Management Systems in Production Engineering

2024, Volume 32, Issue 3, pp. 345-356

Date of submission of the article to the Editor: 03/2024
Date of acceptance of the article by the Editor: 07/2024

DOI 10.2478/mspe-2024-0033

MACHINE LEARNING FOR PROACTIVE SUPPLY CHAIN RISK MANAGEMENT: PREDICTING DELAYS AND ENHANCING OPERATIONAL EFFICIENCY

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Abstract:
Supply chain (SC) efficacy and efficiency can be severely hampered by supplier delays in orders, especially in the fast-paced business environment of today. Effective risk reduction necessitates the identification of suppliers who are prone to delays and the precise prediction of future interruption. Accurately predicting availability dates is therefore a key factor in successfully executing logistics operations. By leveraging machine learning (ML) techniques, organizations can proactively identify high-risk suppliers, anticipate delays, and implement proactive measures to minimize their impact on manufacturing processes and overall SC performance. This study explores and utilizes various regression and classification ML algorithms to predict future delayed delivery, determine the status of order deliveries, and classify suppliers according to their delivery performance. The employed models include K-Nearest Neighbors (KNN) Random Forest (RF) Classifier and Regression, Gradient Boosting (GB) Regression and Classifier, Linear Regression (LR), Decision Trees(DT) Classifier and Regression, Logistic Regression and Support Vector Machine (SVM) Based on real data, our experiments and evaluation metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) demonstrate that the ensemble based regression algorithms (RF Regression and GB Regression) provide the best generalization error and outperforms all other regression models tested. Similarly, Logistic regression and GB Classifier outperforms other classification algorithms according to precision, recall, and F1-score metrics. The knowledge obtained from this study could aid in the proactive identification of high-risk suppliers and the application of proactive actions to increase resilience in the face of unanticipated disruptions, in addition to increasing SC efficiency and decreasing manufacturing disturbances.

Key words: *SC risk management, order delay, machine learning, SC disruption, supplier performance*

INTRODUCTION

The SCs of today function in a very competitive and dynamic context. Companies are always looking for methods for improving their processes and raise customer satisfaction levels because they are always changing [1]. Delayed demand is an issue that SCs encounter, when a good is not provided in the planned period of time. Numerous factors, such as unanticipated changes in customer preferences, production delays, or issues with shipping and receiving, could cause delay.

On-time delivery of order-related products is a key success factor for companies. Ensuring a high level of delivery reliability remains a top priority for manufacturers and, along with costs and quality, is among the most important prerequisites for a successful standing in global competition [2]. The rising complexity of SC means that disruptions that affect an organization are not always the same and might evolve over time. Additionally, each organization should proactively rather than reactively identify the disruption events influencing it in order to guarantee that the SC's objectives are not affected [3]. Production setbacks, inventory imbalances, higher expenses, unsatisfied customers, and SC interruptions can all result from SC delays. Manufacturing processes may stall or slow down when necessary, components are delayed, which could result in backlogs. On the other side, delays in component delivery could result in an excess of inventory buildup and a demand for funding and storage space. Rush orders and expedited shipment could be required in order to reduce delays, which would result in additional costs. Extended lead times and postponed delivery may irritate customers, which could hurt sales and the company's reputation. Delays can also affect downstream partners like retailers and distributors, exacerbating SC disruptions.

Risk managers can create prebuilt strategies by using proactive SC disruption risk events identification to either manage or enhance resilience against them. But it takes time to manually detect such dangers proactively. Therefore, an automated approach that is responsive and flexible in disruption risk event recognition is needed to support risk managers. Because of these technological advancements and the influence of smart gadgets, decision-making procedures in the business world have evolved. Due to this shift, conventional methods of decision-making are no longer suitable. These days, analyses must account for an excessive number of factors and large amounts of data related to these variables. This opens the door to SC risk identification's use of artificial intelligence (AI) models. ML algorithms, one of the popular applications based on AI, make these analyses possible.

Companies are looking to ML algorithms to help them deal with the problem of delayed demand in SCs. According to [4] ,these algorithms have the ability to examine past data, identify patterns and trends, and forecast future demand. Companies that use ML can learn more about the causes of delayed demand and take proactive steps to address them. Additionally, organizations can use ML algorithms to more accurately predict delayed demand, which will allow them to modify their production schedules and control inventory strategies as necessary. Companies may enhance their capacity to manage demand delays and optimize SC processes.

