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Enhancing Supply Chain Management in Manufacturing Plants: Anomaly Detection and Mitigation Using MCDM and Machine Learning Techniques

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ABSTRACT

Supply chain (SC) anomalies, such as inaccurate demand forecasts, inventory imbalances, and production delays, impede operational efficiency and financial performance in manufacturing plants, particularly in third-world contexts where data-driven forecasting methods remain underutilized. This study investigates SC anomalies within Fair Electronics, a key manufacturing partner and authorized distributor of Samsung products in Bangladesh. Through interviews with technicians, supervisors, and management, specific anomalies such as demand volatility, stockouts, and inefficiencies in resource allocation were identified, with a predominant issue being the reliance on experiential forecasting methods that often result in inaccurate demand predictions. Leveraging insights from an extensive literature review, this research introduces machine learning (ML)-based forecasting methodologies tailored to these challenges. Four ML models, including an autoregressive integrated moving average (ARIMA), extreme gradient boosting (XGBoost), long short-term memory (LSTM), and Prophet, were applied to diverse market segments of mobile products, with model evaluation based on metrics such as mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). XGBoost consistently emerged as the superior model in terms of forecasting accuracy and robustness. The study highlights the transformative potential of advanced ML techniques in enhancing demand forecasting within SCs, proposing a comprehensive framework that integrates these methods to optimize inventory management, production planning, and overall operational performance. This study bridges the gap between traditional and data-driven forecasting approaches, providing a robust evidence base for the adoption of ML in SCs operations, paving the way for enhanced decision-making, reduced inefficiencies, and improved financial outcomes in manufacturing environments similar to Fair Electronics. The findings also offer a roadmap for future research and practical applications in the evolving landscape of supply chain management (SCM).

Keywords: Supply Chain Management, Machine Learning, Multi-Criteria Decision-Making, Anomaly Detection, Demand Forecasting

1. Introduction

Supply chain management (SCM) is a critical component of business operations, involving the planning, coordination, and control of all activities from sourcing raw materials to delivering finished products to end consumers [1]. It encompasses procurement, production, logistics, and customer service, integrating multiple stakeholders including suppliers, manufacturers, distributors, and retailers [2]. Effective SCM ensures the smooth flow of goods, services, information, and finances, which directly impacts a company's operational efficiency, cost management, and competitiveness [3]. Businesses with optimized SCs can enhance customer satisfaction, reduce operational costs, and improve productivity [4]. However, the complexity and interconnectedness of modern SCs also expose them to various risks and disruptions, such as natural disasters, economic fluctuations, and unforeseen events like the COVID-19 pandemic [5]. These disruptions can lead to delays, shortages of critical inputs, increased costs, and damage to business reputation [6]. In third-world settings, when dependence on conventional experiential forecasting techniques exacerbates problems like production inefficiency, inventory mismanagement, and demand instability, these problems are especially noticeable.

Anomalies in SCs are deviations from expected patterns, such as sudden fluctuations in demand, unexpected production or delivery delays, inventory imbalances, or fraudulent activities [7]. These anomalies can result from a variety of factors, including inaccurate forecasting, labor strikes, transportation disruptions, and quality control issues [8]. Detecting such anomalies is crucial to maintaining operational efficiency as they can cause significant disruptions, increase costs, and reduce customer satisfaction [9]. Early detection allows managers to take proactive measures, minimizing the impact on SC performance [10]. Machine learning (ML) techniques, combined with artificial intelligence (AI), have emerged as powerful tools for anomaly detection [11]. Through analyzing large datasets, AI-driven systems can identify irregular patterns in real time, offering actionable insights for predicting disruptions and improving decision-making [12]. Large dataset analysis, pattern recognition, and actionable insights for identifying and mitigating anomalies are all made possible by ML. Better resource allocation is made possible by Multi-Criteria Decision-Making (MCDM), which offers an organized method for prioritizing and sorting anomalies according to their impact. Existing research frequently uses these techniques separately, despite their own advantages, losing the chance to combine qualitative anomaly

