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AI-Integrated Risk Management for Healthcare Supply Chains

Ganesh L Professor[1], P. Leslie Dass[2]
[1]School of Business and Management, CHRIST (Deemed to be University), Bengaluru.
Email: ganesh.l@christuniversity.in
[2]School of Business and Management, CHRIST (Deemed to be University), Bengaluru.
Email: leslie.p@res.christuniversity.in

Abstract

This paper presents an AI-driven framework for identifying and prioritizing supply chain risks in the healthcare sector, focusing on factors influencing operational efficiency and sustainability. The proposed model leverages data from various risk indicators, including supplier performance, shipping delays, compliance issues, and geopolitical events, to assess and classify risks such as 'Critical', 'High', 'Medium', and 'Low'. By utilizing machine learning algorithms, specifically Random Forests, the model automatically processes and analyzes historical supply chain data to predict risk factors and prioritize interventions. A key feature of the model is its ability to handle missing data and generate synthetic values for missing columns, ensuring comprehensive risk assessment. The framework also incorporates advanced data visualization techniques to enhance decision-making, offering stakeholders clear insights into risk distributions, correlations, and prioritization. This approach aims to optimize risk management practices, improve resilience in healthcare supply chains, and ensure timely responses to potential disruptions, ultimately enhancing healthcare logistics' overall reliability and efficiency.

Keywords: *Artificial Intelligence, Machine Learning, Risk Management, Supply Chain, Healthcare, Resilience*

1. Introduction

Supply chain risk management (SCRM) has become a crucial element of organizational strategy in today's global and interconnected economy (Gurtu & Johny, 2021). The ability to identify, mitigate, and manage risks across complex supply chain networks is essential for maintaining operational continuity and achieving long-term resilience (Aldrighetti et al., 2021). Artificial Intelligence (AI) and Machine Learning (ML) have proven to be transformative in tackling the dynamic challenges associated with supply chain risk management (Ganesh & Kalpana, 2022). These advanced technologies allow organizations to analyze extensive datasets, detect anomalies, and predict potential disruptions, facilitating a proactive and effective approach to risk mitigation(Wong et al., 2024). The healthcare sector, with its complexity, regulatory constraints, and the necessity for uninterrupted service delivery, stands to gain significantly from AI and ML-driven solutions for efficient supply chain risk management (A. Kumar et al., 2023).

The Indian healthcare industry has an urgent need for resilient supply chains. The COVID-19 pandemic highlighted the vulnerabilities of existing supply chain systems, revealing challenges such as delays in the delivery of essential medical supplies, fluctuating demand for critical resources, and disruptions caused by unforeseen global events (Bilal et al., 2024; Magableh, 2021). Traditional risk management approaches, which relied on manual processes and historical data, were inadequate in addressing the scale and speed of these disruptions (Sudan et al., 2023). However, advancements in artificial intelligence (AI) and machine learning (ML) have transformed supply chain risk management. These technologies provide real-time insights, predictive analytics, and automation capabilities that significantly enhance decision-making. By optimizing inventory management, streamlining logistics, and identifying potential vulnerabilities, AI and ML are redefining how risks are managed in the healthcare sector (Kudrenko, 2024; Riad et al., 2024).

To address the challenges in healthcare supply chain risk management, an AI model was developed to identify, classify, and prioritize risks effectively. The model integrates data from various aspects of the supply chain, including supplier performance, logistics, regulatory compliance, and demand variability. Using a combination of data preprocessing, feature scaling, and Random Forest Classifiers, the model processes real-time and historical data to assign risk levels and categories. For example, it identifies risks such as supplier reliability, shipping delays, compliance issues, and external disruptions like pandemics or geopolitical events. The model also includes a prioritization algorithm that ranks risks based on their impact and urgency, enabling healthcare providers to focus resources on addressing critical vulnerabilities. Additionally, the model incorporates visualization tools to present insights through heatmaps, bar charts, and risk distribution graphs, aiding decision-makers in strategic planning and operational improvements.