Upon reviewing the literature, it becomes evident that the topic of order delay forecasting has limited examples of ML techniques being applied. For this reason, ML is used to handle the problem of order delay and supplier delivery performance predictions across various products and data types, employing a range of regression and classification models. Our study aims to fill a significant gap in the literature on SC risk and offers SC managers a valuable tool for anticipating delayed deliveries and assessing supplier delivery performance. This contribution could provide insights into the future of the global SC, especially considering the growing interest in leveraging ML approaches to transform SCs.

Our work is outlined as follows. We first give a review of the literature. Then, we go into further depth about our approach, and dataset that were employed for prediction. The ML techniques that were evaluated to estimate delivery delay and status are introduced. Then, using several statistical key performance indicators, we assess both the regression and classification models of our experiments. Finally, we provide a summary of our findings and discuss possible avenues for further research in the conclusion.

LITERATURE REVIEW

In this section, we examine papers relevant to our research. Given the global SC disruption experienced after 2020, numerous studies have focused on SC resilience. The areas investigated in the context of SC resilience, spans various sectors from healthcare [5, 6] to food [7] and manufacturing [8], banking [9], performance measurement [10]. Recently, there has been a notable surge of interest in the utilization of ML in SC and logistics, in order quantity forecasting, and order delay [11].

[12] conduct a survey study delving into the papers that specifically address the integration of ML and AI in SC risk management. They also identify gaps that remain underexplored for future research directions [13] presented a customer relationship management approach that uses a SVM based system to learn patterns and identify the risk of churn [14]. Used neural networks and intelligence reconnaissance to create a deep learning-based geological disaster identification model. ML was also used by [15] to identify anomalies and anomalous operations and assess their effects on flight safety [16] presented a novel approach that use an artificial neural network (ANN) for SC risk assessment, improving companies' capacity to recognize, anticipate, and address a range of hazards that may affect their efficacy, resilience, and efficiency [17] work on demand forecasting within the pharmaceutical SC. They design a novel demand forecasting framework that collects time series data across various products and employs pattern recognition algorithms. Additionally, [18] employ deep reinforcement learning, to address a production planning and distribution challenge within a multi-echelon system. They formulate the problem using Markov-decision process and non-linear optimization to capture uncertainty in lead times. Numerous research has been done in this area, and it is anticipated that lead times will strongly correlate with product availability dates. While [19] create an Auto ML system that is coupled with an ERP system to produce accurate forecasts for modifiable in order to predict supplier lead times, [20] suggest an innovative hybrid AI-based decision support system. To the best of our knowledge, [21] carried out the study that employ multiple regression models to forecast the dates of product availability for incoming shipments.

With the same objective of predicting risk in the SC, [22] using historical data from a publicly accessible data repository to train ML algorithms. The models under consideration are the Gaussian Naïve Bayes algorithm, the logistic regression technique, and the random forest classifier algorithm. Next, k-fold cross-validation was used to validate the training models. To determine the best predictive model for the delivery risk prediction problem, the study offers a comparison analysis utilizing performance indicators on the test data, such as receiver operator characteristics (ROC), precision, recall, and F1-score. In general, the random forest model performs well according to a variety of measures. In the eCommerce industry, [23] attempted to predict the risks of delayed deliveries by analyzing past data using ML techniques. They assessed a number of algorithms, including Random Forest, XGBoost, Light GBM, and Logistic Regression, and they concluded that the hybrid approach – which combines all of these models – outperforms other ensemble and individual methods in terms of F1-score, accuracy, specificity, and precision.