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prioritization with quantitative predictive analytics. Organizations' capacity to methodically recognize and handle significant irregularities is hampered by this gap, especially in dynamic and intricate manufacturing settings. Although advanced technologies are increasingly being adopted in SCM, a significant gap persists in the systematic identification and prioritization of critical SC anomalies before applying ML solutions. This research aims to address that gap by integrating Multi-Criteria Decision-Making (MCDM) techniques with ML models. Through a case study of Fair Electronics, a key manufacturing partner and authorized distributor of Samsung products in Bangladesh, this study evaluates and ranks anomalies based on their impact, severity, and associated costs. These anomalies are identified through surveys and interviews across various SC levels. After ranking the anomalies, ML models are applied to enhance demand forecasting and address key operational inefficiencies. This combined approach strengthens both the strategic and operational aspects of SCM, improving resilience and adaptability in a rapidly evolving environment.

This study seeks to address the following research objectives (**ROs**):

1. To identify and rank the most significant anomalies within SCs using MCDM techniques, focusing on issues that severely impact operational performance and financial outcomes.
2. To apply ML models to improve demand forecasting accuracy, particularly targeting demand-related anomalies identified through the MCDM process.
3. To evaluate the effectiveness of integrating MCDM and ML techniques in improving overall SC performance, reducing disruptions, and providing actionable insights for optimization.

Through combining MCDM and ML, this study bridges the gap and develops a single framework for anomaly identification and mitigation in SCM. In addition to ranking anomalies according to their significance, this approach uses advanced forecasting algorithms to target the most pressing problems. With the potential to be replicated in other comparable manufacturing environments, the Fair Electronics case study highlights the usefulness of this paradigm in improving inventory management, production scheduling, and market responsiveness.

2. Literature Review

Numerous studies have developed methods for anomaly detection, leading to various models aimed at identifying anomalies more effectively. Unsupervised learning algorithms, which do not require labeled data, are particularly valuable in detecting anomalies that deviate significantly from the norm, especially as such anomalies are often rare and challenging to label comprehensively. For instance, Glaser et al. 2022 [13] explored techniques like Angle-Based Outlier Detection and Isolation Forest to enhance SC data quality. To improve detection accuracy, they developed an ensemble technique that classified a data point as an anomaly only when multiple algorithms identified it, thus reducing false positives.

Syarif et al. 2012 [14] compared anomaly detection methods for network intrusions, finding that anomaly detection algorithms, including k-Means and Expectation-Maximization clustering, outperformed misuse detection techniques, particularly for unknown intrusions. Semi-supervised learning, combining labeled and unlabeled data, has also proven effective in anomaly detection. Villa-Pérez et al. 2021 [15] compared 29 semi-supervised anomaly detection algorithms, identifying BRM as a top-performing algorithm, particularly on smaller datasets. Vercruyssen et al. 2018 [16] applied a semi-supervised approach to detect anomalies in water usage data, achieving high accuracy with minimal labeled examples.

Supervised learning algorithms, such as support vector machines (SVM) and decision trees, have also been widely applied in anomaly detection, especially when labeled data is available. Kerdprasop et al. 2019 [17] developed a CART model to detect anomalous customer orders, achieving high accuracy, which was further improved using a boosting technique.

In a systematic review, Nassif et al. 2021 [18] analyzed 290 publications on ML-based anomaly detection methods. They found that unsupervised methods were the most common, with a growing trend toward hybrid models.

3. Research gaps and contributions

Despite advances in SCM and the use of technologies like AI and ML, gaps remain in effectively addressing SC anomalies. Most research focuses on either qualitative method, like expert judgment and MCDM, or quantitative approaches, such as ML models, leading to a lack of comprehensive solutions that combine strategic anomaly prioritization with predictive analytics.

Current studies often miss the impact of demand-related anomalies—such as stockouts or production disruptions—especially in complex industries. Furthermore, the integration of real-time data sharing and collaboration with suppliers remains underexplored, limiting forecasting accuracy and SC resilience. While advanced ML models like ARIMA, XGBoost, and LSTM hold potential, their application in real-time anomaly detection is still underdeveloped.

