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A Comparative Study on Backorder Prediction and Risk-aware Demand Forecasting, Using Machine Learning Approaches in the Bangladeshi Garments Industry Under Short-term Disruption

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Abstract

The Bangladesh garment industry is highly vulnerable to short-term disruptions, causing frequent backorders and demand–supply imbalances. This study evaluates and compares multiple ML algorithms to identify the most effective models for backorder prediction and risk-aware demand forecasting, with the aim of reducing backorder frequency and maintaining balanced inventory levels. An initial industry survey established the relevance of the problem, followed by the collection of a real-world dataset from Bangladeshi garment manufacturers. For backorder prediction, XG Boost, ANN, Random Forest, MLP, Cat Boost, Ada Boost, and Light GBM were trained and tested, with performance measured using accuracy, precision, MAE, MAPE, and RMSE. Products were then categorized into high, medium, and low-risk groups based on backorder frequency and demand forecasting was carried out for high and medium-risk categories using XG Boost, Random Forest, and Light GBM. An additional inventory status indicator was calculated to measure the gap between forecasted and actual inventory sufficiency across models and scenarios. Sensitivity analysis with ±10% and ±20% demand variations was performed to assess model robustness under uncertainty. Results show that MLP is the most suitable for backorder classification, while XG Boost and Random Forest perform strongly under stable demand conditions. However, under volatile demand, Light GBM outperformed other models, reducing backorder rates and providing better inventory coverage. Risk-based product segmentation enabled focused forecasting strategies, and sensitivity analysis highlighted model behavior under fluctuating demand. These findings provide actionable insights for manufacturers to select appropriate ML models for minimizing backorders, maintaining inventory balance, and improving supply chain resilience in disruption-prone environments.

Keywords
Backorder Prediction, Demand Forecasting, Machine Learning, Garment Industry, Supply Chain Disruption.

1. Introduction

The ready-made garment (RMG) industry, which accounts for more than 80% of export revenue and a significant share of GDP, is crucial to Bangladesh's economy. Notwithstanding its expansion, the sector continues to be vulnerable to issues including supply interruptions, growing expenses, and growing idle capacity. In an already competitive international market, these difficulties frequently result in backorders, delayed shipments, and fragile buyer relations. Accurate forecasting and effective inventory management are essential when unmet demand increases. In order to improve supply chain resilience, this study assesses machine learning (ML) models for backorder prediction, product risk classification, and inventory adequacy.

1.1 Objectives

- To predict backorder and forecast demand for risk-prone products using various machine learning algorithms and compare their performance to identify the most effective model in the Bangladeshi garment industry.

2. Literature Review

The backorders. Their results indicate that decision-tree methods can effectively capture non-linear relationships, while also providing interpretable rules for managers. In this paper (Ali et al.) used machine learning to maximize supply chain performance by anticipating backorders. Their study emphasizes that misclassification costs strongly affect inventory decisions, as both false positives and false negatives lead to operational inefficiencies. (Hajek and Abedin) propose a profit-maximizing backorder prediction system using big data analytics. Their model adjusts predictions based on cost functions, ensuring alignment between operational outcomes and financial objectives. (Banik et al.) conduct a comparative analysis of machine learning algorithms such as Random Forest, SVM, and XGBoost for backorder prediction. Their findings show that ML-based models achieve higher predictive accuracy compared to statistical approaches. (Shajalal et al.) develop a deep neural network (DNN) model for product backorder prediction on imbalanced data. By applying SMOTE and ADASYN resampling techniques, their model achieves an AUC above 0.95, demonstrating the effectiveness of data rebalancing in rare-event scenarios.(Ntakolia et al.) propose an explainable ML model for material backorder prediction using SHAP values. Their findings highlight that explainability increases trust and facilitates managerial adoption of AI-based forecasting. (Rahman et al.) provide an overview of the growth and challenges of the Bangladeshi RMG industry. They note that disruptions in raw material supply and lead-time variability exacerbate backorder challenges.