[24] They offers three significant contributions: They start by creating a regression model using ML to estimate the severity of supplier delivery delays will be. Secondly, they show that forecasting can be done at the preliminary stages of the buying process. Thirdly, they demonstrate that the dimensionality of high-dimensional input features does not need to be decreased.They demonstrates that a regression algorithm-based prediction model can accurately forecast the degree of supplier delivery delays in a low-volume, high-variety machinery manufacturer's representative case study [25]. In order to anticipate package delivery delays, they tested the performance of a gradient boosting machine (GBM) and an ANN. The F1-score for the relevant class, which represents the required and delayed data points, is used to evaluate the models.
[26] They addresses an unequal class issue in which there are comparatively few orders with delivery risk in relation to those without. The chosen performance metric for the suggested risk prediction problem is the Area Under the Curve (AUC) score. An AUC score of 0.80 indicates that the Random Forest model in the Synthetic Minority Oversampling Technique (SMOTE) with the Tomek link performs better, according to a comparison analysis. Additionally, they discovered that KNN works well in the random oversampling methodology, whereas the Random Forest model performs better in the SMOTE and SMOTE Tomek oversampling methods [27] leverage big data and ML to build a prediction model that predicts late deliveries before they happen. The Dataco SC dataset was employed in the study, and various categorization ML techniques were used to clean, display, and train the dataset [28] Their study offers a novel approach to forecasting the potential of SC delivery delays. Five different deep learning models were used in the framework they presented, including Generative Adversarial Network (GAN), Convolutional Neural Network Long Short-Term Memory (CNN-LSTM), Ensemble learning via bagging, and Ensemble learning [29] developed a predictive model for order delivery delays based on ML. They uses a dataset from a public source, and the performance metric chosen to assess the prediction model is AUC score [30] They utilized ML algorithms to predict the potential of late delivery of a customer's order. It appears as an examination of three Feature Selection situations and Random Forest Classifier algorithms' respective performances.
Despite efforts to manage delayed deliveries, there remains a significant research gap in this domain. This study aims to address this gap by employing a range of regression and classification models across various products, to anticipate delayed deliveries and evaluate supplier delivery status. By leveraging ML models, our study seeks to provide valuable insights to SC managers, empowering them to anticipate and mitigate the risks associated with delayed deliveries and evaluate supplier performance proactively. Ultimately, this research endeavors to equip managers with a robust toolset to navigate SC complexities effectively.

METHODOLOGY

Problem statement

SCs are complex networks made up of numerous stakeholders any disruption to this network, such a postponed order or shipment, may have an impact on the SC ecosystem as a whole. Consider a multinational automotive manufacturer that gets its raw materials and components from a wide range of sources, if one of their important suppliers, who supplies multiple components, is delayed as a result of unanticipated events like production line malfunctions or material shortages. As a result, this throws off the manufacturer's production plan, delaying the assembly of automobiles and the completion of customers' orders. To manage these challenges, the manufacturer can employ advanced predictive modeling methods to pinpoint suppliers that are most likely to experience delays and anticipate potential disruptions. Delivery delays can be predicted using supplier performance, order item specifics, and shipping information, as well as historical shipment data analysis and supplier performance indicators (e.g., delivery status of orders, categorizing them as on-time, late, advanced, or canceled). Predictive models can be used by the manufacturer to anticipate supplier reliability and to proactively control risks. Advanced ML algorithms, can reveal intricate patterns and relationships in our dataset, allowing for more precise predictions for manufacturer supplier management. The purpose of this research study is to analyze and predict delivery delays, evaluate supplier performance within a SC to improve operational efficiency and customer satisfaction. To accomplish this task, we follow the steps outlined in the flowchart Figure 1.

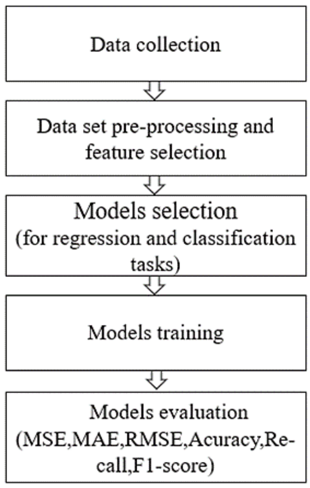

Fig. 1 The overall steps followed to predict supplier performance

Data set pre-processing and feature selection

We employed the manufacturer's database has past information about delivery delays.as Table 1 provides an extensive overview of all the essential variables related to order processing and transportation in our dataset.

Table 1
Dataset explanation

Variables	Description	Type
Supplier name	The name of the supplier	Categorical
order_date	Date and time when the order was placed	Date/Time
Days for shipping (real)	Actual number of days it took for the order to be shipped	Integer
Days for shipment (scheduled)	Scheduled number of days for shipment	Integer
Delivery Status	Status of the delivery (e.g., Advance shipping, Late delivery, Shipping canceled)	Categorical
Order Country	Country where the order was placed	Categorical
Order Item Cardprod Id	Identifier for the product or item in the order	Integer
Order Item Product Price	The price of the product or item included in the order	Numeric
Order Item Quantity	Quantity of items in the order	Integer
Shipping Mode	Mode or method of shipping (such as Standard Class or First Class)	Categorical
delay	Categorical variable indicating whether the shipment was delayed (-1), on time (0), or delivered ahead of schedule (1).	Integer

It is an invaluable resource for comprehending important order management information, such as shipping details, delivery statuses, and processing times. We look for missing values in the dataset and address them throughout the data preprocessing phase. This ensures that the data is reliable, and suitable for training. To improve the prediction power of the models, we identify the key elements that are most relevant for predicting delivery status and delayed delivery.