The integration of AI and ML into supply chain risk management practices provides numerous advantages. AI-powered tools can process and analyze large volumes of structured and unstructured data, identifying patterns and predicting future risks with high accuracy (Y. Kumar et al., 2024). ML algorithms, on the other hand, learn from historical and real-time data, enabling continuous improvement in risk mitigation strategies (Aljohani, 2023). In the context of the Indian healthcare industry, where supply chains are often fragmented and involve multiple stakeholders, these technologies offer a path to overcoming systemic inefficiencies and ensuring the availability of critical medical resources.

The objectives of this study are to formulate a model incorporating AI and ML to identify supply chain risks using historical and real data, classify the identified risks based on the features detected, and prioritise the identified risks. The remainder of the paper is structured as follows: Section 2 provides a comprehensive review of literature on supply chain risk management, with an emphasis on AI and ML applications in healthcare. Section 3 outlines the methodology adopted for this study, including data collection and analysis techniques. Section 4 presents the findings, demonstrating the effectiveness of AI and ML in mitigating supply chain risks. Section 5 discusses the implications of these findings for policymakers, healthcare providers, and supply chain professionals. Finally, Section 6 concludes with recommendations for future research and practical strategies for implementing AI and ML in supply chain risk management within the Indian healthcare sector.

2. Review of Literature

2.1 AI and ML in Supply Chain Risk Management

Artificial Intelligence (AI) and Machine Learning (ML) have gained substantial traction in supply chain risk management (SCRM), offering innovative solutions to address complex challenges (Nezianya et al., 2024; Riahi et al., 2021). Traditional SCRM methodologies have relied heavily on historical data, manual processes, and reactive strategies, which often fall short in today's volatile and dynamic environment (Tirkolaee et al., 2021). The literature highlights the potential of AI and ML to revolutionize SCRM by enabling predictive analytics, real-time decision-making, and adaptive response mechanisms.

Numerous studies have explored the application of AI and ML in enhancing supply chain resilience. According to Ivanov et al. (2020), AI-driven systems can process vast amounts of data from diverse sources, enabling organizations to anticipate disruptions and optimize their supply chain operations proactively (Ivanov & Dolgui, 2021). ML algorithms, in particular, are adept at learning from historical and real-time data, identifying patterns, and predicting potential risks. These capabilities allow for the development of models that can detect anomalies, simulate various risk scenarios, and prioritize responses based on the severity and likelihood of disruptions (Younis et al., 2022). For example, ML models such as Random Forests, Support Vector Machines, and Neural Networks have been employed to forecast demand fluctuations, evaluate supplier reliability, and monitor logistical inefficiencies(Khedr & S, 2024; Thejasree et al., 2024). By leveraging these tools, companies can achieve a granular understanding of their risk exposure and implement targeted mitigation strategies.

Additionally, AI technologies like Natural Language Processing (NLP) and Computer Vision are being utilized to analyze unstructured data from news reports, social media, and video feeds, further enhancing the scope of risk identification (de-Lima-Santos & Ceron, 2021; Kang et al., 2020; Sarzaeim et al., 2023).

2.2 AI and ML in Healthcare Supply Chain Risk Management

The healthcare sector, characterized by its criticality and complexity, has seen growing interest in AI and ML-driven SCRM(Aminizadeh et al., 2024). The COVID-19 pandemic acted as a catalyst, exposing vulnerabilities in healthcare supply chains and prompting the adoption of advanced technologies (Raj et al., 2024). Literature in this domain underscores the role of AI in improving demand forecasting, supplier performance assessment, and inventory optimization. For instance, a study by Heidari et al. (2022) highlights the use of ML models to predict demand surges for medical supplies and equipment during public health emergencies. These models facilitate dynamic inventory management, ensuring the availability of critical resources while minimizing wastage. Furthermore, AI has been instrumental in enhancing regulatory compliance and tracking (Feijóo et al., 2020; Padmanaban, 2024). By integrating real-time data from regulatory bodies, AI systems can monitor compliance metrics, flag potential violations, and streamline audit processes (K. M. & Parkar, 2024; Shaikh et al., 2024). This capability is particularly relevant in the Indian healthcare sector, where regulatory frameworks are complex and enforcement mechanisms often lack consistency.