There is also a lack of emphasis on linking forecast accuracy to key performance indicators (KPIs), such as inventory turnover and customer satisfaction. This study addresses these gaps by integrating MCDM with ML models, creating a unified framework for identifying, ranking, and mitigating anomalies. This approach enhances both strategic and operational SCM, enabling more informed decision-making to improve SC performance and resilience.

Although AI and ML technologies have a lot of promise for detecting and mitigating anomalies, their efficacy is mostly dependent on the availability of reliable, high-quality data. Inaccurate predictions and poor decision-making might result from poor data quality. It is necessary to employ processing steps to ensure the quality of the data, which includes handling missing values, noise, and biases with methods like imputation, normalization.

A unique contribution of this work is its focus on linking forecasting accuracy to key performance indicators (KPIs), such as inventory turnover and customer satisfaction, enabling managers to better assess the operational impact of their forecasting models. By creating a unified framework that combines Multi-Criteria Decision-Making (MCDM) techniques with ML models, the study provides a comprehensive approach to identifying, ranking, and mitigating anomalies in complex SCs. This approach enhances both strategic and operational decision-making, leading to improved SC performance and resilience in the face of disruptions.

Although the goal of this study is to increase forecasting accuracy using ML models, it also emphasizes the necessity of practical frameworks to deal with interruptions in real time. With the help of dynamic decision-support technologies and predictive analytics, SC managers may react quickly to anomalies like unexpected spikes in demand, production hold-ups, or logistical bottlenecks. For example, scenario-based simulation models combined with real-time monitoring dashboards can facilitate rapid resource redistribution or inventory level recalibration. This approach assures that forecasting enhancements result in instant operational advantages, augmenting SCs' robustness and adaptability.

4. Materials and Methods

4.1 Survey Questionnaire and Responses

Fair Electronics' SC processes were mapped through a review of documentation and interviews with personnel across departments, providing insights into operational challenges. Data was collected through targeted questionnaires at three levels: technicians, supervisors, and management. Technicians identified operational hurdles and anomalies, supervisors highlighted planning and communication issues, and management provided a strategic view. The anomalies were categorized by type and impact, facilitating the prioritization of critical issues. The survey questionnaire and dataset are presented in this following link. (https://drive.google.com/drive/folders/19gJsWZM7QmgVnwzq-5mrcfCaXl_XP7o9?usp=sharing)

4.2 MCDM Method

The Multi-Criteria Decision-Making (MCDM) approach combined Weighted Linear Additive Utility (WLAU) and the Analytic Hierarchy Process (AHP) to evaluate anomalies. Ten criteria were identified, including Production Flow, Inventory Management, Demand Volatility, and Forecast Accuracy. Anomalies were grouped into two clusters: Operational Efficiency and Information & Demand Insights, with weights assigned to technicians (25%), supervisors (35%), and management (40%). Each anomaly was scored based on impact, and the rankings were used to identify the most critical areas for improvement.

4.3 ML Models

To address the prioritized anomalies, various ML models were selected based on the type of data and computational requirements:

- **ARIMA (Autoregressive Integrated Moving Average)**: A classical model for time series forecasting, capturing trends through autoregression and moving average components. It is useful for data that shows clear temporal patterns and requires stationarity.
- **XGBoost (Extreme Gradient Boosting)**: A high-performance decision-tree-based algorithm, ideal for handling complex, nonlinear relationships in data. XGBoost uses an iterative boosting approach, refining predictions by minimizing errors at each step.
- **LSTM (Long Short-Term Memory)**: A specialized recurrent neural network (RNN) designed to handle sequences by retaining long-term dependencies, making it effective for sequential data such as time series.
- **Prophet**: Developed by Facebook, this model excels at decomposing time series data into trend, seasonality, and event-based components (e.g., holidays), providing flexible and interpretable forecasting, even with irregular or missing data.

5. Results

5.1 Prioritization of anomalies

Table 1 presents the ranking of the identified SC anomalies. Cluster 2: Information & Demand Insights holds the highest priority, ranked 1, due to its substantial impact on adaptability, efficiency, and market responsiveness. Addressing these challenges requires implementing advanced forecasting models and scenario planning to improve flexibility. Enhancing data quality and improving forecasting models will further ensure the reliability of predictions. Empowering all levels of the organization with data-driven insights through comprehensive training is essential for informed decision-making.