In Figure 2, we use a count plot that shows the count of observations in each category of a categorical variable, giving an average day for shipping with a delivery status in late delivery 4 days, 3 days as an average day for advance shipping.

To identify the most correlated variables, we utilize Cramér's V statistic in Figure 3, which measures the association between two categorical variables: 'Delay' and each of the other variables ('Delivery Status', 'Days for shipping (real)', 'Days for shipment (scheduled)'). A higher correlation coefficient of 0.8 signifies a strong positive association between 'Delivery Status' and 'Delay'. This positive value implies that certain delivery statuses are more prone to causing delays.

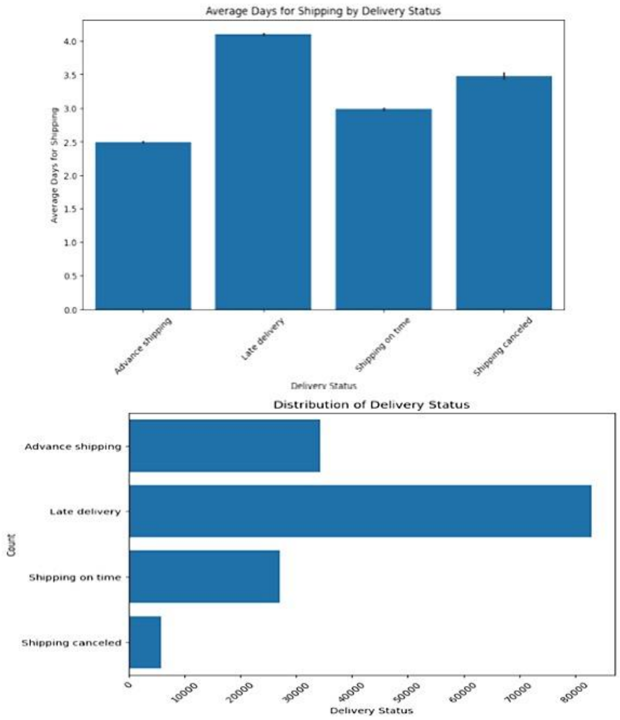

Fig. 2 Count and Bar Plots of categorical variables

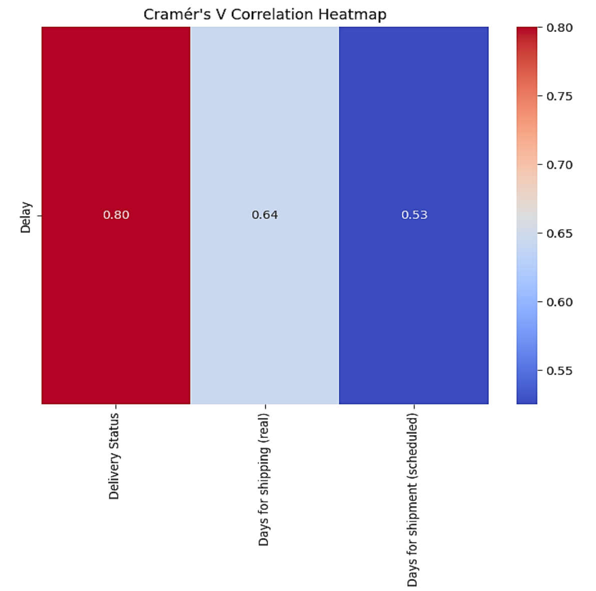

Fig. 3 The correlation between variables Cramér's V statistic

As mentioned in Figure 4 the predicted values are close to the actual meaning that the GB Regression perform good.

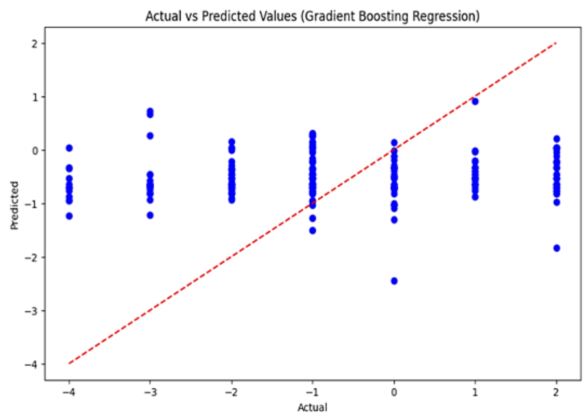

Fig. 4 Actual Vs predicted values with GB regression

Models selection

We choose appropriate regression and classification models for respectively delivery delays prediction and order delivery status were selected.