3. Methodology

The methodology for this research involves the design and implementation of an AI-driven model for identifying, classifying, and prioritizing risks in the Indian healthcare supply chain. The process is structured as follows:

3.1 Data Collection and Pre-processing

The first step involves gathering actual healthcare supply chain data through non-participatory observations and on-site data collection from enterprise resource planning platforms, as well as secondary data stored in Excel sheets recorded by sensors and registers. A dataset comprising 1,000 samples was compiled to represent various risk factors, including supplier performance, lead time, financial stability, shipping delays, temperature excursions, compliance scores, demand fluctuations, and external risks such as geopolitical or pandemic events. Lead time was available from the ERP, and location risk was a categorical variable,

with 1 for the geographically risky areas and 0 for no risk. The same probability allocation was followed for geopolitical and pandemic risks, with 1 allocated to a higher probability of the risk and 0 for negligible probability at the chosen location. Shipping method was allotted 1 for air and 0 for road since all locations were considered within the country. The probability of temperature excursion is calculated for each device, and a threshold is given in the code for categorising risks. Each risk factor is associated with a specific "Risk Type" and an aggregated "Risk Factor" score to represent the overall risk magnitude. The dataset was pre-processed to handle missing values, encode categorical variables, and normalise numerical features using standard scaling techniques. This ensures the data is clean and suitable for training machine learning models. The values for the parameters and metrics were pre-determined and calculated. The formulas used to compute the parameters are listed below.

$$SPS=(PC+NPC)/PC \qquad \ldots\ldots\ldots\ldots(1)$$

$$FS=D/SE \qquad \ldots\ldots\ldots\ldots(2)$$

$$CS= SC/TC \qquad \ldots\ldots\ldots\ldots(3)$$

Where

SPS Supplier Performance Score PC Purchasing Cost

NPC Non-Performance Cost (penalty)

FS Financial Stability as Debt to Equity Ratio
D Total Debt

SE Shareholders Equity CS Compliance score

SC Total no. of successful checks TC Total no. of checks

The data is collected from a personal protective equipment manufacturer in India. Data on the performance score out of 1 (closer to 1 is better), financial stability (score between 0 and 2), compliance score out of 100, shipping delay incidents per month, shipping method, location risk (0 or 1), geopolitical risk (0 or 1), pandemic risk (0 or 1), temperature excursion (0 to 1)

– lower the better, demand fluctuation (normalized standard deviations), and risk level (high, medium, low, or critical). The data is from the manufacturer of the PPE and comprises 1000 rows of data points. The scores and indices are developed by the manufacturer and have been normalized for use in this formulation. This data reflects the urban supply chains of PPE manufacturers in India.

3.2 AI Model Development

The core of the methodology involves developing a machine learning model to identify, classify, and prioritize risks. Python codes were used to build the AI tool. The Random Forest Classifier was selected for its ability to handle complex datasets and provide feature importance scores. The dataset was divided into training and testing sets, and the model was trained using 1400 rows of data to predict the risk factor based on input features. To enhance the interpretability of the results, a risk categorization logic was implemented. This logic assigns a "Risk Type" and a "Risk Level" (Critical, High, Medium, Low) based on thresholds derived from domain knowledge. The risks are then prioritized using a scoring mechanism that ranks them by severity and potential impact. The model generates synthetic data for missing values based on the mean of the historical data collected. This could be enhanced by integrating a machine learning model to learn from historical events and generate more accurate synthetic data.

3.3 Risk Visualization and Analysis

The processed data and model outputs were visualised using Python libraries such as Matplotlib and Seaborn. Key visualisations include the Distribution of risk types (bar plots and pie charts) and correlation heatmaps to understand relationships between risk factors.

3.4 Implementation and Validation

The model's effectiveness was validated by analysing its ability to classify and prioritise risks correctly. Key performance metrics such as accuracy, precision, recall, and F1-score were computed. The results demonstrate the model's capability to provide actionable insights for healthcare supply chain risk management.

