predictive analytics, operational monitoring, reporting systems, and interactive dashboards into logistics management platforms. However, many existing systems still face challenges related to scalability, interpretability, real-time analytics, and prediction explainability. In many cases, traditional systems focus only

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on forecasting or risk analysis individually, without integrating all operational analytics capabilities into a unified framework.

Although substantial progress has been made in supply chain analytics and disruption prediction, many existing systems still suffer from limitations related to reliability, transparency, scalability, and decision-making efficiency. Most current approaches focus primarily on prediction accuracy while giving less importance to advanced feature engineering, explainable AI, operational monitoring, automation, and intelligent visualization. Therefore, there is a growing demand for scalable and explainable supply chain disruption detection systems that combine machine learning prediction, SHAP-based explainability, real-time operational monitoring, and intelligent decision support within a single integrated platform. The proposed research aims to address these challenges through the application of advanced machine learning models, feature engineering, Optuna-based hyperparameter tuning, SHAP analysis, and interactive visualization techniques.

IV. PROPOSED SYSTEM

The proposed system is a comprehensive supply chain analytics and decision support platform designed to improve supply chain visibility, operational efficiency, and disruption management using machine learning and advanced data analytics techniques. The system combines intelligent prediction models, real-time monitoring, and interactive visualizations to assist organizations in making faster and more accurate operational decisions. It is developed as a modular web-based application in which the backend is implemented using Python for data processing and machine learning operations, while the frontend is developed using React to provide an interactive and user-friendly interface.

The core of the proposed framework is the machine learning backend, which consists of multiple predictive models for demand forecasting, shipment delay prediction, supplier risk analysis, and disruption detection.

These models are trained using historical supply chain datasets containing shipment records, inventory information, supplier performance metrics, transportation details, and operational risk factors. The backend is responsible for loading and preprocessing data, performing feature engineering, generating predictions, and exposing prediction services through RESTful APIs for frontend integration.

The supply chain data pipeline begins with the ingestion, cleaning, and transformation of raw operational datasets using customized preprocessing scripts. After preprocessing, the machine learning models are trained, validated, and optimized to ensure accurate and reliable performance across different operational scenarios. The system supports both real-time and batch inference, enabling organizations to perform historical analysis as well as live operational monitoring and prediction.

The frontend of the application provides an interactive dashboard that displays operational insights through graphs, charts, maps, and analytics panels. Users can monitor demand forecasts, shipment risks, supplier performance, delivery delays, and route optimization results in real time. The dashboard is designed to support both operational managers and business executives by providing detailed analytical views as well as high-level strategic summaries for decision-making.

To improve operational awareness, the system includes an intelligent Alerts Panel that automatically highlights critical issues detected by the predictive models. High-risk shipments, unexpected demand fluctuations, supplier failures, and transportation delays are identified and displayed as alerts, allowing organizations to take proactive actions before disruptions occur.

An important feature of the proposed system is the Dynamic Supply Chain Analyzer, which allows users to perform scenario-based “what-if” analysis. Users can modify operational parameters such as demand forecasts, shipment routes, inventory levels, and supplier conditions to observe how these changes affect prediction outcomes and operational performance. This capability helps organizations evaluate different strategies and optimize supply chain operations more effectively.

The architecture of the system is designed to be scalable, modular, and easy to maintain. The backend and frontend components are developed independently and communicate through well-documented APIs, enabling developers to enhance or update individual modules without affecting the entire system. This modular design also simplifies future integration of additional predictive models, analytics services, and external data sources.

Security and privacy are also considered important aspects of the proposed architecture. Access control mechanisms and authorization policies are implemented to ensure that only authorized users can access sensitive operational data and prediction results. Depending on organizational requirements, the platform can be deployed either on-premises or in cloud environments.

V. SYSTEM ARCHITECTURE

The architecture of the supply chain analytics solution involves an advanced modular structure of a web application that is geared towards offering advanced predictive analytics,

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real-time monitoring, and visualizations for the supply chain ecosystem. It is important to note that the architecture of the solution features clear delineations between the backend and the frontend elements along with a structured data layer and effective communication channels.