(Benhamida et al.) design a demand forecasting tool for smart inventory systems. Their approach combines ML-based forecasting with control mechanisms, resulting in more resilient inventory planning. (Ni et al.) propose a hybrid SSA-XGBoost model for supply chain demand forecasting. The results confirm that hybrid approaches significantly improve forecasting performance under volatile demand conditions. In this study (Dixit et al.) demonstrates an end-to-end ML framework for product backorder prediction. (Ali et al.) study the impact of inventory management on customer satisfaction. They conclude that ineffective inventory practices lead to both stockouts and surplus, directly influencing service quality.(Shuvo et al.) review recent technological innovations in Bangladesh's RMG supply chain. Their work identifies predictive analytics and disruption management as underutilized yet promising areas for enhancing resilience. (Chowdhury et al.) investigate strategies for mitigating supply-side barriers in the apparel supply chain. Their findings emphasize that infrastructural issues, such as inadequate port facilities and unreliable power, contribute to instability in inventory systems.(Ranawaka and Jawwadh) focus on demand forecasting in the apparel industry. Their results show that machine learning models outperform Holt's Double Exponential Smoothing under uncertainty. (Kharfan) applies a two-step ML model to seasonal footwear demand forecasting. Their findings demonstrate a 20% improvement in inventory accuracy, reducing both stockouts and overstocking. (Nassibi et al.) study demand forecasting in the food industry using ML models. Their results show that neural networks and tree-based models better capture seasonal demand variability compared to statistical baselines.(Park) compares ML and deep learning methods for order quantity prediction. Their study highlights the superior performance of hybrid CNN-BiLSTM models in volatile supply chain contexts. (Shi et al.) investigate inventory risk management in cross-border e-commerce fashion retail. Their findings confirm that predictive analytics can mitigate risks from long lead times and SKU variability.(Steinberg et al.) propose an ML model for predicting late supplier deliveries in the German machinery industry. Their results highlight that predictive models can significantly enhance supplier risk assessment in high-variety production contexts. (Terrada et al.) Implement deep learning models for demand forecasting in Supply Chain 4.0. Their findings reveal that LSTM networks outperform traditional methods in highly non-linear and noisy environments.(Anchuri) compares advanced ML methods for demand forecasting. Their results emphasize real-time adaptability as a critical advantage of ML approaches in dynamic market conditions. (Jin) evaluates traditional versus ML forecasting approaches in stock markets. Their study confirms that ML models adapt better to volatile and uncertain environments.(Li) investigates backorder prediction in Danish craft beer supply chains. Their study demonstrates that ML can be effectively extended to niche industries beyond mainstream manufacturing. (Mia and Akter) highlight vulnerabilities in Bangladesh's garment sector. Their work emphasizes the necessity of predictive modeling to counteract supply-side risks.

In this study, we address these limitations by: (i) systematically evaluating multiplemachine learning algorithms for backorder prediction, risk-aware demand forecasting,and inventory status analysis tailored to the Bangladeshi RMG industry; (ii) categorizing products based on backorder frequency to quantify risk exposure at the productlevel; (iii) benchmarking and comparing the performance of state-of-the-art ML algorithms under stable and volatile demand conditions, including sensitivity testing with±10% and ±20% demand variations; and (iv) presenting actionable insights for manufacturers and supply chain managers on selecting the most effective models to reducebackorder frequency, balance inventory, and improve short-term supply chain resilience during disruptions .

3. Research Methodology

Step 01: In this step, data was captured through an industry-specific survey along with expert opinions.
Step 02: In this step, classification-based machine learning models were applied to predict which products are most likely to experience backorders. The output of this step provides the initial prediction layer for identifying at-risk items.

Step 03: In this step, the products identified in Step 02 were categorized into three groups: high, medium, and low risk, based on the frequency and severity of backorders (Figure 1).

