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Machine Learning-Based Shipment Risk Classification Using Operational and External Risk Factors in International Logistics Networks

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Abstract

International logistics networks are increasingly exposed to operational, financial, geopolitical, customs, cyber, and environmental risks that can disrupt shipment reliability and increase logistics costs. This study examines how machine learning models can classify shipment risk levels using operational and external risk factors in international logistics networks. A structured dataset containing 3,000 shipment records and 30 variables was developed, including shipment route, transport mode, cargo value, cargo weight, transit time, delay days, weather risk, political risk, customs risk, port congestion, cyber risk, insurance cost, total logistics cost, and actual risk level. The independent variables were operational and external logistics risk factors, while the dependent variable was shipment risk classification level. The dataset was divided into training, validation, and testing sets using a 70:15:15 ratio, resulting in 2,100 training records, 450 validation records, and 450 testing records. Three supervised machine learning classifiers—Random Forest, XGBoost, and LightGBM—were applied to classify shipments into Critical, High, and medium risk categories. Random Forest and XGBoost achieved the highest testing accuracy of 91%, while LightGBM achieved 90%. XGBoost showed strong performance for Critical risk shipments, with precision of 0.97, recall of 0.96, and F1-score of 0.97. The model also achieved AUC values of 0.99, 0.96, and 0.98 for Critical, High, and medium classes, respectively. However, lower Medium-class performance indicated the effect of class imbalance. The findings suggest that machine learning can support proactive shipment risk prediction, early warning, and decision-making in international logistics networks.
Keyword: Machine Learning; Shipment Risk Classification; International Logistics; Supply Chain Risk; XGBoost; Risk Prediction; AI-Enabled Risk Management.

1. Introduction

International logistics networks have become increasingly complex due to globalization, cross-border trade expansion, digital transformation, fluctuating demand, geopolitical uncertainty, climate-related disruptions, port congestion, customs delays, cyber threats, and rising logistics costs. In this context, artificial intelligence (AI) has emerged as an important technology for improving logistics efficiency, optimizing distribution networks, supporting real-time decision-making, and strengthening supply chain resilience. Recent studies show that AI can improve international logistics through demand forecasting, route optimization, inventory management, intelligent warehousing, transportation planning, and data-driven decision support [1], [2]. AI also supports supply chain resilience by helping organizations predict disruptions, manage transportation inefficiencies, optimize resources, and respond more effectively to unexpected events [3], [4]. In addition, AI-based risk management can improve risk identification, mitigation, and resilience planning by using predictive analytics, machine learning, real-time monitoring, and autonomous decision systems [5], [6]. As logistics systems become more digital, cybersecurity risk has also become a major concern, and AI-driven cyber threat detection can support safer logistics operations by identifying anomalies, reducing response time, and protecting supply chain data [7]. AI-driven logistics research further highlights that machine learning and predictive analytics can improve operational efficiency, sustainability, visibility, and decision-making in global supply chain networks, although challenges such as data privacy, implementation cost, workforce readiness, and ethical concerns remain important barriers [8], [9]. However, existing studies have mostly focused on general logistics optimization, supply chain resilience, cybersecurity, or international trade applications, while limited research has applied AI-based classification models to predict shipment risk levels in international logistics networks using multiple operational and external risk factors. Therefore, this study examines how machine learning models can classify logistics risk into Critical, High, and medium levels by using shipment route, transport mode, cargo value, transit time, delay days, customs risk, political risk, weather risk, port congestion, cyber risk, insurance cost, and total logistics cost. This research contributes to AI-enabled risk management by comparing Random Forest, XGBoost, and LightGBM models and identifying how AI-based prediction can support proactive decision-making, reduce uncertainty, and improve resilience in international logistics networks. By integrating operational, financial, and external risk variables, this study provides a practical AI-enabled framework for proactive shipment risk classification and logistics decision support.

2. Literature Review

2.1. Recent Developments in AI-Enabled Risk Management for International Logistics Networks

Recent studies show that AI-enabled technologies are becoming important for improving risk management in international logistics networks. As global supply chains face shipment delays, supplier disruption, geopolitical risk, cyber threats, and environmental uncertainty, traditional risk management methods are often not enough. AI, IoT, blockchain, big data analytics, and real-time data systems can improve risk evaluation, visibility, predictive analysis, and proactive decision-making in transportation logistics[10]. AI-driven digital transformation also supports route optimization, sustainable logistics, autonomous freight systems, and better supply chain decisions[11]. Machine learning and predictive analytics further improve inventory forecasting, transportation efficiency, cost reduction, and resilience in supply chain operations[8], [9]. In international logistics, collaboration and customer relationships also help reduce operational and strategic supply chain risks [12]. Real-time analytics and AI-based anomaly detection can reduce shipping delays, improve visibility, and support early risk response[13]. Therefore, AI-enabled risk management is useful for predicting shipment risks, reducing uncertainty, and improving resilience in international logistics networks.