Table 1 Priority evaluation through MCDM

Anomaly	Technician (1-5) (25%)	Supervisor (1-5) (35%)	Management (1-5) (40%)	Total Points (Weighted)	Rank
Production Flow and Efficiency	5 (1.25)	4 (1.4)	3 (1.2)	3.85	4
Inventory Management	5 (1.25)	4 (1.4)	4 (1.6)	4.25	3
Cluster 2: Information & Demand Insights	4 (1)	5 (1.75)	5 (2)	4.75	1
Cluster 1: Operational Efficiency:	4 (1)	5 (1.75)	4 (1.6)	4.35	2
Data and Information Access	4 (1)	4 (1.4)	3 (1.2)	3.6	5

Rank 2 is assigned to Cluster 1: Operational Efficiency. Tackling inefficiencies in resource allocation and risk management is critical for optimizing production and controlling costs. The key solutions involve integrating demand forecasts with inventory systems and adopting real-time data visibility tools to allow dynamic resource adjustments.

Inventory Management, ranked 3, should integrate solutions from Cluster 1 for a complete approach to optimizing inventory levels. Production Flow and Efficiency, ranked 4, would benefit from lean manufacturing practices and the implementation of proposed solutions in the higher-priority clusters. Finally, Data and Information Access, ranked 5, needs improvements in transparency and collaboration through centralized real-time data sharing.

4.3.1 Data collection and processing

Upon prioritization, emphasis was placed on actual sales data of three models of Samsung mobile phones from distinct market segments. Throughout the data collection process, ethical principles were strictly adhered to, and the confidentiality of the data provided by Fair Electronics was meticulously maintained. Necessary permissions and approvals were obtained to access and utilize the data for academic research purposes. Additionally, compliance with data privacy regulations was ensured, and any proprietary information shared by the company was treated with the utmost respect.

The dataset was found to be free of missing values. It was then divided into a ratio of 80:20, where 80% data were used for training, and the rest of testing. ‘StandardScaler’ was employed to normalize the sets.

5.2 Model evaluation

Initial visual analysis of the time series data revealed key patterns such as trends, seasonality, and residuals. The trend shows a general increase in sales over time, while seasonal variations reflect lower sales in the first half of the year and higher sales in the latter half. The residual analysis indicates minimal unexplained variation, highlighting the effectiveness of the trend and seasonal components in capturing sales patterns. To assess stationarity, ACF and PACF tests (Figures 2 and 3) indicated non-stationarity, with most spikes within significance thresholds. The Augmented Dickey-Fuller (ADF) test confirmed this, with an ADF statistic of 74 exceeding critical values at all levels.

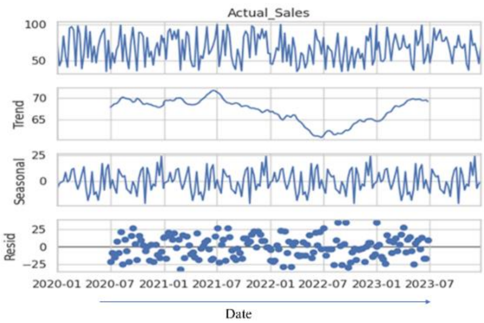

Fig.1 Sales over week graph, Trend, Seasonality and Residuals graph

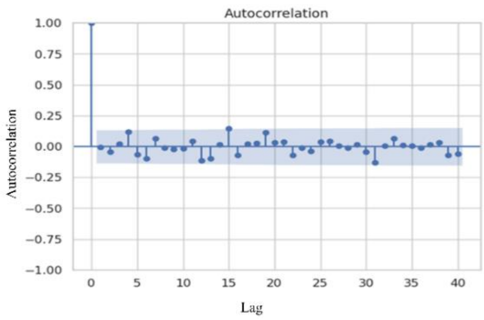

Fig.2 ACF plot

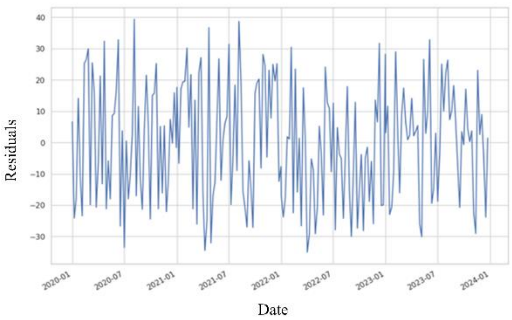

Fig. 3 PACF plot

Therefore, the null hypothesis of non-stationarity could not be rejected. Additional features, like quarter and week, were engineered to capture seasonality, and optional standardization using 'StandardScaler' was applied to ensure uniformity during model training.