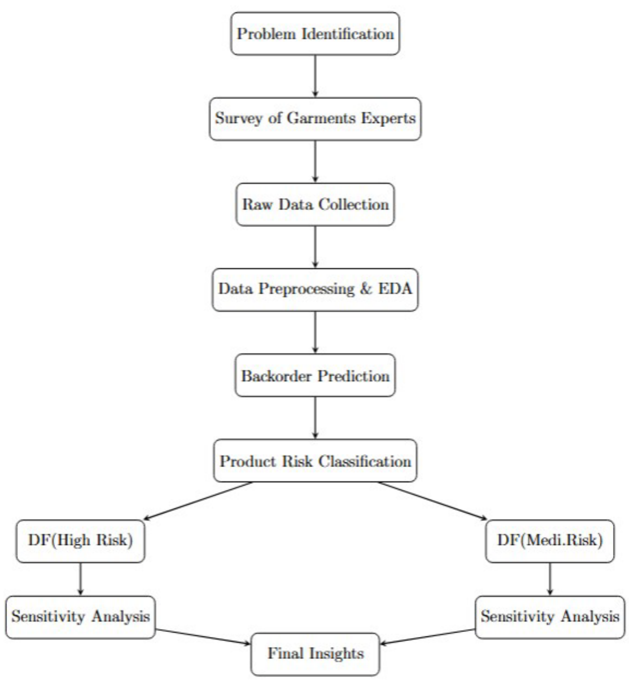

Figure 1. Research Methodology

Step 04: In this step, demand forecasting models were applied specifically to the high- and medium-risk product categories.
Step 05: In this step, inventory status assessment was performed.

Step 06: In this step, sensitivity analysis was conducted to assess the robustness of the framework. Demand forecasts, stock values, and backorder frequencies were adjusted by ±10% and ±20% to test how resilient the system remains under varying uncertainty conditions.
Step 07: In this step, a systematic review of the overall framework was carried out.

4. Data Collection

A total of 519 monthly records were collected from the planning, production, inventory, and logistics departments of three Bangladeshi garment manufacturers. Company identities are withheld for confidentiality under non-disclosure agreements.

5. Data Analysis

Exploratory data analysis and preprocessing

An exploratory analysis was performed to examine data distribution and feature relationships: bar plots (Figure 3) .correlation analysis, histograms (Figure 4),box plots (Figure 5),etc

Data cleaning and transformation.

Missing values were imputed using forward fill or mean replacement; outliers were truncated or removed based on domain expertise. Categorical variables (e.g., Backorder: Yes/No) were encoded as binary (1/0).

Survey on the Necessity of Backorder Prediction in the Bangladesh Garments Industry.Survey findings highlight the critical importance of addressing backorder issues in Bangladesh's garment supply chain. Over 80% of respondents reported experiencing backorders frequently, indicating that this is a systemic challenge rather than an occasional occurrence (Figure. 6). Furthermore, 100% of respondents strongly agreed on the necessity of early-stage backorder prediction, underscoring its role in improving operational efficiency and supply chain resilience (Figure 2).

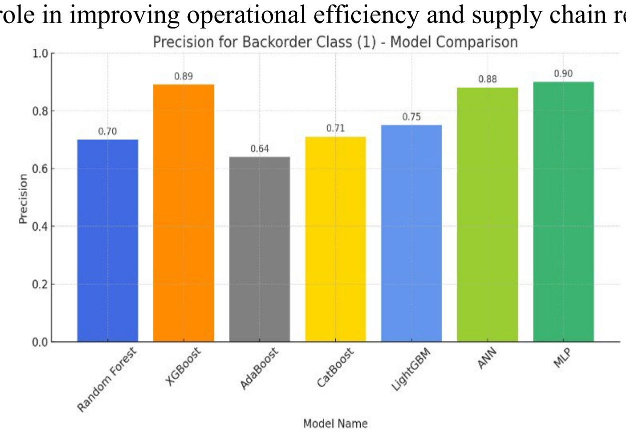

Figure 2. Precision of Selected Models

Backorder Prediction Models (Classification).

MLP outperformed other models in accuracy and precision for backorder classification and XGBoost is the second best and ANN followed later based on minority class detection performance in recall and precision (Figure 2)

Risk segmentation and correlation analysis

Products were classified as low (0–1), medium (2–3), or high risk (4+) based on backorder frequency, enabling targeted forecasting and improved supply chain responsiveness. A strong positive correlation (+0.72) between demand gap and backorders (Table 1- Table 3; Figure 3-Figure 7) confirmed inventory shortages as the main driver of backorders.