2.2. Theoretical and Practical Foundations of Machine Learning-Based Shipment Risk Prediction

Machine learning-based shipment risk prediction is based on the idea that logistics risks can be identified earlier by analyzing operational, financial, security, and external risk-related data. In international logistics, blockchain can support secure and transparent transaction records, while AHP and risk matrix methods help identify and prioritize risk factors[14]. Federated learning also provides a privacy-preserving foundation for cross-border logistics risk prediction by allowing different logistics partners to train models without sharing sensitive data [15].AI-based route optimization shows how real-time traffic, delivery, and transportation data can support adaptive logistics decisions. Predictive machine learning further helps supply chains move from reactive planning to proactive and self-healing decision-making [16]. In supply chain risk management, ML models are useful for demand forecasting, supplier risk assessment, anomaly detection, and early warning system[17]. Therefore, these theoretical and practical foundations support the use of Random Forest, XGBoost, and LightGBM for classifying shipment risk levels in international logistics networks.

2.3. Challenges in International Logistics Risk Management

International logistics risk management faces many challenges because global logistics networks are highly complex, uncertain, and dependent on multiple stakeholders. Major risks include geopolitical instability, economic fluctuations, environmental disruptions, supplier problems, infrastructure limitations, cyber threats, and transportation delays [18]. AI can improve supply chain resilience through real-time visibility, predictive analytics, risk monitoring, and faster recovery, but successful implementation is still difficult due to data quality, scalability, cybersecurity, and organizational readiness issues[11]. IoT-driven logistics systems also face challenges in handling large volumes of sensor data, demand volatility, transportation disruptions, and environmental uncertainty[19]. In drone-based logistics, fixed routing systems often fail to respond to real-time changes such as weather, air traffic, battery condition, and delivery priorities[20]. Therefore, international logistics risk management requires adaptive, AI-enabled, and data-driven approaches to reduce uncertainty and improve resilience.

2.4. Limitations of Current AI-Based Logistics Risk Prediction Research Current AI-based logistics risk prediction research still has some limitations. Many studies focus on multimodal logistics, cost efficiency, sustainability, and crisis resilience, but there is still limited focus on real-time shipment risk classification using multiple risk factors together[21]. AI-based resilience models can support dynamic risk assessment, but they often face challenges in handling human error, unstructured data, and transparent decision-making [22]. AI-driven logistics systems further require strong data infrastructure, cross-functional collaboration, lifecycle management, and change management, which may be difficult for many organizations to implement effectively [23].In addition, AI integration in logistics depends on knowledge capability, dynamic capability, and organizational readiness, especially in emerging markets where digital readiness is often limited[24].Therefore, more research is needed on practical machine learning models that can classify shipment risk levels accurately and support proactive decision-making in international logistics networks.

2.5. Research Gap

Although artificial intelligence and machine learning have been increasingly applied in logistics optimization, supply chain resilience, route planning, demand forecasting, and cyber-risk monitoring, limited studies have focused specifically on shipment-level risk classification in international logistics networks using multiple operational and external risk factors together. Existing studies often examine logistics efficiency, supply chain disruption, sustainability, or general risk management, but they provide less empirical attention to classifying shipment risk into practical decision categories such as Critical, High, and Medium. In addition, previous logistics risk studies frequently depend on conceptual frameworks or single-risk analysis, while fewer studies compare multiple machine learning classifiers using a structured shipment-level dataset. Therefore, this study addresses this gap by developing a machine learning-based shipment risk classification framework using 3,000 shipment records. The study investigates how independent variables such as customs risk, political risk, weather risk, cyber risk, port congestion, delay days, insurance cost, and logistics cost influence the dependent variable, namely shipment risk classification level. By comparing Random Forest, XGBoost, and LightGBM classifiers, the study contributes to AI-enabled logistics risk management by showing how machine learning can support early risk identification, proactive decision-making, and resilience planning in international logistics networks.

2.6. Research Questions

1. How can machine learning models support shipment risk prediction in international logistics networks?
2. Which operational and external logistics risk factors influence shipment risk classification levels?
3. How effectively can machine learning models classify shipments into Critical, High, and medium risk categories?
4. Which model among Random Forest, XGBoost, and LightGBM performs best for shipment risk classification?
5. How can AI-enabled shipment risk prediction support logistics decision-making and network resilience?

2.7. Research Objectives

1. To examine the role of machine learning models in predicting shipment risk levels in international logistics networks.
2. To identify key operational and external risk factors that influence shipment risk classification.
3. To classify shipment risks into Critical, High, and medium categories using supervised machine learning models.
4. Comparing the performance of Random Forest, XGBoost, and LightGBM classifiers.
5. To evaluate how AI-enabled shipment risk prediction can support proactive decision-making and logistics network resilience.