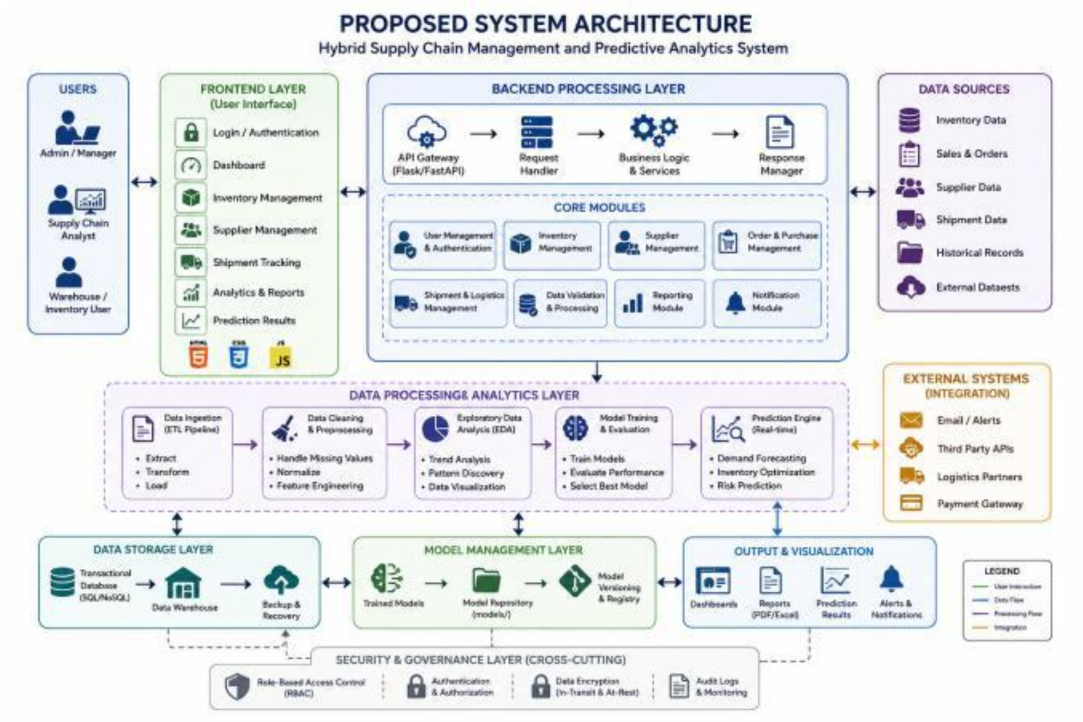

Figure 5.1: System Architecture

Backend Architecture: The backend is written in Python using the Flask web framework, which provides an efficient RESTful API layer that can be used for interaction between data processing/modules inference and the front-end part of the application.

Data Loader and Preprocessing Module: Data is loaded into the system by means of the data_loader.py module. The main purpose of this module is to load and preprocess the initial supply chain data. Such operations include cleaning and transforming the dataset to make sure it is ready to be processed by predictive analytics models.

Predictive Analysis: The actual analytical capabilities of our platform are provided by modules such as delay_predictor.py, demand_forecast.py, risk_analyzer.py. They represent predictive analytics models that process incoming supply chain data and produce relevant predictions based on them.

API Layer: The primary logic of the application is contained within app.py, which contains RESTful services for submitting data, making predictions, and retrieving results. These services are stateless and scalable, allowing them to process multiple simultaneous requests from various users or applications. The system employs authentication and authorization services to secure access to confidential data and model predictions.

Model Management: Models are saved to a special folder (trained_models). This allows for easy management, including versioning and rollback. There are tools for serializing/deserializing, validating, and monitoring model performance.

Frontend Architecture: The frontend framework used is React, delivering a dynamic and responsive user interface. This project employs a component-based architecture, in which the various functionalities of the dashboard are organized into distinct React components. The major components used in this project include:

Dashboard and Visualizations: In the main dashboard, visual representation of the supply chain performance measures, including delay risk analysis map and demand forecasting chart, are provided. Components such as Dashboard.js, DelayRiskMap.js, and DemandForecast.js use visualization libraries like Chart.js and D3.js.

Alerts and Notifications: The component used to display alerts is called AlertsPanel.js. It receives alerts from the

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backend models and displays them to notify users of any disruptions or irregularities that might occur.

Scenario Building and User Interaction: Modules like DynamicSupplyChainAnalyzer.js, RoutePredictionPanel.js enable users to experiment with different scenarios, change parameters, and assess the results to analyze how these changes will affect supply chain efficiency.

Integration: HTTP requests are used for communication between the frontend and the backend. Fetch API or Axios are some of the commonly used APIs. All information displayed is generated based on API queries.

