The Impact of Supply Chain Delays on Inventory Levels and Sale Demand Fulfillment: Analyzing the Effects of Lead Times and In-Transit Quantities

A Quantitative Exploration of Logistics Efficiency and Inventory Optimization

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ABSTRACT

Efficient inventory management is essential for maintaining a balance between supply and demand in various industries. This research study aims to quantitatively examine the impact of supply chain delays, with a specific emphasis on lead times and in-transit amounts, inventory levels, and the ability to meet sales demands. Mathematical modeling and statistical analysis are utilized to create prediction models that assess the impact of variations in lead time and quantities in transit on inventory stability and fulfillment rates. The study used regression analysis to ascertain the relationships between the indicated parameters and inventory outcomes. Also, machine learning algorithms like Random Forest and Linear Regression are applied to predict possible disruptions and optimize inventory levels. The methodology followed focuses on the Tri-Model Fusion Stacking approach, which combines various models to improve the predicted accuracy and offer a more comprehensive analysis. The main goal of this research is to provide practical insights that help organizations optimize their inventory management techniques, resulting in cost reduction and enhanced service levels. The findings aim to simplify the modification of inventory management techniques in light of up-to-date supply chain information, providing a notable improvement in the resources available to supply chain experts.

Keywords-inventory management; supply chain delays; predictive analytics; machine learning; sales forecasting

I. INTRODUCTION

Proper inventory management is important in supply chain operations [1], since it aims to achieve both demand fulfilment and cost reduction. Still, this equilibrium is sometimes disturbed by supply chain uncertainties such as delays in delivery times and fluctuations in shipment amounts, resulting in notable difficulties involving shortages or overstock inventories. It is essential to understand and forecast the consequences of these disruptions in the supply chain on the levels of inventory. This research aims to meet this requirement by implementing the Tri-Model Fusion Stacking technique, which combines the predictive skills of Linear Regression (LR), Random Forest (RF), and Gradient Boosting Machines (GBM). This ensemble method in accordance with the utilization of real-world data not only enhance the accuracy of predictions, but also offer a comprehensive framework to manage the nonlinear difficulties frequently encountered in supply chain and inventory data, providing practical insights and strategic recommendations for organisations to enhance their inventory management procedures in the face of supply chain uncertainty. The Tri-Model Fusion Stacking method advances inventory disruption forecasting accuracy and robustness by merging various predictive models while it addresses supply chain and inventory data complexity and nonlinearities more precisely than single-model solutions. The Tri-Model Fusion Stacking methodology is specifically developed to be both robust and user-friendly, ensuring that it can be easily utilized by supply chain experts and data scientists. This strategy simplifies the analytical process by incorporating well-established data processing tools and automated Machine Learning (ML) algorithms. The utilization of well-known software tools and libraries, such as Python's scikit-learn and pandas, simplifies the execution and personalization of the models. Also, the presence of thorough documentation and a modular coding framework guarantees that users may easily customize the technique to different business scenarios and individual data requirements. The high level of user-friendliness greatly reduces the difficulty of implementing complex predictive analytics in practical inventory management situations. This, in turn, improves the quality of strategic decision-making and operational efficiency.

II. LITERATURE REVIEW

Authors in [2] explore the correlation between production management decisions and supply chain strategy to improve Supply Chain Integration (SCI) through supply chain digitalization. The subject matter involves strategic elements, such as product design, material selection, process design, and facility layout, as well as tactical considerations including production scheduling and quality management. Every part ends with suggestions for progressing SCI, highlighting the need of digitalization in achieving integrated supply chain operations. Authors in [3] worked presented the SSB model, which is a system dynamics model designed for multi-echelon supply chains. The model primarily focuses on financial features and ordering procedures, with a specific emphasis on analyzing the effects of payment delays on the financial performance of the supply chain. Conducted in the specific setting of food distribution in Morocco, the model detects notable impacts of payment delays on supply chain surplus, cash flow, and coordination. It also stresses the wider consequences of these delays on the overall economic performance of the supply chain. This approach offers practitioners and scholars unique perspectives on effectively managing financial difficulties in supply chain operations, allowing more informed decision-making. Instead of using individual organizational data to anticipate supply chain risks, authors in [4] propose a federated learning approach that permits collective risk prediction without exposing sensitive data. An empirical case study analyzes order delays among buyers sharing suppliers before and after the COVID-19 epidemic. Federated learning improves risk prediction, especially for purchasers with minimal data. Training data imbalance, disturbances, and algorithm choice greatly affect this technique. The study also shows that data-sharing or collaborative risk prediction may not benefit large order buyers. The balance between local and group learning paradigms in supply chain management needs additional study. Author in [5] discusses manufacturing supply chain interruptions caused by natural disasters, raw material shortages, regulatory changes, technological failures, labor concerns, transportation issues, and political instability. It emphasizes the importance of proactive risk management, technological investments, and stakeholder collaborations to improve supply chain resilience. These steps along with the deployment of holistic techniques help manufacturers manage disruptions and keep customers satisfied. Authors in [6] analyze how AI and ML optimize inventory management in online and offline buying. They demonstrate how ML, natural language processing, and computer vision help manage stock, supply handling, and other inventory issues with minimal human participation. These strategies have been successful at Amazon and Oracle, demonstrating their usefulness in meeting industry needs. AI transforms inventory management, facilitating firms estimate demand [7], detect anomalies, and improve operational efficiency, according to this study. Authors in [8] analyze Supply Chain Financing (SCF) financial risks, especially supplier liquidity crises due to late payments. This issue is addressed by developing and validating an XGBoost financial risk prediction model using buyer transaction behavior data. The study evaluates single and hybrid models utilizing ROC, AUC, and F1-Score measures. Model analysis also engages feature importance and PDPs. The results exhibit that the XGBoost model accurately predicts financial risks, providing insights into payment behaviors that could inform managerial decisions. This study adds to the small but growing collection of empirical studies on SCF financial risk management methods. A Vendor Managed Inventory (VMI) model for a complicated three-layer supply chain with numerous suppliers, manufacturers, and retailers is presented in [9] to manage defective and deteriorating products during production and storage. The model incorporates resupply cycles, production rates, order timings, and raw material production rates for products with ongoing deterioration and uncertain retailer demand. A joint optimization model maximizes the supply chain's benefit function by including order, degradation, holding, screening, manufacturing, disposal, and other operational costs. Manufacturers collaborate on inventory rules to reduce deterioration risks. The work deploys the Taylor series expansion to approximate exponential terms, and thus discovers optimal solutions, a methodological novelty. A dairy case study displays the model's effectiveness in handling perishable products and doing sensitivity analysis. The VMI approach improves retailer-manufacturer collaboration by following confidentiality policies to exchange sales estimates, operating expenses, and storage plans. This study lays the groundwork for future supply chain optimization research under complicated settings.