Given the data's non-stationarity, the Auto ARIMA algorithm from the pmdarima library was used to find the optimal ARIMA model by minimizing AIC and BIC values. A custom ARIMA model (2, 0, 2) was also developed and found to fit the data well, matching the results from Auto ARIMA. The model's performance was validated through residual diagnostics, including the Durbin-Watson statistic, which confirmed no significant autocorrelation, indicating a good fit. Residual and QQ plots (Figures 4 and 5) further support the model's adequacy for forecasting.

The ARIMA model’s predictive accuracy is visualized in Figure 6, comparing actual and predicted sales from 2020 to 2023. An XGBoost regression model, optimized using a grid search and Time Series Cross-Validation (TSCV), is used to forecast sales, with results shown in Figure 7.

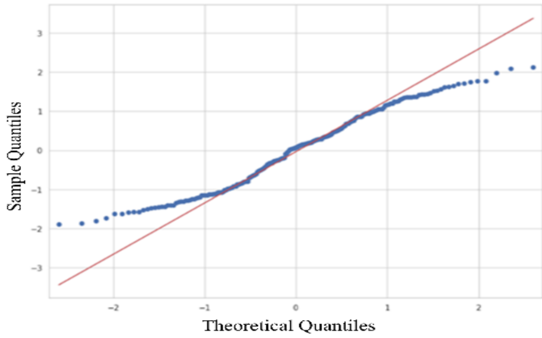

Fig.4 QQ plot

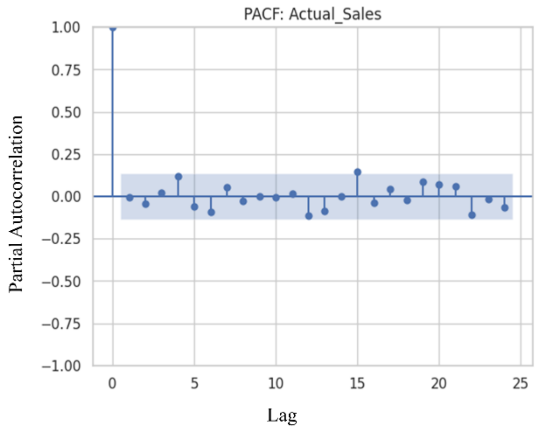

Fig.5 Residual graph

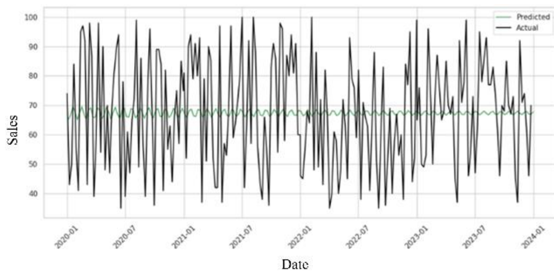

Fig.6 Actual vs Predicted Sales graph

Additionally, a Long Short-Term Memory (LSTM) network, trained on normalized data with two LSTM layers, predicts sales values. Figure 8 compares actual versus predicted values, highlighting the LSTM model's performance in capturing time series patterns. The Prophet model is used to forecast sales by capturing complex temporal patterns and seasonality. After adjusting the dataset to fit Prophet's requirements, the model was set to account for yearly, weekly, and daily seasonality. A future data frame with a 365-day prediction horizon was created, and forecasts were generated. Figures 9–11 visualize the overall forecast and its components, providing insights into sales trends and seasonality for strategic planning.