Forecasting Demand for Risk-Prone Products

Separate datasets were built for medium-risk and high-risk products with balanced backorder samples to avoid model bias. For medium-risk products, Light GBM achieved the highest accuracy for non backorder items while Random Forest performed best for backorder items. For high-risk products, XGBoost provided the most accurate forecasting for backorder items, whereas Random Forest obtained the lowest error for non-backorder items. Light

GBM showed the least negative inventory status for backorder items, suggesting superior balance in avoiding stockouts. Despite XG Boost's slightly higher accuracy, the marginal improvement does not outweigh the risk of over fitting, making Light GBM the more reliable option in this context.

From the aggregate backorder frequency, individual product performance cannot be fully defined, as products do not exhibit uniform behavior. The heatmap (Figure. 9) highlights which products require greater attention and which demand less focus. Across the forecast scenarios, Tank Tops (C3) and Night Dresses (C3) showed the highest backorders, largely concentrated in the +30% over-forecast condition. Medium-risk items like Jackets (C1), Lingerie (C2), Girls Slip (C1), Boys Boxer (C3), Shorts (C1), and Leggings (C3) showed moderate backorders spread mainly across the +10% to +30% over-forecast scenarios.

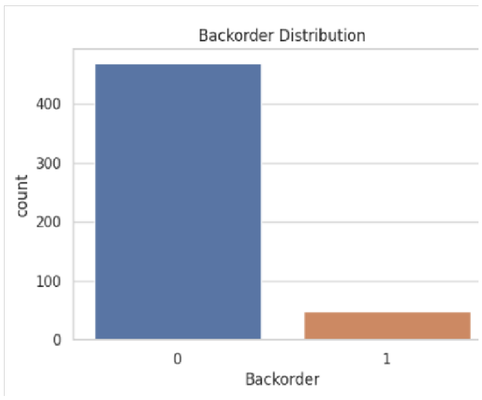

Figure 3. Product went to backorder

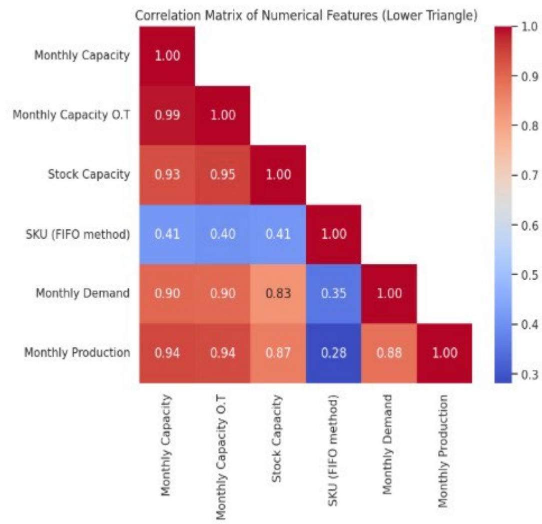

Figure 4. Pearson Correlation Matrix

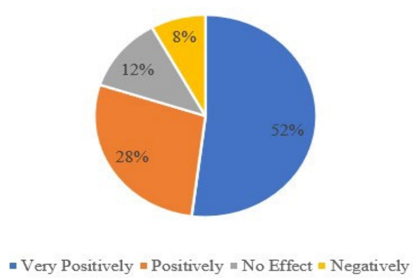

Figure 5. Effect of the backorder situation

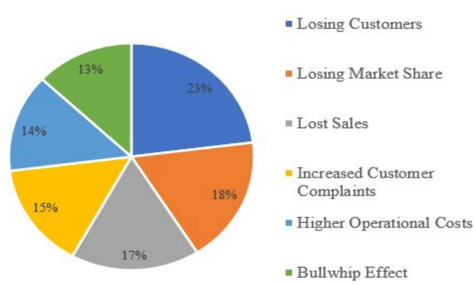

Figure 6. Key challenges of backorder

Table 1. Error for Medium-Risk Products

Category	**Model**	**Backorder**	**Non-Backorder**
MAPE%	RF	37%	23%
	LGBM	41%	17%
	XGB	25%	20%
MAE	RF	287292	62647
	LGBM	322485	50523
	XGB	109821	127543
RMSE	LGBM	336657	68450
	RF	304073	77757
	XGB	96694	92455
Average Inventory Gap	RF	-62421	140494
	LGBM	-67300	130962
	XGB	-289451	184281