In [10], a data-driven evolutionary algorithm is added to supply chain digital twins to optimize inventory management within service restrictions. Supply chain digital twins have traditionally been utilized for scenario-based what-if assessments. This research differs by using digital twin historical data to save expenses and maintain service levels. RF algorithms build substitute models that estimate costs and service levels, which are optimized by a differential evolution algorithm and ensemble technique. This algorithm optimizes computation performance by adapting search methods. This strategy is proven to work with a three-echelon supply chain digital twin on a real-time GIS map. Experimental results reveal that the data-driven evolutionary algorithm decreases total costs and maintains service levels, suggesting it could improve inventory decisions based on historical data. This highlights the method's advancement in digital twin-based supply chain strategy. In [11], a distributionally strong optimization model is developed to improve assortment planning, inventory control, and e-fulfilment in omnichannel retailing. The model balances expected profit with risk exposure using a worst-case mean-Conditional Value-at-Risk (WMCVaR) to handle uncertain demand. Authors also estimate client time preferences using quasi-hyperbolic discounting. The model employs a box ambiguity set to make imprecise probability distributions easier to compute. Numerical studies corroborate the validity and efficiency of this approach and offer omnichannel retailers useful managerial insights, namely optimizing product offerings across online and offline channels and choosing the best fulfilment methods from distribution centres or physical stores. This comprehensive strategy gives a sophisticated tool to navigate modern retail settings. Authors in [12] present an enhanced inventory optimization model that captures supplier-repair shop purchasing dynamics to improve automotive repair shop inventory management. Traditional models ignore these linkages, causing inefficiencies and higher costs. The model includes realistic features like supplier-imposed minimum and maximum purchase amounts, changeable pricing, and supplier-specific buying situations utilizing binary variables. It reduces timing belt procurement costs by over BGN 2500 in a year compared to existing methods. This method saves money and optimises stock levels and cost-efficiency by aligning inventory management with automobile repair sector challenges. The study emphasizes the need to adapt inventory techniques to changing market conditions and supplier relationships, contributing to academic literature and industry practises. A supplier with stochastic production and delivery times and a manufacturer with variable on-site job processing times are studied in a two-stage decentralized project supply chain in [13]. The leader manufacturer sets the buffer time and early delivery requirements, while the follower supplier sets the production start time in a Stackelberg game. A delayed payment contract delays production start times under constant buffer conditions, but this effect changes when buffer time is flexible, as the study reveals. Results show no apparent preference for either party under all scenarios, contrary to early beliefs that suppliers would prefer non-delayed payment and manufacturers delayed payment. Central models may have higher on-time delivery probabilities, but they may not lower costs compared to decentralized models. The data also imply that solutions that work for single providers may not work for several suppliers, underscoring the complexity of decentralized supply chain contract and operation management. The influence of delays on human-computer decision-making in supply chain decision-making is often overlooked. In [14] a conceptual model is presented to measure the cumulative effects of human, interface, and computer delays on supply chain performance. The approach examines losses and improvement opportunities across strategic, tactical, and operational planning timeframes in an automotive manufacturer's digital planning framework. Simulations indicate that these delays can significantly impact supply chain efficiency. The report also presents a way to assess supply chain performance sensitivity to delays, highlighting important inefficiencies and optimizing decision-making. A differential equation model for supply networks with delivery time delays between nearby enterprises is presented in [15]. With this model, the bullwhip effect is revealed to be inherent in supply chains due to the combined impact of order fulfilment on order placement, proceeding towards consumer demand. When the end retailer's inventory decisions are proportional to consumer demand, consumer demand affects equilibrium stability. This shows the complex dynamics and interdependencies of supply chain management and the importance of time delays in supply chain stability. In [16], nonlinear dynamics theory is deployed to create a discrete dynamic model with temporal delays to study how market information delays and incompleteness affect supply chain decision-making. The paper defines necessary requirements for the model's local asymptotic stability and a time delay threshold, which supply chain players use to make decisions and assess system stability. The examination distinguishes manufacturers' static and dynamic quality strategies. It explores how CSR preferences and decision-making speed affect supply chain stability. The findings manifest that a dynamic quality approach and higher CSR preferences can reduce supply chain instability and improve member benefits. Strategic decision-making and CSR stabilize supply chain operations and improve performance in complex, information-delayed environments, according to this research.