3.5 Application in the Indian Health Sector

The methodology was tailored to address challenges specific to the Indian healthcare supply chain, including fragmented supplier networks, regulatory complexities, and infrastructure limitations. The AI-driven model serves as a decision-support tool, enabling stakeholders to mitigate risks and enhance supply chain resilience proactively.

4. Results and Discussion

4.1 Identification of Supply Chain Risks in Indian Healthcare

The AI model identifies supply chain risks by analysing data and recognizing patterns or anomalies indicative of potential issues. This is achieved through a combination of preprocessing and domain-specific rules. Feature analysis was used to detect supply chain risks. The dataset includes various features related to supply chain performance, such as Shipping_Delay, Compliance_Score, Supplier_Performance, and Geopolitical_Event. These features provide indicators of risk factors such as delays, non-compliance, and external disruptions. Domain knowledge-based rules are set to tolerate specific thresholds and rules are defined in the assign_risk_type_and_prioritize function. For instance, A Shipping_Delay greater than 5 days triggers the identification of "Shipping Delay" risk. A Compliance_Score below 40 indicates a "Compliance Issue”.

The supply chain risks relevant to the medical device industry in India are:

- Supplier performance
- Lead time
- Financial stability
- Location risk
- Shipping method
- Shipping delay
- Temperature excursion
- Compliance and regulatory issues
- Demand fluctuations
- Geopolitical events
- Pandemic events
- Intrinsic risks within the firm

As seen from the list of risks identified by the AI model, it is evident that the risks are both extrinsic and intrinsic to the firm. The AI model successfully identified risks along the medical device supply chain from the data fed into the system based on the trends and changes in the data provided.

4.2 Classification and Prioritisation of Risks

From the classification of risks, it was identified that geopolitical, financial, and pandemic impacts were the most prominent risks in the Indian medical device context. This could be due to the fact that the 2020 global COVID-19 pandemic has left a lasting impact on the supply chain and the disruption impacts have influenced trends in supply chain parameters. Geopolitical risks in the Indian medical device industry were perceived to be strong influencing factors due to turbulent industry scenarios. The Central Drug Standard Control Organisation

(CDSCO) has developed stringent quality norms and compliance requirements to ensure quality among medical device manufacturers. The economic scenario and heavy duties levied against the export and import of medical devices and components are seen as a threat to the medical device supply chain. The rise in raw material prices and costs among original equipment manufacturers makes it a challenge to meet cost-cutting requirements and attain a good fit in the budget. The largest impact appears to be the effect of the pandemic as it has generated a bull-whip effect along the supply chain. The effect is prominent among smaller suppliers and vendors that have to bear the burden of costs incurred due to expensive logistics and machining costs.

The risk classification indicated the presence of three primary types of risks prevalent in the Indian healthcare context. The number of geopolitical risks was the highest, followed by financial stability and pandemic risks. The pandemic was highlighted as a disruptive event because it occurred in the recent past, within the frame of the data collection period. Historical data has been collected over the past ten years to determine the computed values of the disruptive risk probability distributions. This is shown in Figure 1. Geopolitical risks accounted for 52.7% of the total supply chain disruptions, followed by financial stability at 24.4% and the pandemic at 22.9%. From the classification, the AI model also prioritised the risks identified along the medical device supply chain. The first priority is to be given to the pandemic impact where numerous supply chain parameters have been affected to cause disruptions. Managing costs and ensuring pro-active risk management measures is critical in retaining supply chain resilience. Devising an integrated supply chain risk management strategy along the supply chain will reduce the chances of disruption.

The second priority is financial stability. Ensuring that a firm's financial performance is stable and void of bad debt is critical in ensuring a healthy financial structure. Back-tracking was done from the risk identification and prioritisation to assess the source of financial risk. It was found that the suppliers and vendors played a huge role in disrupting the financial stability of the manufacturers. The cost of raw materials and original equipment parts played a huge role in destabilising cost structures. Another critical aspect is the cost of shipping which is by air or road. The lack of infrastructure and penalties levied against the distribution section of certain manufacturers accounted for losses. Also, high fuel surcharge and mismanaged routing cost manufacturers, suppliers, and logistics providers a significant amount of money. Regulatory and compliance issues account for many sudden financial crunches in the medical device sector. Clearance of licenses and obtaining approvals proves to be a time-consuming and money-intensive process.