Data Layer and Storage: The system's data layer is flexible and scalable. Raw and transformed data will be saved in the data folder, with the possibility of integrating with any external database if needed. For larger implementations or persisting the data, a relational database such as PostgreSQL can be included, or alternatively, a NoSQL database like MongoDB. Artifacts generated by the models are kept separate from the data for tracking and reusability.

Security and Deployment: Security is an integral part of the system architecture. Authentication and role-based security are implemented in the backend, such that only those who are permitted to access sensitive API endpoints will have the privilege to do so. HTTPS protocol is used in all transactions made between the frontend and the backend. The application can either be hosted on-premises or in the cloud. Containerization is supported by Docker.

Scalability and Extensibility: A modular architecture allows for easy scalability and the ability to develop new parts without affecting other existing functionalities. Additional predictive models, data inputs, or visualization widgets may easily be added without breaking any of the existing functionalities. This is achieved due to the API architecture that also makes it possible to integrate third-party applications.

System Monitoring and Maintenance: System monitoring can be achieved through logging and performance metrics at both backend and frontend levels. Automation testing and CI pipeline guarantee that the source code is reliable and of high quality. The system will have a maintenance-friendly design with well-separated modules.

VI. IMPLEMENTATION

The implementation of the above AI-Powered Supply Chain Disruption Detection and Decision Support System relies on creating a powerful and scalable logistics intelligence platform, which would be able to process high volume operational datasets and detect supply chain disruptions in real-time. The system implementation includes the use of modern machine learning frameworks and data analytics packages, visualization tools, and backend services according to the modular design approach.

The front-end of the application is based on React, which allows for implementing the interactive user interface used by the logistics managers and analysts for uploading datasets, predicting disruptions, forecasting demand, analyzing suppliers, generating reports, visualizing dashboard metrics, and monitoring operations. The backend services were created using Flask, which facilitates efficient API communication and performs data processing and machine learning inference tasks.

The suggested system will employ several ML and Analytics techniques such as Pandas, NumPy, Scikit-learn, XGBoost, Random Forest, LightGBM, SHAP Explainability Model, Matplotlib, and Seaborn for prediction and visualization.

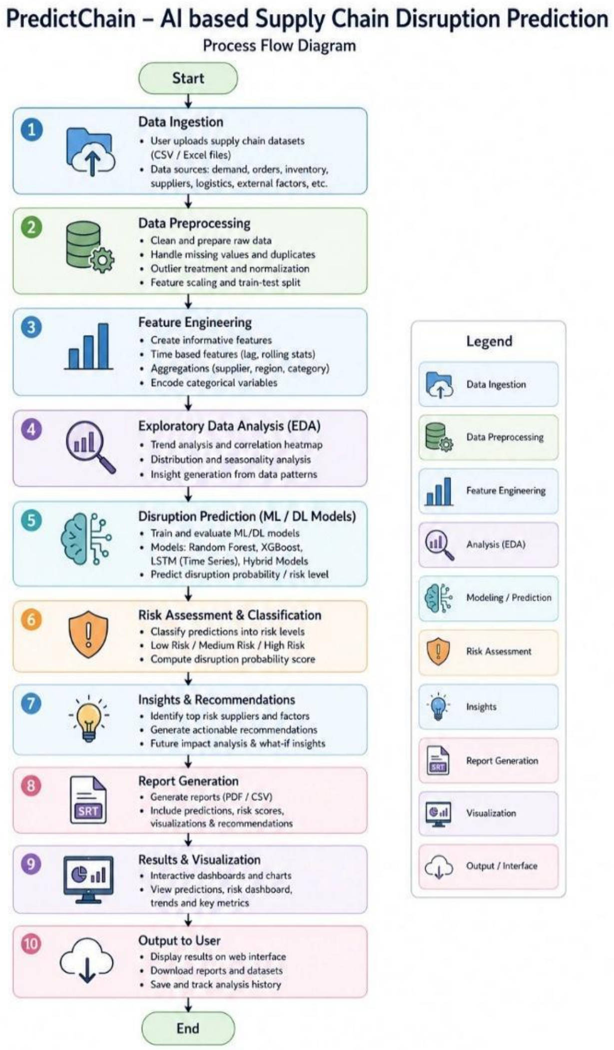

Figure 6.1: Implementation Workflow of the Supply Chain Disruption

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Implementation pipeline of Figure 6.1 comprises end-to-end execution pipeline involving operational data acquisition, data preprocessing, feature extraction, exploratory data analysis, machine learning predictions, risk assessment, knowledge creation, report generation, dashboard display, and result distribution via the web interface. Implementation is done using a modular approach whereby the entire system is broken down into several functional modules. Each module plays its own role in the supply chain analytics pipeline as well as communicates effectively with other modules through proper interfaces.