3. Materials and Methods

3.1. Study Area

This study was conducted in the context of international logistics networks, where shipments are often exposed to different types of risks such as operational risk, financial risk, customs risk, geopolitical risk, cyber risk, port congestion, weather risk, and environmental risk. The study focused on how artificial intelligence-enabled models can support risk prediction and improve risk management in international logistics operations.

3.2. Study Design

This study followed a quantitative and machine learning-based research design. The main purpose of the study was to classify shipment risk levels in international logistics networks using AI-based classification models. The target variable of the study was the actual risk level of shipments, which was classified into three categories: Critical, High, and medium risk.

3.3. Sample Size and Selection

For this research, a structured constructed dataset was developed containing 3,000 shipment records. The dataset included information related to shipment routes, transport mode, cargo characteristics, transit time, delay days, risk factors, insurance cost, logistics cost, and actual risk level. The dataset was divided into training, validation, and testing sets using a 70%, 15%, and 15% split. This helped the models to learn from training data, tune performance using validation data, and evaluate final performance on unseen test data.

3.4. Dataset Development and Risk Label Assignment

This study used a structured constructed dataset of 3,000 shipment records with 30 operational, financial, and external risk-related variables. The dataset was developed through a rule-based and literature-informed process to represent international logistics shipment conditions. The dependent variable was shipment risk classification level, categorized into Critical, High, and Medium.

Risk labels were assigned using predefined scoring logic based on key factors such as delay days, customs risk, political risk, weather risk, port congestion, cyber risk, insurance cost, and total logistics cost. Before model training, the dataset was checked for missing values, duplicate records, and inconsistencies. The data were divided into training, validation, and testing sets using a 70%, 15%, and 15% split.

3.5. Measures and Variables

The major variables used in this study included shipment route, transport mode, cargo value, cargo weight, transit time, delay days, weather risk, political risk, customs risk, port congestion, cyber risk, insurance cost, total logistics cost, and actual risk level. The dependent variable was the shipment risk level. The independent variables were used as predictors for developing machine learning classification models.

3.6. Data Collection Procedure

The data were organized in a structured format to represent international logistics shipment conditions. Before applying the machine learning models, the dataset was cleaned and prepared for analysis. Relevant shipment and risk-related variables were selected so that the models could identify important patterns associated with logistics risk levels.

3.7. Research Tools and Techniques

Three supervised machine learning classifiers were applied in this study: Random Forest Classifier, XGBoost Classifier, and LightGBM Classifier. These models were selected because they are effective for classification problems and can handle complex risk-related patterns in logistics datasets. The models were used to classify shipments into Critical, High, and medium risk categories.

3.8. Data Analysis Techniques

The performance of the models was evaluated using accuracy, precision, recall, F1-score, and classification report. Random Forest and XGBoost both achieved the highest accuracy of 91%, while LightGBM achieved 90% accuracy. Among the models, XGBoost was selected as the best-performing model because it showed strong and balanced performance, especially for the Critical and High-risk categories. Therefore, further analysis was mainly focused on the XGBoost Classifier.

3.9. Validity and Reliability

Validity was supported by selecting relevant logistics risk variables, including delay days, customs risk, political risk, weather risk, port congestion, cyber risk, insurance cost, and logistics cost. Internal reliability was maintained by using a fixed 70%, 15%, and 15% train-validation-test split and applying the same preprocessing and evaluation metrics across Random Forest, XGBoost, and LightGBM models. However, external validity is limited because the dataset was constructed rather than collected directly from real logistics companies.

4. Results and Analysis

4.1. Classification Report on the XGBoost Classifier

The study applied three machine learning classifiers: Random Forest Classifier, LightGBM Classifier, and XGBoost Classifier. Among these models, Random Forest and XGBoost both achieved the highest accuracy of 91%, while LightGBM achieved 90% accuracy. Although Random Forest and XGBoost produced almost identical overall classification performance, the XGBoost Classifier was selected as the best-performing model because it provided strong and balanced performance across the major risk classes, especially for the Critical and High-risk categories. Therefore, the detailed results and analysis below are presented for the XGBoost Classifier in Table 1.

Table1: Classification Report of XGBoost Classifier

Risk Level	Precision	Recall	F1-Score	Support
Critical	0.97	0.96	0.97	355
High	0.73	0.77	0.75	79
Medium	0.47	0.44	0.45	16
Accuracy			**0.91**	**450**
Macro Avg	**0.72**	**0.72**	**0.72**	**450**
Weighted Avg	**0.91**	**0.91**	**0.91**	**450**

The classification report shows that the XGBoost Classifier achieved an overall accuracy of 91% on the test dataset. The model performed very strongly for the Critical risk class, with a precision of 0.97, recall of 0.96, and F1-score of 0.97. The High-risk class also showed acceptable performance, with an F1-score of 0.75. However, the medium class showed comparatively lower performance due to its smaller support value, which indicates class imbalance in the dataset.