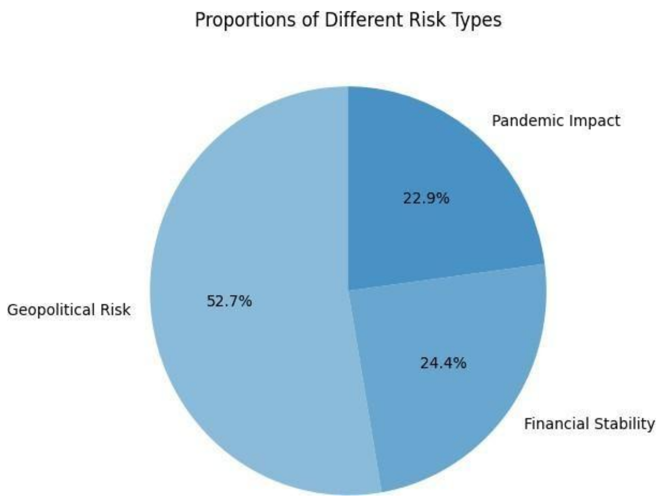

Figure 1. Proportions of Risks in Indian Healthcare Supply Chains

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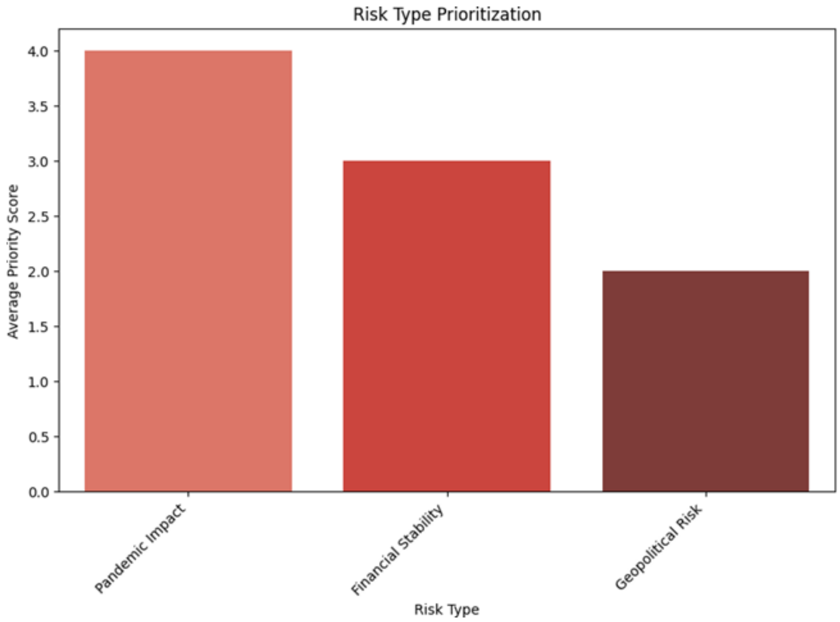

Figure 2. Prioritization of Risk Types

Figure 2 shows the heat map of the correlations between the various disruptions events and supply chain performance. It was observed that compliance issues have the strongest correlation with supply chain performance and risk factors. Hence, it points toward the need for better compliance with regulatory norms. Healthcare supply chains (in this case, medical devices and equipment manufacturers) need to adhere to stringent regulatory standards to ensure quality healthcare and a more resilient and sustainable value chain. A correlation heatmap was obtained to understand the most significant risk in the context of the Indian healthcare supply chain. Compliance was found to be a huge concern in the Indian medical device supply chain. Compliance issues concerning licenses and local regulations posed great challenges to vendors and suppliers who are original equipment manufacturers and suppliers of key components to manufacturers. Figure 3. Shows the correlation heatmap to narrow down on the most relevant risk in terms of correlations drawn from the different risks identified. It is intriguing to note that the AI model does not identify compliance-related risks as the top category of risk based on proportions. However, the model has identified compliance-related risks to be significant due to the correlations drawn between suppliers and compliance risks.