The major modules implemented in the proposed system include:

- Data Ingestion Module
- Data Preprocessing Module
- Feature Engineering Module
- Exploratory Data Analysis (EDA) Module
- Machine Learning Prediction Module
- Risk Assessment and Classification Module
- Insights and Recommendation Module
- Report Generation Module
- Dashboard Visualization Module
- Output and User Interface Module

A. Data Ingestion Module

The Data Ingestion Module will be used to ingest and preprocess supply chain data sets that have been uploaded into the web application. Data sets will be available in CSV and Excel formats containing logistics data, inventory data, transaction data, supplier data, transport data, and operational indicators from third-party sources.

The data sets are ingested, preProcessed, and made ready for processing while retaining operational metadata as well as consistency of the data.

B. Data Preprocessing Module

Data Preprocessing Module will take care of preprocessing the raw data sets before analysis via machine learning. Missing values, duplicate rows, inconsistencies in operational data sets, and outliers are detected and processed using standard preprocessing approaches.

Data normalization, feature encoding, train/test splitting, and scaling are performed on the datasets.

C. Feature Engineering Module

The Feature Engineering Module creates operational indicators that are useful in improving disruption prediction and forecasting capabilities. Time-based features, rolling statistics, supplier aggregates, logistics aggregates, and categorical encoding are created using raw data from the supply chains. The use of these features by the system allows for better analysis of operational indicators and helps in understanding the relationships between the different variables of the supply chain.

D. Exploratory Data Analysis (EDA) Module

The Exploratory Data Analysis (EDA) Module is used to analyze operational datasets statistically and graphically to determine various patterns including trends, distributions, seasonality, and correlations in the operational indicators. Trend analysis graphs, heatmaps, distributions, and operational statistics can be generated.

EDA allows for the discovery of important patterns in operations while helping with intelligent feature selection.

E. Machine Learning Prediction Module

The Machine Learning Prediction Module predicts operational disruptions and forecasts future operations using various machine learning and deep learning models such as Random Forest, XGBoost, LightGBM, LSTM, among others.

These models are trained on past data in order to predict shipment delays, supplier risks, inventory disruptions, and demands. The prediction model gives disruption probabilities, forecast results, and risk ratings for effective decision-making.

F. Risk Assessment and Classification Module

The Risk Assessment Module categorizes the predictions from the operations under different risk classifications such as Low Risk, Medium Risk, and High Risk. The disruption probability ratings are based on predictions made by machine learning models.

The module allows logistic managers to detect risky operations and implement mitigation strategies before any disruption arises.

G. Insights & Recommendations Module

The Insights & Recommendations Module evaluates operational forecasts and creates valuable business insights for optimizing the supply chain. The module highlights risky suppliers, weak transport links, unstable stock, and operational issues that hamper logistics efficiency.

Insights through intelligent recommendations and what-if analysis are developed to aid effective planning and supply chain management.

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H. Report Generation Module

The Report Generation Module automates the creation of reports in PDF and CSV formats including forecasting data, disruption analysis, operational metrics, risk categories, visualization, and business recommendations.

Reports can be useful for organizations in operational reporting, logistics planning, analytics tracking, and decision-making.

I. Dashboard Visualization Module

The Dashboard Visualization Module is used for the provision of interactive dashboards and analytics that are useful for monitoring and prediction analysis purposes. The dashboard visualization interface provides visualization services including forecasting chart visualization, supplier analytics, shipping analytics, disruption alert analytics, operation analytics, and risk visualizations.

The dashboard visualization module makes operations transparent and facilitates the interpretation of prediction output via the graphical visualization.

J. Output and User Interface Module

The Output and User Interface Module offers the prediction output, operational dashboard, report generation, and visualization of analytics through the web application user interface. The user will be able to download reports, record operational analysis history, analyze disruptions, and monitor system analytics.

The module ensures a seamless interaction between the user and the AI-based system for efficient logistics analysis and decision making.