III. METHODOLOGY

The dataset [17] implemented in this study includes detailed inventory management indicators, such as national_inv (current inventory level), lead_time (product transit time), in_transit_qty (number of products in transit), and numerous sales data points over different time periods. These data are essential for analyzing the effects of supply chain [18] variabilities on inventory efficiency. Table I lists the utilized abbreviations, which is a broader description of the fields employed in this dataset

TABLE I. ABBREVIATIONS OF DATASET USED

Name	Description
sku	Stock Keeping Unit (ID)
national_inv	Current inventory level for the part
lead_time	Transit time for product (if available)
in_transit_qty	Amount of product in transit from source
forecast_3_month	Forecast sales for the next 3 months
forecast_6_month	Forecast sales for the next 6 months
forecast_9_month	Forecast sales for the next 9 months
sales_1_month	Sales quantity for the prior 1 month time period
sales_3_month	Sales quantity for the prior 3 month time period
sales_6_month	Sales quantity for the prior 6 month time period
sales_9_month	Sales quantity for the prior 9 month time period
min_bank	Minimum recommend amount to stock
potential_issue	Source issue for part identified
pieces_past_due	Parts overdue from source
perf_6_month_avg	Source performance for prior 6 month period
perf_12_month_avg	Source performance for prior 12 month period
local_bo_qty	Amount of stock orders overdue
deck_risk, oe_constraint, ppap_risk, stop_auto_buy, rev_stop	Part risk flag (various operational risks)
went_on_backorder	Product actually went on backorder

A. Data Preparation

Handling Missing Values: The presence of missing data creates major challenges in the field of predictive modeling. Median approximation is a technique followed to handle missing values in continuous variables, such as lead_time. In this method, the missing values are replaced with the median value of the observed values.

$$Imputed\ Value = median\ (X) \quad (1)$$

where X represents the set of observed lead times.

Feature Engineering: New metrics are created to improve the understanding of inventory changes. The inventory turnover ratio is calculated to evaluate the efficiency of converting inventory into sales.

$$inventory\ turnover\ ratio = \frac{total\ sales\ over\ period}{average\ inventory\ level\ over\ the\ same\ period} \quad (2)$$

This ratio gives useful insights into the effectiveness of the inventory management systems.

Encoding Categorical Variables: Categorial data, such as the variable potential_issue, can be converted into a numerical format that is suitable for modeling. This is accomplished via techniques like one-hot encoding, where binary variables are assigned to each category.

Normalization/Standardization: In order to ensure that each feature has an equal contribution to the predictive models, Z-score normalization is applied:

$$Z = \frac{X-\mu}{\sigma} \quad (3)$$

In this case, X represents the original feature value, μ denotes the mean, and σ represents the standard deviation. The aim of this transformation is to normalize the distribution of each feature, which helps improve the learning process of the models.

B. Model Development and Integration

Linear Regression: An efficient and robust approach for discerning linear correlations between independent factors and the dependent variable. The model represents the target variable as a linear combination of the input features:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \quad (4)$$

where Y is the predicted outcome, β_n are the coefficients for each feature X_n, and ϵ is the error term.

Random Forest: The term "ensemble method" refers to a training procedure that involves building many decision trees and then producing a single class that represents the average prediction or mode of the classes from each tree:

$$Y = \frac{1}{T}\sum_{t=1}^{T} tree_t(X) \quad (5)$$

where T is the number of trees and $\mathrm{tree_t}$ is the prediction of the t^{th} tree.

Gradient Boosting Machines (GBM): This boosting method builds trees in a sequential manner, with each new tree aimed at rectifying faults committed by earlier constructed trees. The ultimate model is a combination of these trees, with each tree being assigned a specific weight.

$$GBM\ (X) = \sum_{t=1}^{T} \gamma_t tree_t(X) \quad (6)$$

where γ_t are the weights assigned to each tree, optimizing the overall predictive performance.

C. The Stacking Model

The Stacking Model in the Tri-Model Fusion Stacking technique employs the predictions generated by each base model (LR, RF, and FBM) as input characteristics for a meta-model. This technique is highly efficient in integrating the distinct capabilities of different models to enhance the overall prediction accuracy. During the process of stacking, the separate models are initially trained and subsequently used to generate predictions on the dataset. The predictions, instead of the original characteristics of the dataset, serve as inputs (features) for training a secondary model, known as the meta-model. This method seeks to combine the predictive skills of models, resulting in a reduction of bias and variation compared to utilizing a single base model.

1) Base Model Predictions

Let the predictions from each base model be denoted as:

- Let p_1 be the predictions from the LR
- Let p_2 be the predictions from the RF model.
- Let p_3 be the predictions from the GBM.

Each prediction vector p_i represents the forecasted output generated by the i-th model using the input attributes X.

2) Meta Model Training

The meta-model, usually acting as an LR in classification problems, is then trained on a fresh dataset consisting of these predictions. The training dataset for the meta-model can be described as:

$$X_{meta} = [p_1, p_2, p_3] \quad (7)$$

where $\mathrm{X_{meta}}$ is the feature matrix for the meta-model, consisting of predictions from each base model presented as columns.

3) Logistic Regression Meta-Model

The LR meta-model then gains the ability to forecast the ultimate outcome Y by utilizing this combined input. The logistic function used in LR can be expressed as:

$$P(Y = 1|X_{meta}) = \frac{1}{1+e^{-z}} \quad (8)$$

where z is the linear combination of the inputs (predictions from base models), given by:

$$z = \beta_0 + \beta_1 p_1 + \beta_2 p_2 + \beta_3 p_3 \quad (9)$$

where β_0 is the intercept, and β_1, β_2, and β_3 are coefficients associated with each set of predictions made by the LR model. The coefficients are obtained through the training process and define the significance or impact of each base model's predictions on the ultimate choice.

LR mixes the inputs in a manner that optimizes the probability of detecting the specified outputs in the training data. This allows it to successfully learn which models are more dependable or which combinations of models provide the best results. Through the process of training on these predictions, the meta-model is able to rectify any errors made by the different base models and make use of their respective strengths, resulting in predictions that are more precise and robust.