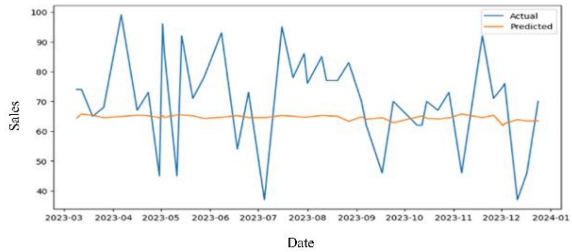

Fig.7 Actual vs Predicted Sales

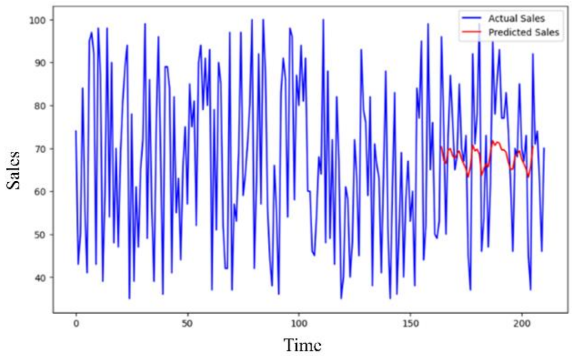

Fig.8 Actual vs predicted sales

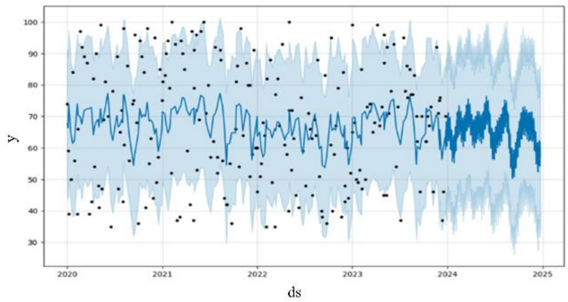

Fig.9 Sales forecast

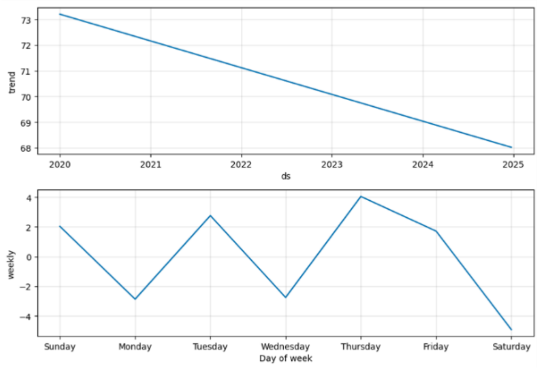

Fig.10 Different forecast components (trend and weekly sales)

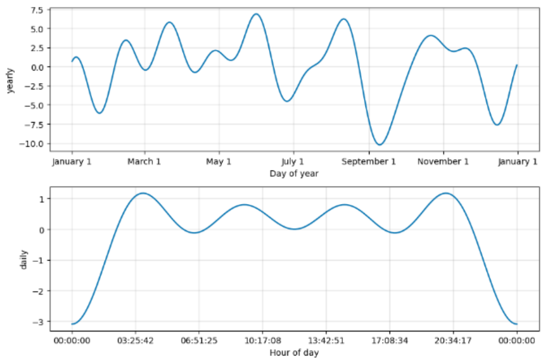

Fig.11 Different forecast components (yearly and daily sales)

The models' performance was evaluated using MAE, MSE, RMSE, and MAPE. As shown in **Table 2** (budget range), **Table 3** (midrange), and **Table 4** (flagship), XGBoost and ARIMA consistently outperformed LSTM and Prophet across all metrics, demonstrating lower error rates and superior predictive accuracy. XGBoost, with its flexibility to model nonlinear patterns and handle diverse datasets, was identified as the most robust and adaptable model for mobile phone sales forecasting, making it the preferred choice for this application.