VII. RESULTS

In order to investigate the effectiveness of the proposed AI-Powered Supply Chain Disruption Detection and Decision Support System for disrupting event prediction, supply chain operational monitoring, forecasting, optimizing, and intelligent analytics capabilities, the system implementation and performance were evaluated. The performance of the system was assessed in terms of predictive accuracy, forecasting precision, operational clarity, risk classification capability, and efficiency of analytics.

Firstly, the performance of the proposed system framework was investigated by assessing the accuracy of disruption prediction via a machine learning pipeline incorporating feature engineering and preprocessing methods as well as ensemble models. It was established through experimental observations that applying advanced feature engineering techniques in combination with the use of machine learning models such as Random Forest, Gradient Boosting, XGBoost, and LightGBM provided higher disruption prediction accuracy and forecasting efficiency in comparison to statistical forecasts.

Table 1 presents the quantitative performance evaluation of the proposed Supply Chain Disruption Detection System.

Table 1: Performance Evaluation of Proposed Supply Chain System

Metric	Value
Prediction Accuracy	91%
Precision Score	0.89
Recall Score	0.87
F1-Score	0.88
Avg. Prediction Latency	2.1 seconds

Evaluation results show that the suggested approach has very good disruption prediction accuracy and operational reliability with acceptable delay for enterprise application.

The performance of the different ML models for disruption prediction is also analyzed based on prediction accuracy and operational reliability. The experimental result shows that LightGBM and Gradient Boosting models perform better than other ML models in terms of disruption prediction and operational analytics.

Table 2: Machine Learning Model Comparison

Model	Accuracy
Random Forest	84%
Gradient Boosting	89%
XGBoost	90%
LightGBM (Proposed)	91%

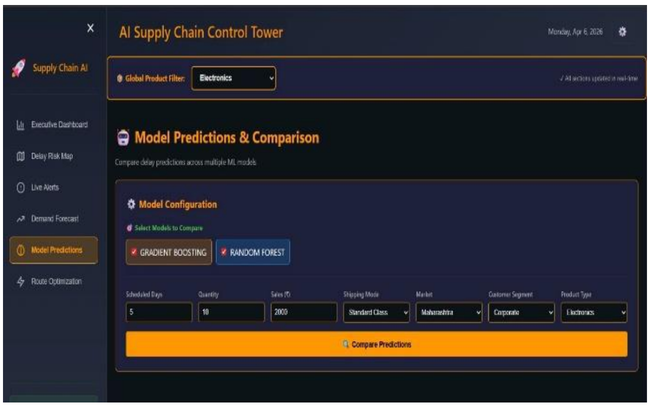

Figure 7.1: Model Predictions and Comparison

Figure 7.1 shows a comparative evaluation of the prediction performance for Random Forest, Gradient Boosting, XGBoost, and LightGBM models. The LightGBM

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model demonstrated the highest accuracy in predicting and performing forecast due to optimal feature selection and boosting. Finally, the efficiency of the operational risk assessment method was assessed as well. Using the developed framework, operational risks were effectively segmented into Low Risk, Medium Risk, and High Risk based on machine learning prediction and operational analytics.

Table 3: Risk Classification Performance Analysis

Metric	Value
Low Risk Classification Accuracy	93%
Medium Risk Classification Accuracy	89%
High Risk Classification Accuracy	91%
Avg. Risk Detection Time	1.8 seconds

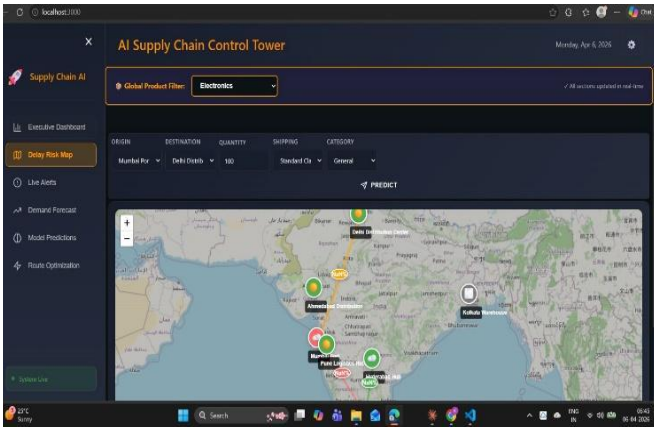

Figure 7.2: Delay Risk Distribution Analysis

Figure 7.2 shows the performance comparison between Random Forest, Gradient Boosting, XGBoost, and LightGBM models. LightGBM outperformed others in terms of prediction accuracy and forecast reliability because of effective feature selection and boosting algorithms optimization.