IV. RESULTS AND DISCUSSION

A. Analyzing the Data

During the preliminary examination of the proposed extensive inventory management dataset, comprising more than 590,000 records, the current study conducted a complex statistical analysis to better understand the distribution and attributes of each aspect. The dataset includes a diverse range of both quantitative and qualitative variables, which represent many elements of inventory and supply chain processes. The dataset was divided into 80-20 ratio, allocating 80% for training and 20% for evaluation. Figure 1 portrays the summary statistics of numerical columns.

```
                sku  national_inv      lead_time  in_transit_qty  \
count  5.920020e+05  5.920020e+05  555982.000000   592002.000000
mean   1.547195e+06  4.747630e+02       7.859321       42.244084
std    2.766031e+05  2.701051e+04       7.072300     1157.399442
min    1.026827e+06 -1.349100e+04       0.000000        0.000000
25%    1.259523e+06  4.000000e+00       4.000000        0.000000
50%    1.643994e+06  1.500000e+01       8.000000        0.000000
75%    1.791994e+06  8.000000e+01       9.000000        0.000000
max    2.041236e+06  1.233440e+07      52.000000   288960.000000

       forecast_3_month  forecast_6_month  forecast_9_month  sales_1_
count      5.920020e+05      5.920020e+05      5.920020e+05  592002.0
mean       1.784947e+02      3.486715e+02      5.104203e+02      55.9
std        4.928845e+03      9.812052e+03      1.446446e+04    2088.1
min        0.000000e+00      0.000000e+00      0.000000e+00       0.0
25%        0.000000e+00      0.000000e+00      0.000000e+00       0.0
50%        0.000000e+00      0.000000e+00      0.000000e+00       0.0
75%        4.000000e+00      1.200000e+01      2.000000e+01       4.0
max        1.218328e+06      2.446072e+06      3.760840e+06  741774.0

       sales_3_month  sales_6_month  sales_9_month       min_bank  \
count   5.920020e+05   5.920020e+05   5.920020e+05  592002.000000
mean    1.715000e+02   3.355569e+02   5.203141e+02      52.134951
std     4.926828e+03   9.287766e+03   1.451783e+04    1185.426716
min     0.000000e+00   0.000000e+00   0.000000e+00       0.000000
25%     0.000000e+00   0.000000e+00   0.000000e+00       0.000000
50%     1.000000e+00   2.000000e+00   4.000000e+00       0.000000
75%     1.500000e+01   3.100000e+01   4.700000e+01       3.000000
max     1.091281e+06   2.145715e+06   3.201035e+06  313319.000000

       pieces_past_due  perf_6_month_avg  perf_12_month_avg   local_b
count    592002.000000     592002.000000      592002.000000  592002.0
mean          2.202455         -6.992549          -6.577594       0.5
std         257.384058         26.752341          26.074621      35.7
min           0.000000        -99.000000         -99.000000       0.0
25%           0.000000          0.630000           0.660000       0.0
50%           0.000000          0.820000           0.810000       0.0
75%           0.000000          0.970000           0.950000       0.0
max      146496.000000          1.000000           1.000000   12530.0
```

Fig. 1. Summary statistics of numerical columns.

In this study, research was initiated by examining basic descriptive statistics, which exhibited significant variation in numerous important characteristics. The national_inv (national inventory level) had a broad spectrum of values, suggesting a variety of inventory levels across the products listed in the catalog. The summary statistics for lead_time, which represents the duration of product transit, demonstrated significant gaps, with more than 36,000 missing records as evidenced in Figure 2. This highlights probable problems in data collection or abnormalities in supply chain procedures.

```
print(train_data.isnull().sum())
print(test_data.isnull().sum())

sku                      0
national_inv             0
lead_time            36020
in_transit_qty           0
forecast_3_month         0
forecast_6_month         0
forecast_9_month         0
sales_1_month            0
sales_3_month            0
sales_6_month            0
sales_9_month            0
min_bank                 0
potential_issue          0
pieces_past_due          0
perf_6_month_avg         0
perf_12_month_avg        0
local_bo_qty             0
deck_risk                0
oe_constraint            0
ppap_risk                0
stop_auto_buy            0
rev_stop                 0
went_on_backorder        0
dtype: int64
sku                      0
national_inv             1
lead_time            14725
in_transit_qty           1
forecast_3_month         1
forecast_6_month         1
forecast_9_month         1
```

Fig. 2. Missing values.

The substantial number of missing values in the lead_time variable was solved by employing several imputation approaches. The goal was to ensure the integrity of the introduced predictive modeling in the future. The decisions on imputation were based on additional exploratory data analysis, which involved studying the distribution of missing data across various product categories and time periods. The Distribution Analysis disclosed that the histograms for numerical features, such as sales_1_month, sales_3_month, and sales_6_month displayed highly skewed distributions with extended tails as observed in Figure 3. This suggests that a limited number of products are responsible for very large sales volumes. The presence of such asymmetry presents difficulties for modeling and has been solved by applying logarithmic adjustments to equalize the distribution of data, hence improving the reliability of subsequent analysis. Correlation analysis was also deployed to determine the links between features, specifically examining how sales projections are related to actual sales data. Initial results revealed robust associations between short-term sales numbers and inventory levels, suggesting potential predictive connections that could be utilized to enhance inventory management strategies. By deploying precise graphs, such as box plots and histograms, anomalies in several significant measurements could be detected. In this case, the perf_6_month_avg and perf_12_month_avg scores, which assess historical performance, exhibited unusually low values that may suggest either data input mistakes or actual performance problems as exhibited in Figure 3. The outliers were evaluated for their influence on the entire dataset and handled appropriately to provide precise analyses.

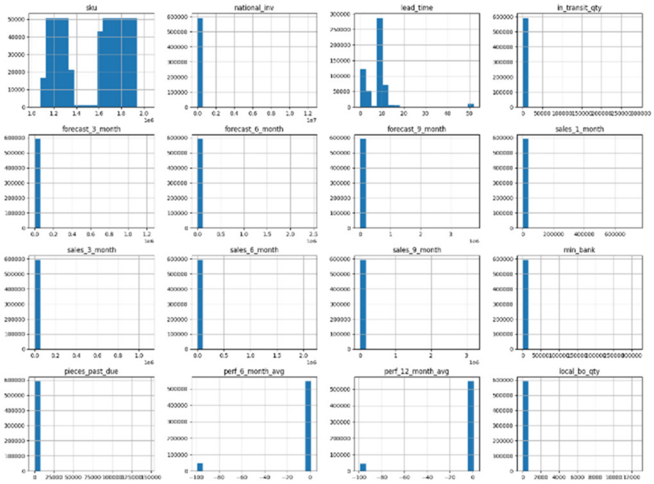

Fig. 3. Histograms of numerical data.