4.2. Confusion Matrix of the XGBoost Classifier

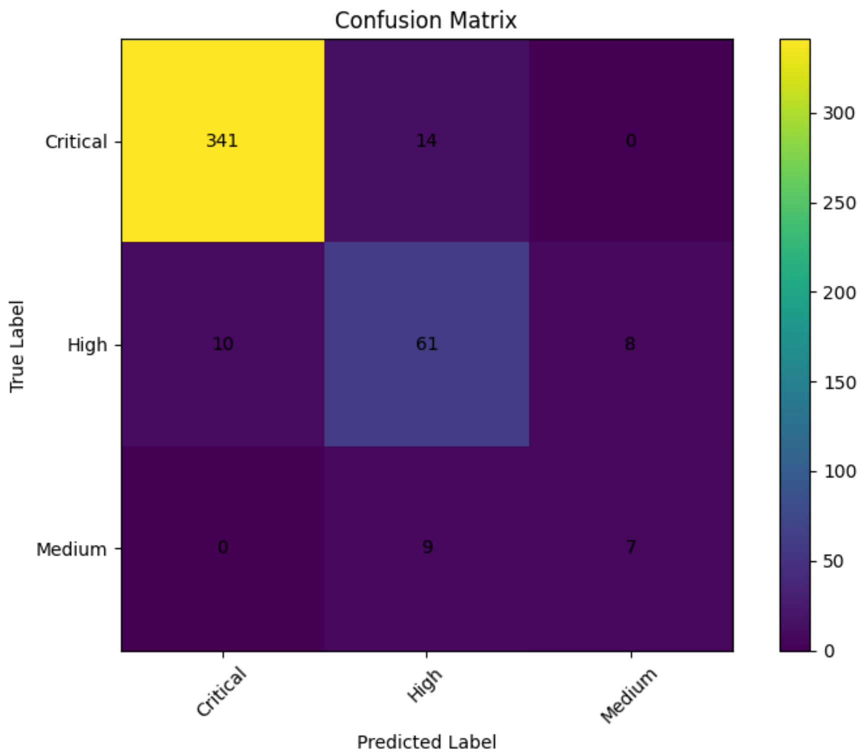

Fig. 1. Confusion matrix of the XGBoost Classifier.

Fig. 1 shows the confusion matrix of the XGBoost Classifier. The model correctly classified 341 Critical, 61 High, and 7 Medium risk cases. Most of the misclassifications occurred between the High and Medium classes, while the Critical class was predicted with very high accuracy. This indicates that the model is highly reliable in identifying severe logistics risks, which is important for AI-enabled risk management in international logistics networks.