Table 2. Error for High-Risk Products

Category	**Model**	**Backorder**	**Non-Backorder**
MAPE%	RF	41%	17%
	LGBM	39%	24%
	XGB	28%	27%
MAE	RF	244510	90940
	LGBM	320863	99708
	XGB	147343	90999
RMSE	LGBM	403919	109636
	RF	276757	113898
	XGB	194761	90999
Average Inventory Gap	RF	-142007	202822
	LGBM	-202398	32403
	XGB	186213	-241613

Sensitivity Analysis of Forecasting Model of Medium Risk Product

Table 3. Model-wise Forecast Sensitivity and Backorder Impact

Model	Backorder (Total)	Month	Scenario	Avg Inventory status	Backorder
RF	14	1	+10%	-112834	7
		0		100370	7
	7	1	-10%	-12007	4
		0		180618	3
	15	1	+20%	-163248	7
		0		60245	8
	4	1	-20%	38405	3
		0		220743	1
LGBM	7	1	+10%	-74122	5
		0		113329	2
	4	1	-10%	19665	3
		0		191221	1
	12	1	+20%	-121016	8
		0		74384	4
	3	1	-20%	66560	3
		0		230160	0
XGB	12	1	+10%	-370312	6
		0		133616	6
	7	1	-10%	-208589	4
		0		234946	3
	17	1	+20%	-451174	10
		0		82950	7
	6	1	-20%	-127727	3
		0		285611	3

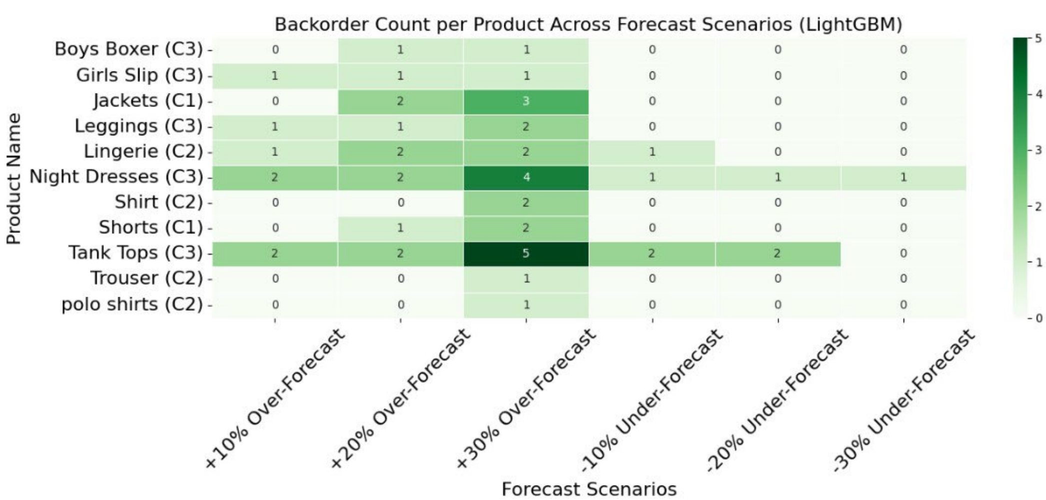

Figure. 7. Product Backorder Frequency Heatmap – Medium Risk (LightGBM) .

Sensitivity Analysis Evaluation For High Risk Product

In this case, use Light GBM for backorder months, as it offers more stable inventory coverage under fluctuating demand, and Random Forest for non-backorder months (Table 4).

Table 4. Model-wise Forecast Sensitivity and Backorder Impact

Model	Backorder (Total)	Month	Scenario	Avg Inventory status	Backorder
RF	14	1	+10%	-232298	14
		0		173928	0
	12	1	-10%	-98348	12
		0		294752	0
	15	1	+20%	-299273	15
		0		131516	0
	10	1	-20%	-313773	10
		0		355165	0
XGB	16	1	+10%	-316217	15
		0		120988	1
	15	1	-10%	-167009	15
		0		251438	0
	17	1	+20%	-309821	14
		0		55763	3
	12	1	-20%	-92405	12
		0		316663	0
Light GBM	11	1	+10%	-138792	11
		0		186625	0
	5	1	-10%	-86086	5
		0		212807	0
	16	1	+20%	-266005	13
		0		75183	3
	3	1	-20%	-74961	3
		0		329611	0

Per Product Backorder Evaluation For High Risk Product Sensitivity Analysis

Jogging Suits (C1) and Sweatshirts (C3) show moderate backorder fluctuations. Ladies' Pajama Sets (C3) and Pant (C2) exhibit the highest vulnerability. In contrast, Trouser (C1) shows a more evenly distributed pattern across scenarios, with moderate increases under +20% and +30% over-forecast conditions and lower counts in under-forecast ranges (Figure 8).