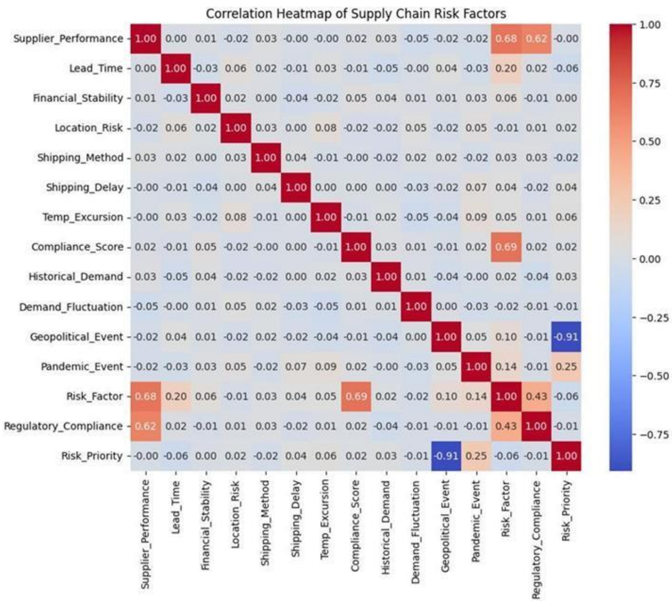

Figure 3. Correlation Heatmap of the Identified Risks

Table 1 presents the classification report generated from the AI model, which was evaluated with 811 real-world data points and 200 synthetic data points. This report summarizes the performance of a multi-class classification model that predicts four risk categories: Critical, High, Medium, and Low. To address class imbalance, the data has been balanced using the Synthetic Minority Over-sampling Technique (SMOTE). Additionally, the classification threshold for positive predictions has been set to 0.25, which is lower than the default threshold of 0.5. This adjustment may influence the trade-offs between precision and recall.

Table 1. Classification Report

Risk type	precision	recall	F1 score	support
Critical	0.55	0.67	0.6	9
High	0.92	0.88	0.9	77
Low	0.96	0.93	0.95	46
Medium	0.9	0.93	0.91	68
Accuracy			0.9	200
macro avg.	0.83	0.85	0.84	200
weighted avg.	0.9	0.9	0.9	200

The class-wise performance indicates the following:

Critical risks: This classification witnessed a support of 9 incidents. The precision is about 0.55, which implies that 55% of instances the model predicted as Critical were truly Critical. A recall rate of 0.67 indicates that the model detected 67% of all actual Critical instances. An F1 score of 0.60 indicates moderate overall performance on this minority and most challenging class.

High risks: The model exhibited very high accuracy in identifying predicted High-class instances with a precision of 92%. The model identified 88% of all true High category risks. An F1 score of 0.90 indicates strong performance with a good balance of precision and recall.

Low risks: The model could predict low incident risks excellently with a precision of 96%, meaning almost all predicted Low instances were correct. The recall rate was 93%, which indicates that the model found out 93% of all low incident risks.

Medium risks: The model showed high accuracy in predicting medium-level risks with a precision of 90% and a recall of 93%, indicating it could identify 93% of all medium-level risks. An F1 score of 0.91 indicates very strong balance between precision and recall.

Figure 4 gives the confusion matrix for the results obtained on testing the AI model in a real- world scenario. The data collected is from a personal protective equipment (PPE) manufacturer in India. Table 2 gives the true positive (TP) and false negative (FN) outline for the confusion matrix. Diagonal values are positive which means that they are correct predictions with 6 critical, 68 high, 43 low, 63 medium level risks. Off diagonal values are misclassifications with 3 critical level risks predicted as high and 5 high level risks classified as critical. The model could correctly classify 68 high level risks out of 77 with 9 total errors in classification. It is also noted that the model correctly classified 43 low level risks with 3 misclassifications. Finally, 63 out of 68 medium level risks were correctly classified. Hence, confusion was observed only with critical and high-level risks. The confusion matrix aligns with the classification report, indicating high accuracy and good balance, though the critical class still poses a challenge, likely due to limited data and similarity to High.