4.3. Training and Validation Accuracy Curve of the XGBoost Classifier

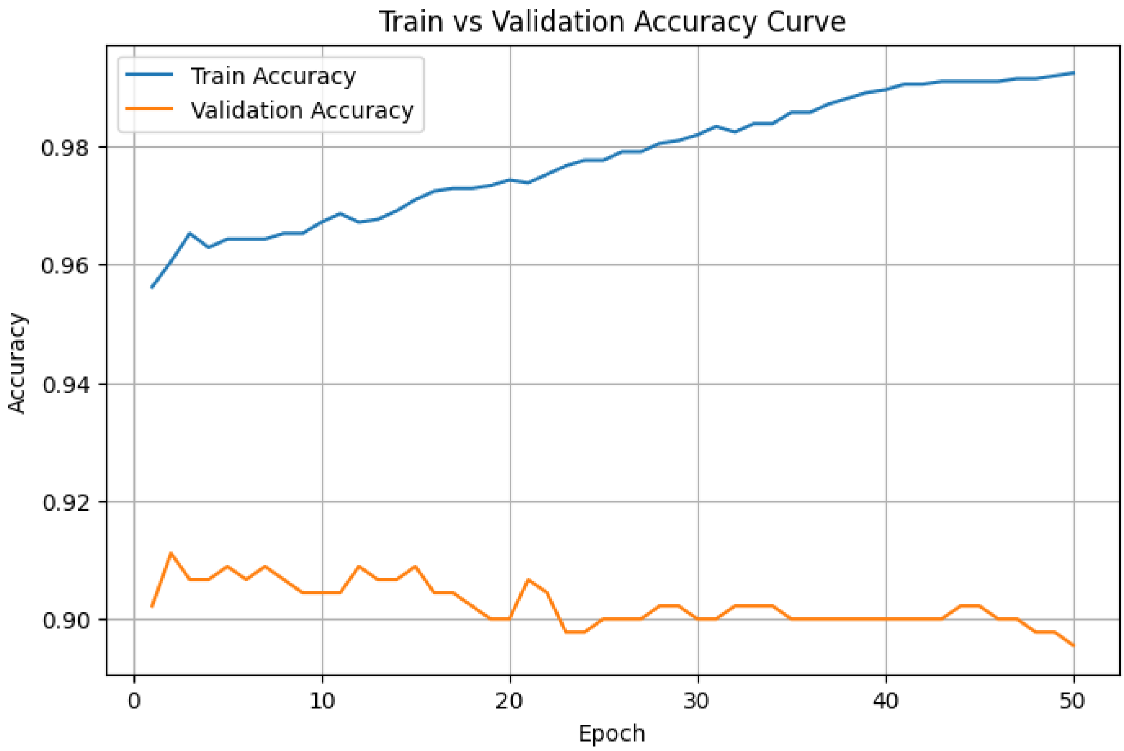

Fig. 2. Training and validation accuracy curve of the XGBoost Classifier.

Fig. 2 shows the training and validation accuracy curve of the XGBoost Classifier. The training accuracy gradually increased across the 50 epochs, reaching a very high level near the final epoch. The validation accuracy remained around 90%, showing that the model maintained stable performance on unseen validation data. However, the gap between training and validation accuracy suggests that the model learned the training data more strongly than the validation data.

4.4. Training and Validation Loss Curve of the XGBoost Classifier

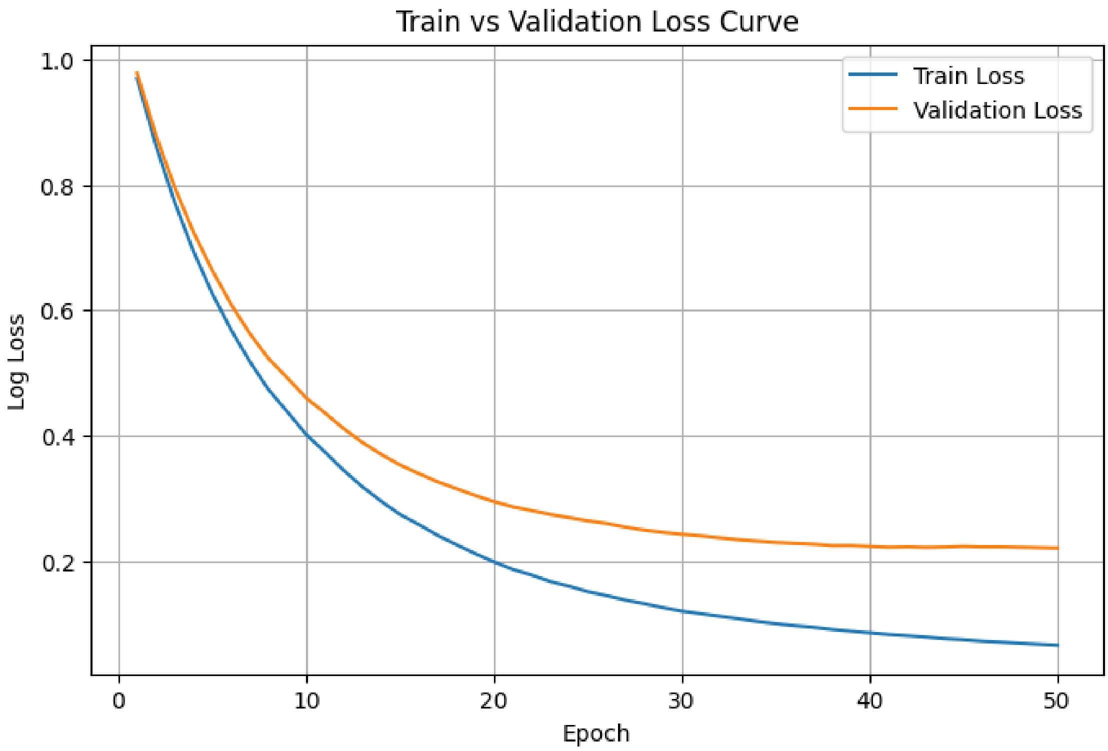

Fig. 3. Training and validation loss curve of the XGBoost Classifier.

Fig. 3 shows the training and validation loss curve. Both training and validation loss decreased sharply during the early epoch, indicating that the model quickly learned important patterns from the dataset. After around 30 epochs, the validation loss became more stable, while the training loss continued to decrease. This result suggests that the model achieved good learning performance, although a small overfitting tendency may be present.