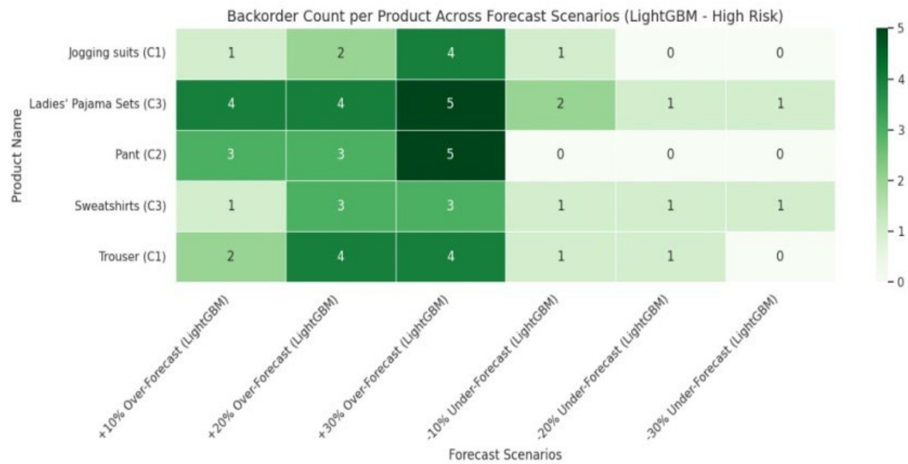

Figure 8. Product Backorder Frequency Heat map High Risk (Light GBM)

Result Analysis

This hybrid modeling approach is based on observed performance under different demand risk scenarios (Table 5).

Table 5. Final result evaluation for medium risk product

Scenario Type	Best Performed Model
Stable Months	XG Boost (BO), RF (Non-BO)
Volatile Months	Ligh tGBM (BO) ,Light GBM (Non-BO)

Table 6. Final Model Evaluation and selection (High Risk)

Scenario Type	Recommended Model
Stable Months	XG Boost (BO), RF (Non-BO)
Volatile Months	Light GBM (BO), RF (Non-BO)

For stable months, XG Boost during backorder periods and Random Forest during non-backorder periods perform best.In contrast (Table 6), under volatile months with high backorder risk, Light GBM consistently outperforms others for backorder periods by maintaining better inventory buffers.

4. Discussion

This study evaluated the performance of machine learning models in predicting backorders and supporting inventory management decisions in the Bangladeshi garments industry. The results demonstrate that no single model universally outperformed across all scenarios; rather, the strengths of each algorithm varied by risk level and inventory condition. LightGBM consistently offered superior accuracy for medium-risk, non-backorder items, while Random Forest proved more effective for medium-risk backorders. For high-risk categories, XGBoost provided the most accurate backorder forecasts, although LightGBM achieved the most balanced inventory sufficiency by minimizing negative stock positions. A key insight from the sensitivity analysis is that forecast deviations significantly influence backorder behavior, with over-forecast scenarios (+30%) producing the majority of shortages. Specific product categories were particularly vulnerable, reflecting the need for differentiated risk management strategies. Although XGBoost delivered marginally better MAPE scores for high-risk products, the associated risk of overfitting and less stable inventory balance indicates that LightGBM is a more reliable choice for practical implementation. From a managerial perspective, the study provides evidence that ensemble learning methods, particularly LightGBM, can be integrated into decision-support systems to improve demand planning and reduce backorder frequency. Moreover, product-level heatmaps proved useful in visualizing backorder concentration, offering actionable insights into which product groups require closer monitoring (Figure 9- Figure10).