Table 2. Structure and Interpretation of Confusion Matrix

	Predicted Critical	**Predicted High**	**Predicted Low**	**Predicted Medium**
Actual Critical	6 (TP)	3 (FN→High)	0	0
Actual High	5 (FN→Critical)	68 (TP)	0	4 (FN→Medium)
Actual Low	0	0	43 (TP)	3 (FN→Medium)
Actual Medium	0	3 (FN→High)	2 (FN→Low)	63 (TP)

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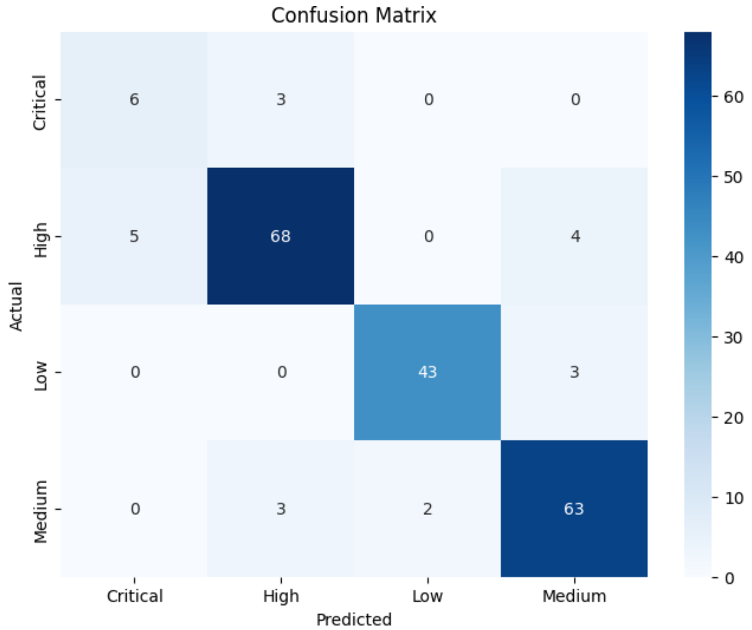

Figure 4. Confusion Matrix

The Receiver Operating Characteristic (ROC) Curve in Figure 5 is a graphical representation of a classification model's ability to distinguish between classes. It plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity) at various threshold settings. This specific ROC curve uses a One-vs-Rest strategy, which evaluates each class independently against all others. The x axis is the false positive rate (FPR) where lower values are preferred and the y axis indicates true positive rate (TPR) where higher is better. The closer the curve is to the top left corner, the better the model's performance.