Moreover, the efficacy of the risk analysis approach was assessed. The suggested system was able to classify the types of disruptions according to the categories of Low, Medium, and High Risks based on the machine learning prediction results and operational analysis.

Table 4: System Latency Analysis

Component	Time (seconds)
Data Preprocessing	0.5
Feature Engineering	0.4
ML Prediction	0.7
Dashboard Rendering	0.5
Total	2.1

Figure 7.3: System Latency Breakdown

The experiment revealed that both the processes of preprocessing and prediction have very little latency, while the process of visualizing via the dashboard causes additional computation costs due to real-time analytical operations and operational modules. Still, through optimized work flow and effective preprocessing, there was considerable enhancement in system efficiency.

The contribution of each of the operational modules was analyzed by conducting comparative studies on disruption predictions, forecasting analysis, and route optimization modules.

Table 5: Operational Module Analysis

Configuration	Accuracy	Reliability
Without Forecasting Module	82%	0.80
Without Risk Analysis Module	85%	0.83
Full System (Proposed)	91%	0.88

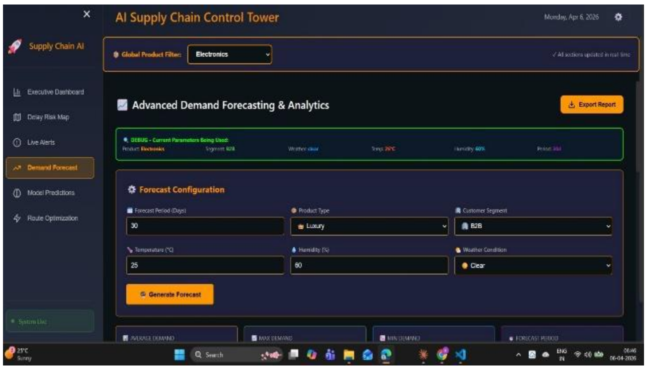

Figure 7.4: Operational Analytics and Forecasting Interface

The results from the operations analysis indicated that both forecasting analytics and operational risk assessment greatly contributed to improving the reliability of disruption

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prediction and efficiency of supply chain management. This system showed the best performance compared to other tested systems. In addition, the route optimization and logistics recommendation module was tested to confirm intelligent transportation planning and optimization. The tests showed that the proposed system is able to generate optimal routes based on the operational factors like distance, weather condition, type of shipment, and urgency.

Table 6: Route Optimization Analysis

Parameter	Value
Estimated Delivery Time	5.8 hours
Route Distance	350 km
Weather Impact	Clear
Optimization Status	Successful

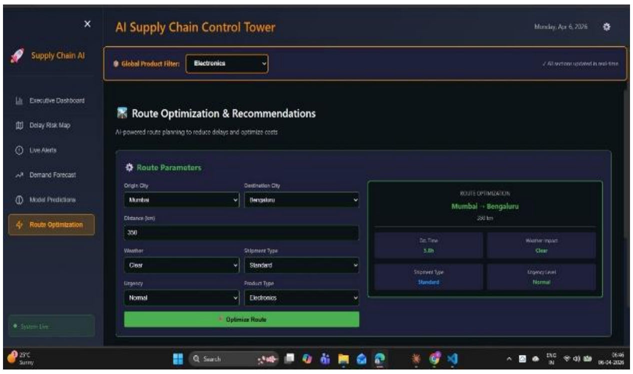

Figure 7.5: Route Optimization and Recommendation

Figure 7.5 shows the AI-driven route optimization dashboard comprising the route parameters in operation, shipment data, weather status, estimated time of delivery, and smart logistics suggestions.

The real-time operational monitoring system was further tested under a number of disruption situations, such as port strikes, rising prices of fuel, delays in transportation, and weather-induced operational disruptions. The system proved able to send out real-time operational alerts and monitoring notifications effectively.