The boxplot examination of many attributes, including national_inv, in_transit_qty, and sales-related data such as sales_1_month, sales_3_month, sales_6_month, and sales_9_month, indicated the presence of notable outliers. Outliers are data points that deviate significantly from the upper quartiles, indicating very high values in comparison to the usual range of data. These abnormalities may suggest exceptional scenarios such as large-scale transactions or mistakes in data input. The data for lead_time disclosed a notable clustering around lower values, with a few outliers indicating exceptionally long lead times as shown in Figure 4. These scenarios may indicate either inefficiencies in the supply chain or particular situations where parts or products have significantly longer manufacturing or delivery cycles.

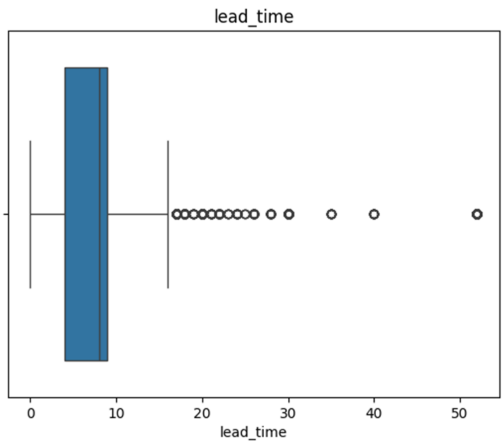

Fig. 4. Box Plot for lead_time checking outliers.

The variable national_inv manifested a substantially skewed distribution, with several inventory levels reaching into the tens of millions, which strongly contrasted with the remainder of the data Figure 5. This could indicate several products with unusually high stock levels, which might affect average inventory calculations and suggest potential problems with overstocking.

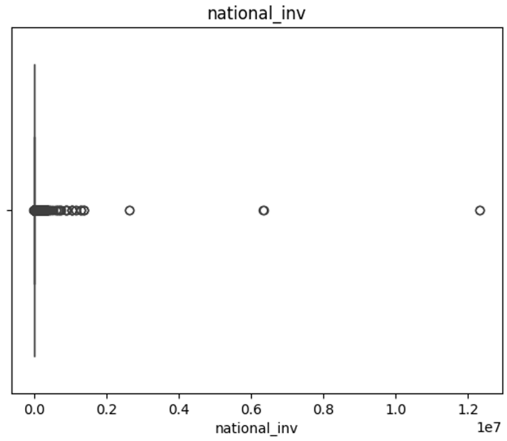

Fig. 5. Box Plot for national_inv checking outliers.

The forecasts (forecast_3_month, forecast_6_month, and forecast_9_month) exhibited a noticeable skewness, with outliers suggesting excessively optimistic projections or maybe seasonal bulk orders that vary from regular operations as noticed in Figures 6-8. Also, the sales factors showed significant variation, and the presence of outliers could possibly skew demand planning and inventory management methods.

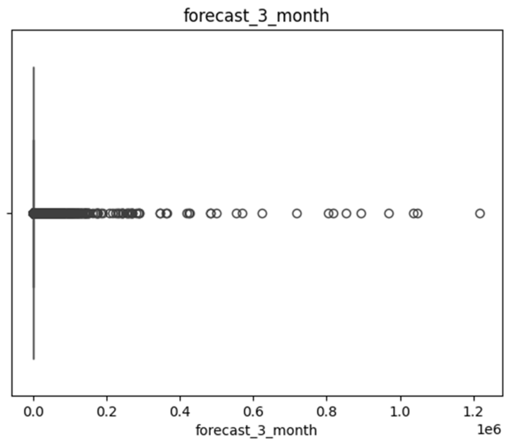

Fig. 6. Box Plot for forecast_3_month checking outliers.

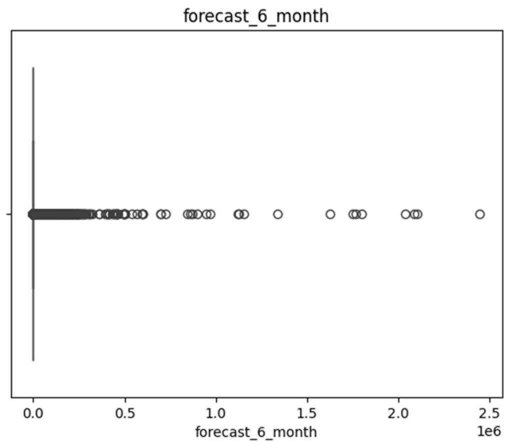

Fig. 7. Box Plot for forecast_6_month checking outliers.

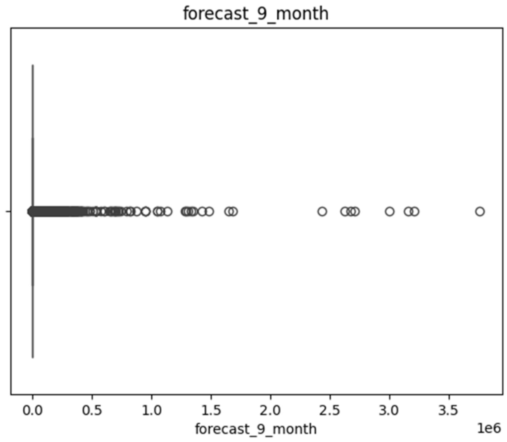

Fig. 8. Box Plot for forecast_6_month checking outliers.

The presence of outliers in performance indicators, such as perf_6_month_avg and perf_12_month_avg, including occasional negative values, displayed possible problems with the supplier performance rating system or abnormalities in data acquisition, presented in Figure 9. Unless explicitly permitted by the scoring system, negative performance scores may signal data integrity issues that require attention.