4.5. Multi-Class ROC Curve of the XGBoost Classifier

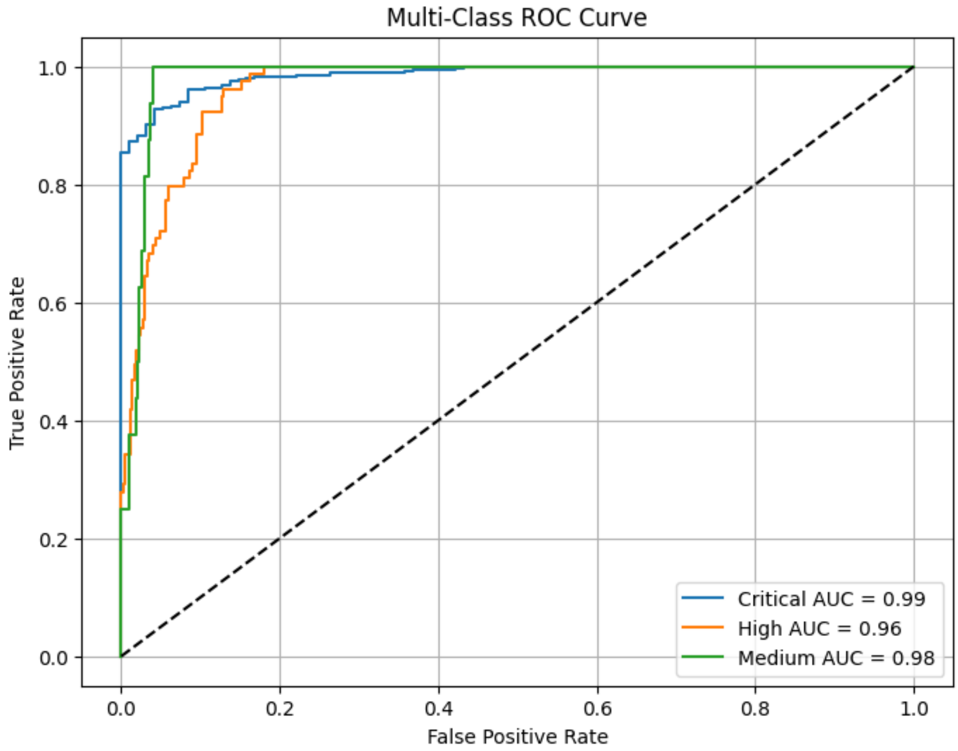

Fig. 4. Multi-class ROC curve of the XGBoost Classifier.

Fig. 4 shows the multi-class ROC curve for the XGBoost Classifier. The AUC values are very high for all three classes: Critical AUC = 0.99, High AUC = 0.96, and Medium AUC = 0.98. These values indicate that the model has strong discriminative ability in separating different logistics risk levels. The high AUC score confirms that XGBoost is effective for AI-based risk prediction in international logistics networks.

4.6. Precision–Recall Curve of the XGBoost Classifier

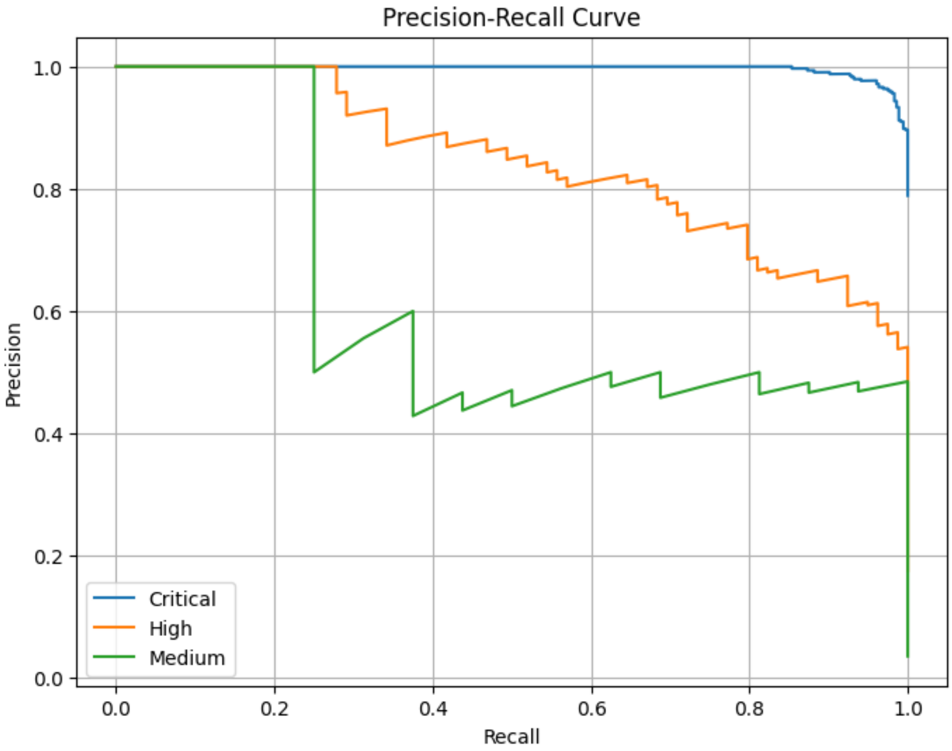

Fig. 5. Precision-recall curve of the XGBoost Classifier.