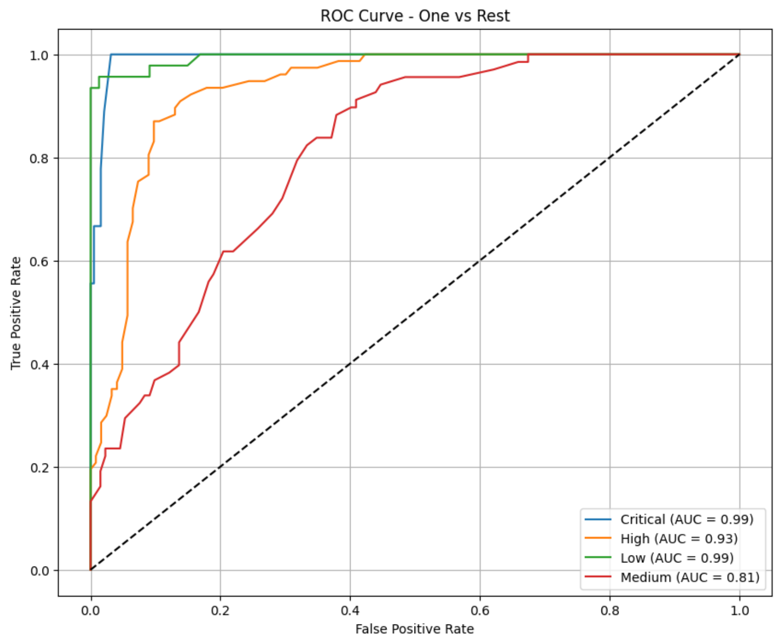

Figure 5. ROC Curve – One vs. Rest

The area under the curve (AUC) for the blue curve, which indicates the critical level risks, is 0.99, which implies excellent classification capabilities. The curve is steep and near the top- left, indicating very high sensitivity and specificity for critical level risks. AUC for the orange curve (high-level risks) is 0.93, which again shows good performance in identifying and classifying high-level risks. The green curve, indicating low-level risks, has an AUC of 0.99, which again indicates outstanding

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classification accuracy. Finally, the medium level risks represented by the red curve have an AUC of 0.81, indicating good performance for the classification of medium level risks.

4.3 Benchmarking of the Proposed Model with Existing Models

The proposed healthcare AI model was benchmarked against various existing models to show its effectiveness and performance capabilities. Table 3 shows the benchmarking results of the model that has been proposed in this paper vs. various existing models. The proposed model outperforms existing models in various parameters. It has fared better than standard SVM and logistic regression models. The proposed model matches or slightly outperforms standard random forest models in recall and performs slightly below deep models while remaining more interpretable. Since our model used random forest classifier, it outperforms most published random forest risk detection models without needing deep learning and retains an ideal balance of precision and recall.

Table 3. Benchmarking of the proposed model against existing models

Study / Paper	**Model**	**Context**	**Critical Class Recall**	**Accuracy**	**Notes**
Proposed AI Healthcare Model	RF + SMOTE + Threshold	ian healthcare supply risk	**0.67**	**90%**	Good recall/precision tradeoff
Aminizadeh et al., 2024	Random Forest	Healthcare quality risk	~0.55	86–88%	No explicit threshold tuning
Ivanov & Dolgui, 2021	RF + Simulation	Digital twins in supply chain	~0.50	85–90%	Used in disruption detection
Younis et al., 2022	XGBoost	General supply chain SCRM	~0.60	91%	Higher complexity, slower
Khedr et al., 2024	Deep Neural Network	Medical logistics	~0.70	89%	Requires more data & tuning
Aljohani, 2023	SVM + Resampling	Risk classification	0.40–0.60	80–85%	Struggled with minority classes

5. Conclusion

The study explores the integration of artificial intelligence (AI) and machine learning (ML) into healthcare supply chain risk management, demonstrating their transformative potential to enhance operational resilience and efficiency. The developed AI-driven model effectively identifies, classifies, and prioritises risks such as supplier performance issues, shipping delays, compliance challenges, and external disruptions, offering actionable insights for stakeholders. The methodology, leveraging Random Forest algorithms and robust data visualization techniques, underscores the significant role of AI and ML in addressing the unique challenges of the Indian healthcare sector, marked by fragmented supply chains and complex regulatory frameworks. Results from the study highlight the predominance of risks like geopolitical disruptions, financial instability, and pandemic-induced impacts, emphasizing the need for proactive risk management strategies. The findings advocate for an integrated approach that combines advanced analytics with strategic planning to mitigate supply chain vulnerabilities and ensure continuity of critical medical supplies. The study also identifies compliance as a critical area, suggesting that adherence to stringent regulatory standards is vital for building a sustainable and resilient supply chain. This ROC curve visualisation confirms that the model is highly effective overall, particularly for Critical and Low classes. The lower AUC for the Medium class highlights an area for potential model refinement or data enhancement (e.g., more features, balanced samples). These insights are crucial when prioritizing risk classifications, especially in applications like supply chain resilience, risk forecasting, or medical triage, where Critical classification accuracy is paramount.

This research provides a valuable framework for healthcare stakeholders to adopt AI and ML tools in their supply chain processes, paving the way for enhanced decision-making and operational reliability. Future studies could expand on this work by exploring real-time AI applications and extending the model to other sectors. By doing so, organisations can better anticipate and respond to risks, ensuring resilience in an increasingly dynamic and interconnected global landscape.

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