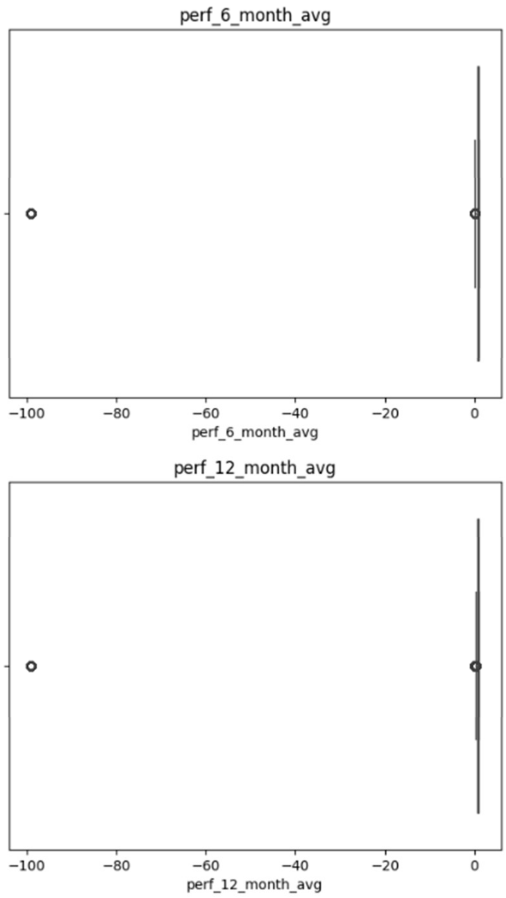

Fig. 9. Box Plot for perf_6_month and perf_12_month avg checking outliers.

The presence of local_bo_qty outliers indicates that specific items are consistently unavailable, perhaps leading to lower customer satisfaction and highlighting issues with inventory management or demand prediction.

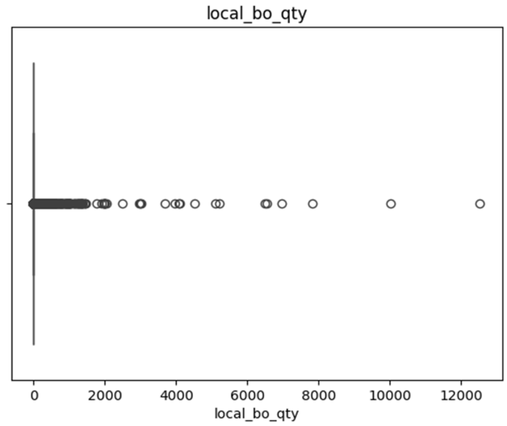

Fig. 10. Box Plot for local_bo_qty checking outliers.

The presence of these exceptional data points emphasizes the necessity for thorough data cleaning and preprocessing prior to modeling. In order for predictive analytics and machine learning models to be successful, it is essential to understand and deal with these outliers, as they can have a substantial impact on model accuracy and the capacity to interpret the results.

The correlation heat map displayed in Figure 11 gave numerous robust associations between forecast variables and sales measures, suggesting a significant level of interdependence. For instance, the projections for forecast_3_month, forecast_6_month, and forecast_9_month demonstrated strong relationships with each other, which is expected given that they are sequential time-based predictions. Moreover, robust correlations were detected between sales_1_month, sales_3_month, sales_6_month, and sales_9_month, indicating that the sales performance in the recent past can effectively forecast sales in the near future. There is a moderate association between the national_inv and the min_bank, suggesting that larger inventory levels are slightly linked to higher minimum stock needs. This could showcase a strategy to prevent running out of stock. The lead_time had a weaker link with inventory levels, but a stronger correlation with in-transit amounts. This implies that longer lead times may require bigger quantities in transit in order to uphold service standards. Further exploratory data analysis was conducted using pairplots as shown in Figure 12 to visually examine the correlations suggested by the correlation analysis. The visual analysis revealed:

- Lead_time clusters vs sales and forecast metrics which suggests data categories that act differently, such as product or supplier categories.
- Plots showing went_on_backorder data points, which demonstrates how rarely products go on backorder, an important fact for predictive modeling. Class imbalance is visible and will need to be corrected in model training.

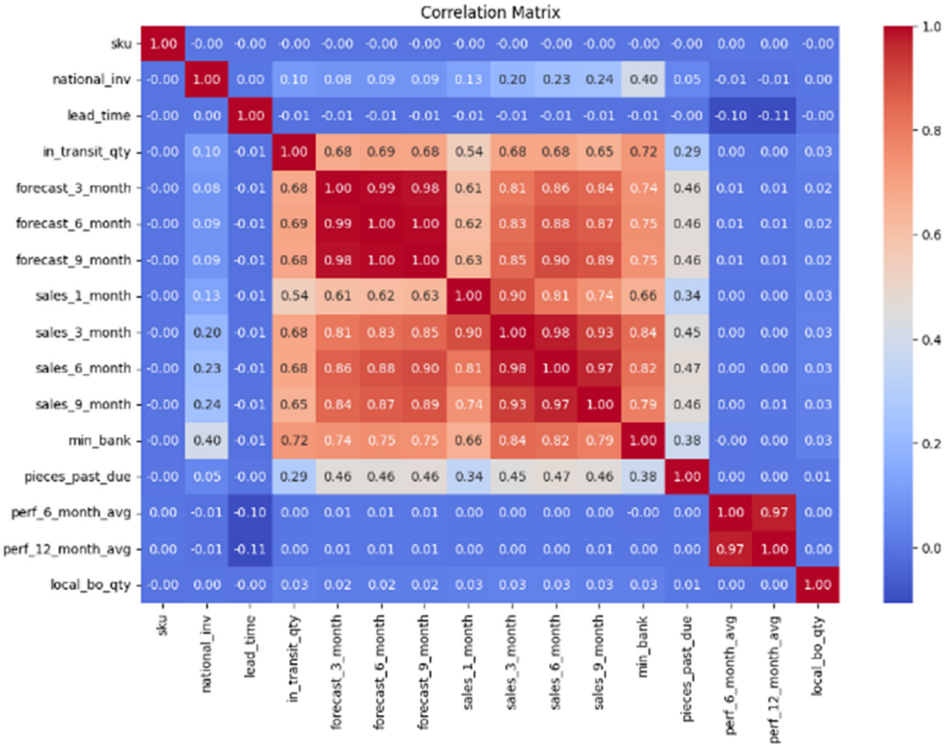

Fig. 11. Correlation heat map.