Fig. 5 shows the precision–recall curve of the XGBoost Classifier. The Critical class maintained very high precision across most recall levels, showing strong prediction reliability for severe risk cases. The High class also showed moderate performance, while the medium class had more fluctuation due to the smaller number of samples. This indicates that class imbalance affected the prediction performance of the minority class.

4.7. Top 20 Feature Importance of the XGBoost Classifier

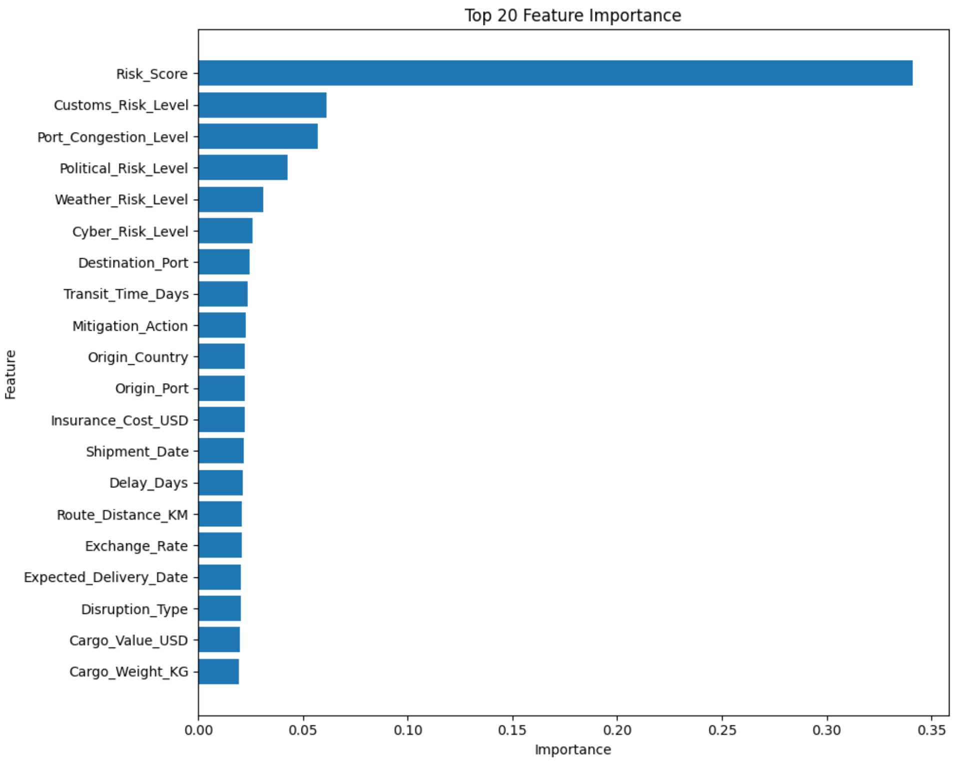

Fig. 6. Top 20 feature importance of the XGBoost Classifier.

Fig. 6 shows the top 20 feature importance values generated by the XGBoost Classifier. The most influential feature was Risk Score, which had the highest contribution to risk classification. Other important features included Customs_Risk_Level, Port_Congestion_Level, Political_Risk_Level, Weather_Risk_Level, and Cyber_Risk_Level. This finding shows that both operational and external risk factors play an important role in predicting logistics network risk.

4.8. Alignment of Research Questions with Findings

The findings of this study directly address the research questions. RQ1 is answered by the overall model performance, where Random Forest and XGBoost achieved 91% accuracy, showing that machine learning can support shipment risk prediction. RQ2 is addressed by the feature importance results, which show that customs risk, port congestion, political risk, weather risk, cyber risk, delay days, insurance cost, and logistics cost influenced shipment risk classification. RQ3 is supported by the classification report and confusion matrix, which show that the model successfully classified shipments into Critical, High, and medium risk categories. RQ4 is answered by the comparative model results, where XGBoost was selected as the best-performing model due to its strong and balanced performance. RQ5 is addressed by practical findings, which suggest that AI-enabled risk prediction can support early warning, proactive decision-making, and logistics network resilience.