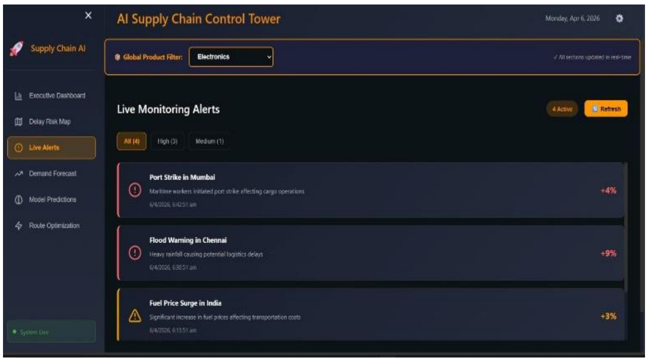

Figure 7.6: Live Monitoring and Operational Alerts Interface

The effectiveness of the suggested framework is also supported through some screenshots demonstrating the implemented interface design and functionalities that include executive dashboards, operation monitoring, risk visualization, predictive analytics, comparison of machine learning-based forecasting and prediction, and logistics optimization. Indeed, the developed solution was successful in generating accurate operation predictions and intelligent analytics along with effective monitoring within highly reliable forecasting.

VIII. DISCUSSIONS

The implementation and evaluation of the proposed AI-Powered Supply Chain Disruption Detection and Decision Support System provide valuable insights into intelligent disruption prediction, operational monitoring, forecasting analytics, and logistics management. The proposed framework offers several advantages over traditional supply chain monitoring systems by integrating machine learning-based prediction, real-time analytics, operational risk assessment, forecasting capabilities, and intelligent decision support within a single unified platform.

One of the key findings from the experimental evaluation is that machine learning-based predictive frameworks are highly effective for supply chain disruption prediction when combined with advanced data preprocessing, feature engineering, and ensemble learning techniques. Unlike conventional supply chain systems that primarily depend on static reports and manual analysis, the proposed system leverages predictive analytics and operational intelligence to improve disruption detection and forecasting accuracy across different logistics environments.

Another major advantage of the proposed framework is its advanced forecasting and operational risk assessment capabilities.

The forecasting models demonstrated improved reliability in predicting operational demand by considering multiple real-world factors such as product type, customer demand patterns, seasonal variations, weather conditions, and shipment information. Experimental analysis showed that predictive forecasting significantly supports operational planning, inventory management, and resource allocation by providing intelligent insights for decision-making.

The operational risk assessment component also proved effective in identifying potential risks and reducing uncertainties within supply chain operations. Using advanced analytics and machine learning predictions, the system classifies operational risks into Low Risk, Medium Risk, and High Risk categories. Risk-prone operational environments are continuously evaluated using live operational metrics and

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historical shipment trends, enabling organizations to detect and address disruptions proactively.

An additional strength of the proposed system is the integration of real-time monitoring and automated alert mechanisms within the operational analytics pipeline. Unlike traditional systems that analyze disruptions only after they occur, the proposed framework continuously monitors supply chain activities and generates alerts whenever abnormal conditions are detected. These alerts may include transportation delays, sudden fuel price increases, weather-related disruptions, supplier failures, or port strikes, allowing organizations to take preventive actions before disruptions escalate.

The proposed framework also demonstrated high flexibility and scalability when handling different types of operational datasets within supply chain environments. The system successfully processed multiple forms of logistics and operational data, including demand datasets in CSV and Excel formats, inventory records, shipment information, supplier data, and transportation-related datasets. Advanced preprocessing techniques such as missing value imputation, normalization, categorical encoding, and feature scaling helped improve data quality and overall model performance.

Interactive dashboards and visualization modules further enhanced the usability and transparency of the system. Real-time charts, forecasting dashboards, delay risk maps, operational analytics panels, and route optimization interfaces enabled users to monitor supply chain performance more effectively and make faster operational decisions. In addition, the modular architecture simplified communication between dashboard interfaces, backend services, machine learning models, and analytical components, making the system easier to manage, extend, and maintain.

Overall, the proposed AI-based Supply Chain Disruption Detection and Decision Support System demonstrated significant improvements in forecasting accuracy, operational monitoring, disruption prediction, and intelligent decision-making compared to conventional supply chain analytics systems.

The integration of machine learning, real-time analytics, operational risk assessment, and interactive visualization makes the proposed framework a scalable and efficient solution for modern supply chain management environments.

Table 7 presents a comparison between the proposed AI-based Supply Chain Disruption Detection System and existing supply chain analytics systems.