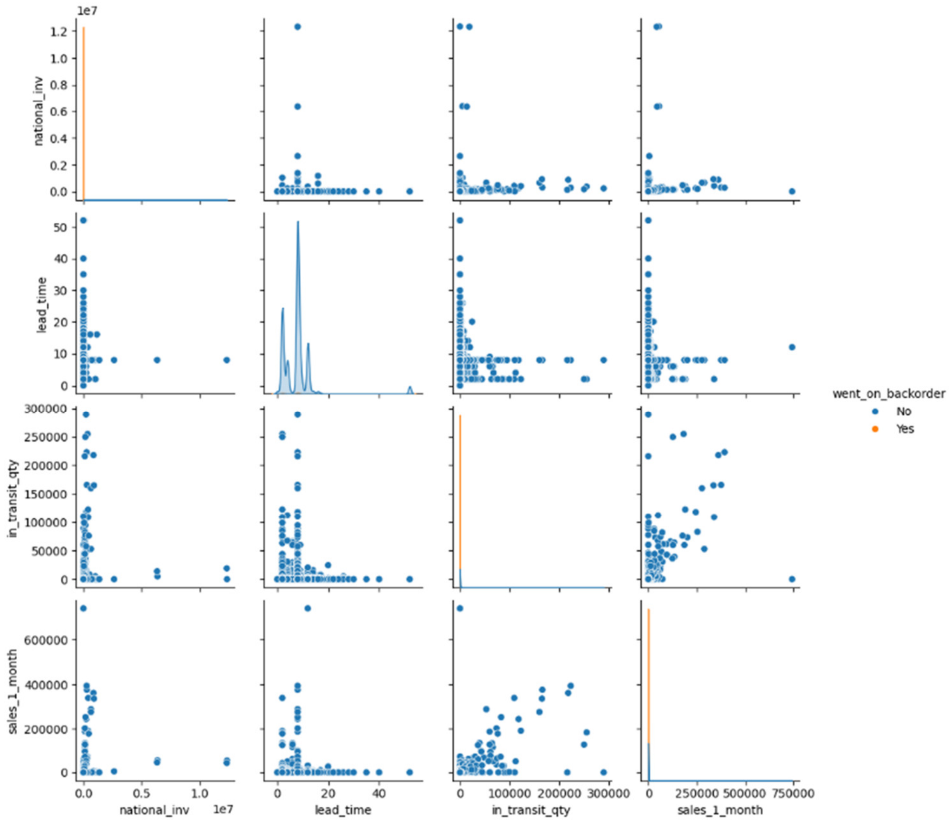

Fig. 12. Pair Plot for a subset of features to see relationships.

The plots presented in Figure 12 also visually confirmed the presence of outliers and their distribution throughout the dataset, highlighting the importance of meticulous data cleaning and potentially employing robust modeling strategies to manage extreme values without compromising the predictive modeling process.

The knowledge obtained from the correlation heatmap and pairplots is essential for selecting features in predictive modeling. The robust correlations discovered indicate that dimensionality reduction techniques, such as Principal Component Analysis (PCA) or feature selection based on correlation thresholds, could be successful in streamlining the model while retaining substantial predictive capability. Comprehending these connections helps to develop hypotheses on causal links and possible overlap across variables, which is necessary when evaluating model outputs and making well-informed decisions based on model predictions. These studies improve the understanding of the dataset and provide guidance for the later stages of developing predictive models, ensuring that the models are both effective and easy to interpret. This strategy is in line with the objective of maximizing inventory efficiency and enhancing forecast precision, ultimately leading to improved inventory control and decreased operational expenses.

B. *Final Results*

The proposed model utilized a sequence of steps that combined several data preparation approaches and a stacked ensemble of classifiers. The procedure concluded with the implementation of a logistic regression model to generate final predictions. The implemented model included an MLg pipeline, as portrayed in Figure 13, containing various essential components with the goal of enhancing its predictive performance:

- The preprocessing steps involved a ColumnTransformer that independently processed numerical and category information. Missing values in the numerical data were replaced with the median, and the data were standardized using StandardScaler to guarantee consistent scaling. The missing values in categorical variables were replaced with a placeholder and then the variables were transformed utilizing OneHotEncoder. OneHotEncoder is a technique that deals with non-numeric data by producing binary columns for each category.
- The primary predictive model deployed in this study was a stacking classifier, which integrated the predictions generated by three separate algorithms: LR, RF, and GBM. The selection of each base estimator was based on its specific capabilities in addressing distinct features of the data. LR was chosen as a linear baseline, RF was selected for its ability to handle overfitting, and GBM was employed to optimize loss reduction in a sequential fashion. The final predictions were produced utilizing a LR model, guaranteeing a balanced technique to evaluate the results from each fundamental model.