5. Discussion

The findings of this study show that AI-enabled classification models can effectively support risk prediction in international logistics networks. Random Forest and XGBoost achieved the highest accuracy of 91%, while LightGBM achieved 90%, which indicates that machine learning models can classify shipment risks with strong performance. This slight performance difference indicates that XGBoost was more effective than LightGBM in capturing complex and non-linear relationships among logistics risk variables. XGBoost was selected as the best performing model because it showed stronger and more balanced performance for the Critical and High-risk categories. This result supports previous research showing that transportation and logistics risk management now requires proactive strategies, advanced technologies, flexibility, and real-time information sharing to reduce disruption exposure [25]. The importance of AI in logistics is also supported by studies showing that AI can improve route optimization, demand forecasting, warehouse automation, real-time tracking, and autonomous delivery systems. In this study, customs risk, political risk, weather risk, port congestion, cyber risk, delay days, insurance cost, and total logistics cost were important factors for risk classification. These variables emerged as important predictors because they directly affect shipment delay, transportation reliability, cost increase, documentation risk, and disruption probability. For example, customs risk and port congestion can delay clearance and delivery, while political, weather, and cyber risks can disrupt route stability and operational security. This finding is consistent with research showing that AI-driven logistics can reduce delivery time, inventory cost, fuel consumption, and improve resilience in complex international trade routes[26]. The result also supports the view that AI-based predictive analytics can help organizations identify disruptions early, improve risk assessment, and maintain business continuity in logistics operations[27]. Moreover, technological convergence in logistics, including AI, IoT, blockchain, cloud computing, and robotics, can improve visibility, predictive risk management, operational efficiency, and sustainability, although it may also create cybersecurity and data governance challenges[28]. Since cyber risk is an important part of logistics risk, AI capabilities can also strengthen supply chain cyber risk management by supporting risk sensing, response, and transformation across supply chain systems [29]. The lower performance of the medium risk class also indicates the influence of class imbalance. The test set contained fewer Medium risk cases than Critical and High-risk cases, which limited the model's ability to learn stable patterns for this minority class. Therefore, future studies should consider larger and more balanced datasets, class-weighted learning, or oversampling techniques to improve minority-class prediction. Overall, this study confirms that AI-enabled risk prediction can help logistics managers identify high-risk shipments earlier, reduce uncertainty, support proactive decision-making, and improve resilience in international logistics networks.

5.1. Findings

1. The study found that AI-enabled models can support risk prediction in international logistics networks.

2. Key logistics and risk-related factors such as shipment route, transport mode, delay days, weather risk, political risk, customs risk, port congestion, cyber risk, insurance cost, and total logistics cost influenced shipment risk levels.
3. Machine learning models successfully classified shipment risks into Critical, High, and Medium categories.
4. Among the applied models, XGBoost performed best because it showed strong and balanced performance, especially for Critical and High risk categories.
5. AI-based risk prediction can support better decision-making, reduce uncertainty, and improve resilience in international logistics networks.

5.2. Recommendations

1. International logistics networks should use AI-enabled models to improve shipment risk prediction.
2. Logistics managers should monitor important risk factors such as customs risk, political risk, port congestion, weather risk, cyber risk, shipment delay, and logistics cost.
3. Machine learning models can be used to classify shipment risks in advance and support proactive decision-making.
4. XGBoost can be applied as an effective model for predicting Critical and High risk shipments.
5. AI-based risk management systems should be developed to reduce uncertainty and improve logistics network resilience.

5.3. Limitations and Future Research

This study has some limitations. First, the dataset was constructed to represent international logistics shipment risk conditions and may not fully reflect real-world logistics operations across different industries, countries, and trade routes. Second, the medium risk class had fewer samples than the Critical and High classes, which affected minority-class prediction performance. Third, the study used selected logistics risk variables and only three machine learning models: Random Forest, XGBoost, and LightGBM. Future research should validate the proposed framework using real operational logistics datasets from shipping companies, freight forwarders, port authorities, customs systems, and international trade platforms. Future studies may also use larger and more balanced datasets, include additional risk indicators, and apply explainable AI techniques such as SHAP or LIME to improve model interpretability and practical decision-making.

6. Conclusion

This study examined the role of AI-enabled classification models in predicting shipment risk levels in international logistics networks. The results show that machine learning models can effectively classify risks using factors such as shipment route, transport mode, delay days, weather risk, political risk, customs risk, port congestion, cyber risk, insurance cost, and total logistics cost. Among the three models, Random Forest and XGBoost achieved the highest accuracy of 91%, while LightGBM achieved 90%. XGBoost was selected as the best performing model because it showed strong and balanced performance, especially for Critical and High-risk categories. Therefore, this study concludes that AI-based risk prediction can support better decision-making, reduce uncertainty, and improve logistics network resilience. Future studies should further validate the proposed model using real operational logistics data and more balanced datasets to improve generalizability and minority-class prediction.

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