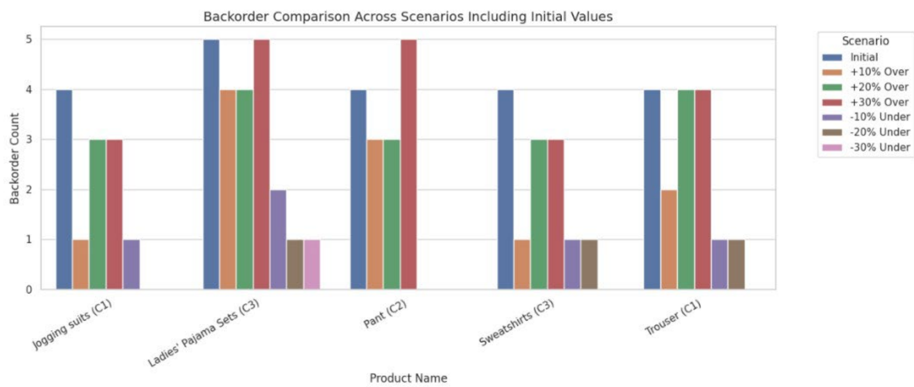

Figure 9. Backorder Count per Product for high- risk products (Initial & Final)

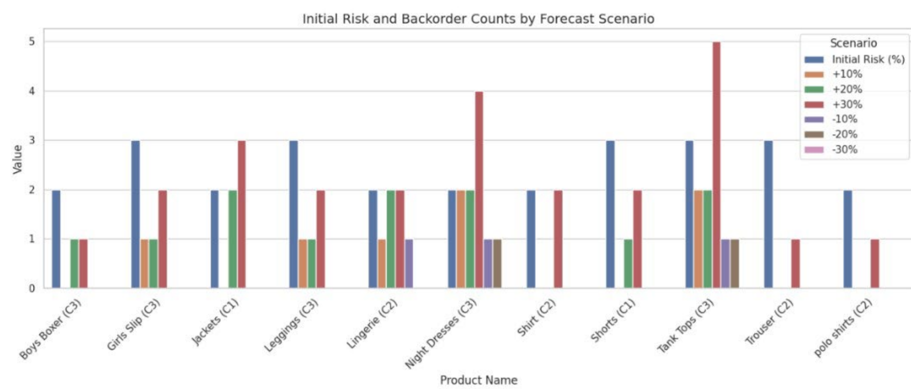

Figure 10. Backorder Count per Product for Medium risk product (Initial & Final)

While these results contribute valuable practical implications, some limitations should be acknowledged. The analysis was based on a specific dataset from the Bangladeshi garments sector, which may limit generalizability to other industries or regions. In addition, only three machine learning models were examined. Overall, the study demonstrates that machine learning-based forecasting can significantly enhance supply chain resilience by reducing uncertainty in backorder management. The combination of predictive accuracy and inventory stability achieved by LightGBM positions it as a promising tool for practical deployment in the garments industry and beyond

4.1 Conclusion

This study systematically evaluated multiple machine learning algorithms to predict backorders and perform risk-aware demand forecasting. By classifying products into low-, medium-, and high-risk categories based on historical backorder frequency, the study enabled risk-specific forecasting and inventory planning. Among the tested models,MLP achieved the highest precision and F1 score for backorder prediction, while XG Boost and Artificial Neural Networks (ANN) demonstrated competitive performance with balanced predictive capability. For high-risk products, XG Boost provided the most accurate backorder-month predictions, whereas Light GBM delivered more conservative forecasts, reducing the risk of stockouts. Random Forest showed consistent performance instable, non-backorder months. Sensitivity analysis revealed that no single algorithm consistently outperformed others under all demand scenarios. XG Boost was optimal when accuracy was the priority, Light GBM excelled in volatile conditions, and Random Forest offered stable forecasts. The approach demonstrated in this study can serve as a practical decision-support tool for the Bangladeshi RMG sector, helping manufacturers reduce lost sales, maintain customer satisfaction, and improve preparedness for future disruptions.

Future Work

Although this study shows that historical data can reliably predict backorders and demand, several future extensions are recommended. Incorporating deep learning models like LSTM or Transformers and integrating real-time data such as supplier reliability or shipment delays could improve responsiveness to disruptions. Adding cost-based factors, including backorder penalties and opportunity costs—would strengthen financial evaluation. Finally, developing a decision support system to visualize risks and inventory needs would enhance practical use for supply chain managers.

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