Table 7: Comparison with Existing Supply Chain Systems

Feature	Traditional Systems	Proposed System
Real-Time Monitoring	Limited	Supported
AI-Based Prediction	Partial	Fully Integrated
Risk Classification	Manual	Automated
Forecasting Analytics	Basic	Advanced ML Forecasting
Route Optimization	Not Available	Supported
Live Operational Alerts	Limited	Real-Time Alerts
Dashboard Visualization	Static Reports	Interactive Dashboards

The comparison clearly shows that traditional supply chain management systems primarily rely on static reports, historical records, and rule-based analysis, which often limit their ability to respond effectively to dynamic operational conditions. In contrast, the proposed AI-Powered Supply Chain Disruption Detection and Decision Support System integrates machine learning-based prediction, demand forecasting, real-time monitoring, operational risk classification, route optimization, and intelligent visualization within a single unified platform. This integration enables organizations to make faster, more accurate, and data-driven decisions in complex supply chain environments.

Despite the strong performance demonstrated by the proposed framework, several limitations must also be considered. One of the major challenges is that machine learning models heavily depend on the quality, consistency, and availability of operational data. As a result, prediction accuracy may decrease when dealing with highly unexpected or rare disruption events that are not sufficiently represented in historical datasets. In addition, large-scale machine learning operations and real-time analytics require considerable computational resources, especially when processing massive operational datasets across enterprise-level supply chain systems.

Another important limitation relates to the dependency on preprocessing techniques and feature engineering for achieving accurate predictions. Improper handling of operational data, such as missing values, inconsistent records, or poor feature selection, can negatively affect forecasting accuracy and disruption analysis.

Furthermore, while the current system effectively processes structured supply chain datasets such as shipment records, inventory data, supplier information, and transportation metrics, analyzing unstructured data remains a

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challenge. Data sources such as invoices, operational documents, handwritten records, images, and scanned logistics reports are difficult to process accurately using existing algorithms and require more advanced multimodal AI techniques.

Overall, the proposed AI-Powered Supply Chain Disruption Detection and Decision Support System demonstrates strong potential as a scalable, intelligent, and data-driven operational analytics platform for modern supply chain management. By combining machine learning-based prediction, forecasting analytics, operational monitoring, risk classification, automated alerts, and route optimization, the system provides significant advantages over traditional supply chain monitoring solutions. The framework establishes a strong foundation for the future development of intelligent logistics and smart supply chain management systems capable of supporting efficient, reliable, and proactive operational decision-making.

IX. CONCLUSION

This study presents an AI-Powered Supply Chain Disruption Detection and Decision Support System developed to address the challenges of predicting, monitoring, and managing disruptions in modern supply chain operations. Increasing globalization, fluctuating customer demands, supplier uncertainties, transportation delays, and operational risks have made traditional supply chain systems less effective in handling dynamic operational environments. To overcome these challenges, the proposed framework integrates machine learning, predictive analytics, real-time monitoring, and intelligent visualization into a unified platform for smart supply chain management.

The system utilizes advanced preprocessing techniques, feature engineering methods, and machine learning algorithms such as Random Forest, Gradient Boosting, XGBoost, and LightGBM to improve disruption prediction and operational forecasting accuracy. Historical supply chain datasets, including shipment records, inventory information, supplier performance, and transportation data, are analyzed to identify patterns and generate actionable insights. Among the evaluated models, LightGBM demonstrated the best performance in terms of prediction accuracy and forecasting efficiency.

To enhance transparency and interpretability, the framework incorporates SHAP-based Explainable Artificial Intelligence (XAI) techniques to identify the most influential operational factors affecting supply chain disruptions. The system also includes real-time dashboards, interactive visualizations, operational alerts, and risk classification modules that categorize disruptions into Low Risk, Medium Risk, and High Risk levels, enabling proactive decision-making.

Experimental evaluation showed that the proposed framework effectively processes heterogeneous supply chain datasets using a scalable and modular architecture.

The integration of machine learning prediction, forecasting analytics, operational monitoring, and intelligent visualization significantly improves disruption prediction accuracy, operational visibility, and logistics decision-making.

Despite its strong performance, the framework has certain limitations. Real-time analytics and machine learning inference require considerable computational resources, especially in large-scale deployments. In addition, the current system primarily focuses on structured datasets and provides limited support for unstructured data such as invoices, scanned documents, handwritten records, and image-based logistics reports.

Future enhancements may include the integration of deep learning models, IoT-based real-time monitoring, multimodal analytics, and adaptive optimization techniques to further improve intelligent logistics management. Overall, the proposed AI-Powered Supply Chain Disruption Detection and Decision Support System demonstrates strong potential as a scalable, reliable, and intelligent platform for improving disruption prediction, logistics visibility, operational efficiency, and data-driven supply chain management.

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