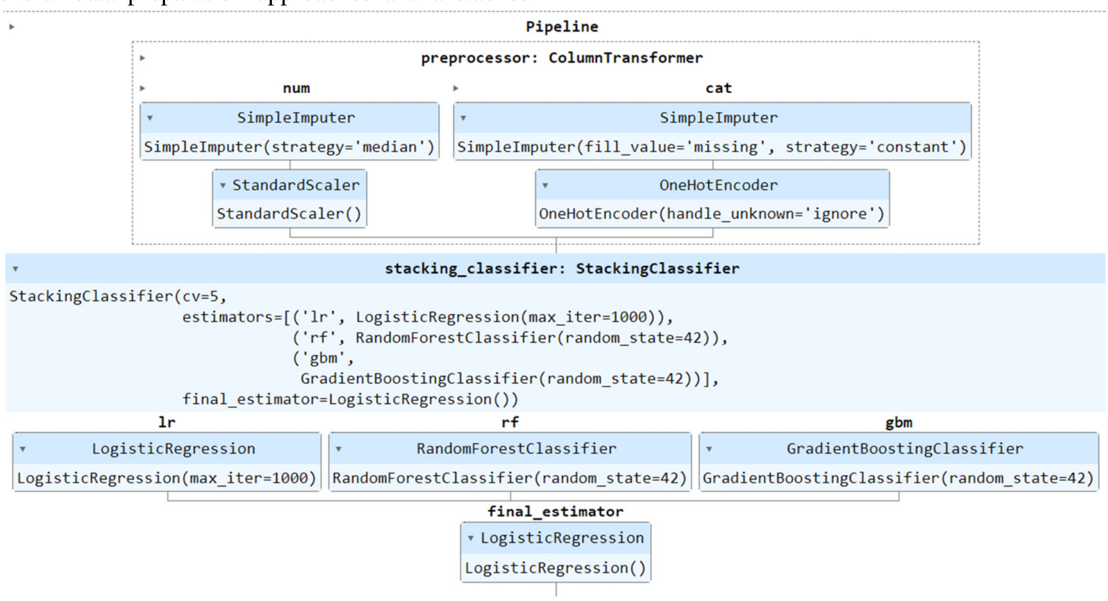

Fig. 13. Pipeline.

Through the conducted comprehensive research and further modeling, the predicted accuracy of the stacking model was thoroughly analyzed. The categorization metrics and Receiver Operating Characteristic (ROC) curve gave valuable insights into the performance of the proposed technique.

The classification report in Table II disclosed the model's observable performance variations among several classes, highlighting significant discrepancies in predicting occurrences of went on backorder, the major event of interest. The findings revealed:

- The model demonstrated a high level of precision, specifically 0.99, in predicting items that would not go on backorder. This indicates a strong capability to accurately detect true negatives. However, the recall rate for the positive class (products that were backordered) was just

0.38, displaying difficulties in accurately identifying all possible instances of backorders.

- Challenges in accurately detecting all true positive cases were exhibited by the model's lower recall of 0.11 for backorders. This manifests a preference for making cautious predictions about non-backorders, which could result in lost chances to prevent true backorder situations.

TABLE II. CLASSIFICATION REPORT

	Precision	Recall	F1-score	Support
0.0	0.99	1.00	0.99	239387
1.0	0.38	0.11	0.17	2688
Accuracy			0.99	242075
Macro avg	0.69	0.55	0.58	242075
Weighted avg	0.98	0.99	0.98	242075

The ROC curve, which is an essential metric for evaluating model performance, showed a remarkable Area Under the Curve (AUC) value of 0.91, as depicted in Figure 14. This indicates that the model had a robust ability to distinguish between different classes at different threshold levels. The high AUC value suggests that the model is successful in accurately differentiating between cases of backorder and non-backorder, given the appropriate adjustment of the classification threshold.

The implications of the ROC curve are that although the AUC suggests the model performs well overall, the accuracy and recall metrics reveal an imbalance. This imbalance is likely to exist due to the algorithm's tendency to be cautious in predicting the majority class, which stresses the importance of improving the model's ability to detect the minority class. This can be achieved by incorporating advanced techniques like SMOTE (Synthetic Minority Over-sampling Technique) to balance the distribution of classes or by using cost-sensitive learning to assign greater penalties for misclassifying the minority class.

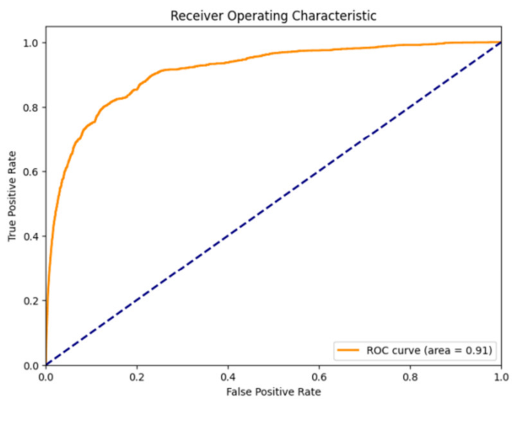

Fig. 14. ROC curve.

The difference between a high AUC and the specific difficulties in achieving precision and recall for backorders emphasizes the complex nature of predictive modeling in inventory management. The results show that the proposed model exhibits strong overall performance.

V. CONCLUSION AND FUTURE WORK

The analysis performed on the effects of supply chain delays on inventory levels and the fulfilment of sales demand revealed numerous important results. After carrying out a thorough research, it became clear that the duration it takes to receive orders and the amount of goods in transit have a major effect on the stability of inventory and the ability to meet sales needs. The ensemble of machine learning algorithms used in the predictive model successfully identified the complex connections between inventory management variables. However, it also identified certain areas where the predictive performance may be enhanced. By considering these criteria, organizations can enhance their ability to forecast probable backorders and adapt their inventory management methods accordingly, resulting in improved operational efficiency and cost reduction by minimizing excess inventory and stockouts.

In the future, there will be a chance for expanding this research by incorporating more detailed data from other market categories and geographical regions. This might provide more precise information about regional supply chain dynamics and local market demands. Incorporating real-time data analytics into this study approach has the potential to significantly enhance the agility of supply chain operations. This would enable more flexible adjustments to inventory levels in response to current market trends and urgent interruptions in the supply chain. Future research might look into the incorporation of sophisticated machine learning methods, such as deep learning, to improve the precision of predictive models, particularly in complex situations that involve extensive datasets with significant variability. These developments will enhance the accuracy of predictions and make a substantial contribution to the existing knowledge in supply chain management. They will provide strong solutions to current difficulties.

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