Table 2 Model Performance on budget range Mobile Sales Data

Model	MAE	MSE	RMSE	MAPE
XGBoost	13.97	276.8	16.64	21.54%
ARIMA	13.58	267.08	16.34	22.57%
LSTM	67.15	4512.91	67.18	22.17%
Prophet	15.13	318.55	17.85	25.42%

Table 3 Model Performance on Midrange Mobile Sales Data

Model	MAE	MSE	RMSE	MAPE
XGBoost	14.06	283.3	16.83	21.20%
ARIMA	13.06	262.38	16.2	21.14%
LSTM	67.32	4536.84	67.36	21.50%
Prophet	15.33	325.69	18.05	26.05%

Table 4 Model Performance on Flagship Range Mobile Sales Data

Model	MAE	MSE	RMSE	MAPE
XGBoost	16.36	365.56	19.12	24.50%
ARIMA	15.77	348.81	18.68	24.93%
LSTM	67.01	4493.67	67.03	25.38%
Prophet	14.31	293.58	17.13	23.80%

6. Discussion

The proposed restructuring of Samsung Bangladesh's SC involves integrating advanced ML models, especially XGBoost, to enhance demand forecasting accuracy. With an accuracy of 72.18%, XGBoost improves inventory management, production scheduling, and procurement strategies, fostering collaboration with suppliers and minimizing stockouts.

This optimization leads to better production planning and distribution efficiency, ultimately reducing costs and increasing customer satisfaction.

The findings show the combination MCDM and ML models to mitigate supply chain irregularities that have been observed. Using MCDM methodologies, critical anomalies like inventory mismanagement and demand volatility were highlighted, and forecasting models were used to target them. XGBoost performed better than other models, which can reduce demand volatility through improved reliability of forecast, which advances inventory management, and optimize production scheduling. In addition to minimizing inefficiencies in resource allocation and reducing stockouts and overstocking, this approach can improve decision-making across supply chain activities and show notable operational improvements.

However, challenges include system compatibility, data management, and stakeholder training. Ensuring data quality is crucial, as market shifts or inconsistencies can affect performance, and ethical concerns regarding data privacy and algorithmic bias must be addressed.

7. Conclusion

Accurate demand forecasting is vital for optimizing Samsung Bangladesh's SC, minimizing costs, and improving customer satisfaction. The effectiveness of using MCDM and ML models to recognize, prioritize, and resolve SC irregularities was demonstrated in this study. The results highlight the potential of XGBoost, with 72.18% forecasting accuracy, in driving better inventory management, production scheduling, and procurement strategies. The company can improve its response to demand volatility and reduce resource allocation inefficiencies by employing MCDM to prioritize anomalies and applying sophisticated forecasting tools to resolve them. Adopting data-driven decision-making tools and real-time monitoring systems can also increase operational resilience by helping managers foresee and respond to disturbances more skillfully. To promote a culture of continuous improvement, this strategy highlights the significance of empowering SC stakeholders through training and access to useful insights.

To optimize the usefulness of the suggested framework, the study outlines a number of obstacles that must be overcome, such as problems with data quality, the complexity of system integration, and stakeholder resistance. For automated data collecting, cleansing, and validation procedures that guarantee data accuracy and consistency, Samsung Bangladesh should make an investment in centralized data management systems. Forecasting accuracy can be further increased by better transparency and real-time data sharing with SC partners. Furthermore, stakeholder training is necessary to give staff members the abilities they need to interpret ML-driven insights and swiftly carry out corrective measures. Incorporating scenario-based planning tools helps improve preparedness and agility by honing reactions to possible SC interruptions.

Future studies that investigate the combination of blockchain and IoT technologies can greatly improve Samsung Bangladesh's SC operations. While blockchain guarantees safe and transparent data sharing throughout the SC network, IoT sensors can offer real-time tracking of production and inventory variables. Improved anomaly detection and prediction accuracy may be possible with advanced ML models, especially hybrid systems that combine deep learning methods with conventional algorithms. Furthermore, forecasting and anomaly management frameworks that integrate sustainable practices like maximizing energy use and limiting waste can help operations match with environmental objectives. Development of real-time adaptive systems that can both anticipate disturbances and carry out corrective actions on their own, such adaptive production scheduling or dynamic rerouting in logistics, is another area of investigation. Samsung Bangladesh can ensure long-term competitiveness in a changing market by tackling these issues and achieving increased SC agility, operational efficiency, and sustainability.

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