Linear Regression: This model establishes a linear relationship between input features and the target variable (delivery times). It's straightforward and interpretable, making it a good choice for our prediction task.

$$\hat{y} = w_0 + w_1x_1 + w_2x_2 + \cdots + w_nx_n \quad (1)$$

where:

$\hat{y}$ is the predicted value,

$w_0, w_1, \ldots, w_n$ are the model coefficients,

$x_1, x_2, \ldots, x_n$ are the input features.

Random Forest Regression/Classifier: An ensemble learning technique, made up of numerous separate decision trees. By creating a set of N regression trees, it combines the bagging and random subspace. The training set for each tree is chosen using bootstrap sampling from the original sample set, and each node's partitioning is based on a random subset of the original feature set. This helps to diminish the correlation between the regression trees that are produced, thus the variance of the error is reduced by averaging their predicted outcomes. It's effective at handling non-linear relationships and capturing complex patterns in the data. Gradient Boosting Regression/Classifier: GB builds multiple weak learners sequentially, with each one correcting the errors of its predecessor. This ensemble technique often leads to highly accurate predictions, especially when there are interactions between features. Decision Trees Classifier/Regression: Decision trees recursively split the data based on feature attributes to classify instances. Making them suitable for our classification task.

Support Vector Machines: SVM finds the optimal hyperplane to separate data points into different classes. It's particularly useful for supplier's delivery status classification tasks. Logistic Regression: Logistic regression models the probability of a binary outcome using a logistic function. It's useful for our regression task in classifying supplier performances.

$$\hat{y} = \frac{1}{1 + e^{-(w_0 + w_1x_1 + w_2x_2 + \ldots + w_nx_n)}} \quad (2)$$

where:

$\hat{y}$ is the predicted probability of belonging to a certain class,

$w_0, w_1, \ldots, w_n$ are the model coefficients,

$x_1, x_2, \ldots, x_n$ are the input features.

K-Nearest Neighbors: In the realm of supplier performance analysis, KNN is utilized to classify suppliers into different categories based on their performance metrics. Distances for two points p and q in n-dimensional space are calculated as part of the prediction process, and the nearest neighbor with the majority class label is chosen.

Based on the outputs of k comparable neighbors, the k-NN rule calculates the output value of an input vector. Typically, a distance function of some form is used to calculate a similarity measure. k-NN algorithms have been developed using a variety of distance functions, including the Euclidean distance in equation (3).

$$\text{Euclidean Distance (p, q)} = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \quad (3)$$

where:

p_i and q_i are the i-th features of points p and q, respectively.

The selected models will offer various approaches for predicting delivery times and analyzing supplier performance, models will be trained separately using the features 'Days for shipping (real)' and 'Days for shipment (scheduled)', 'Supplier name', and the target variable 'Delay'. Then, making predictions on the testing set and evaluate the models their performance using accuracy score such as RMSE, MAE, and MSE. Table 2 summarize the performance of each model.

Table 2

Regression models performance metrics analysis

Metrics/Regression models	Mean RMSE	Std RMSE	Mean MAE	Mean MSE
Linear Regression	37.66	71.77	6.94	6569.9
Decision Tree Regression	2.13	0.10	1.67	4.57
Random Forest Regression	1.81	0.05	1.47	3.3
Gradient Boosting Regression	1.66	0.07	1.37	2.79

Metrics analysis and models performance

We employ suitable metrics, such as accuracy (8), precision (9), recall (10), and F1-score (11) for classification models and MAE (6), MSE (7), and RMSE (4) for regression models, to assess how well the trained models perform.

Mean RMSE: This metric measures the average magnitude of the errors in the predictions made by the models, GB Regression has the lowest mean RMSE of all the models (1.669), closely followed by RF Regression (1.81). Linear Regression has the highest mean RMSE (37.66), indicating poorer performance in comparison.

$$\text{RMSE} = \sqrt{MSE} \quad (4)$$

Std RMSE: This column represents the standard deviation of RMSE values across different evaluations or samples. It provides a measure of the performance of the model's variability.

In this case, Decision Tree Regression has the smallest standard deviation (0.10), indicating consistent performance.

$$\text{Std RMSE} = \frac{\mathbf{1}}{\boldsymbol{Std(y)}} \quad (5)$$

Mean MAE: MAE measures the average magnitude of the errors between predicted and actual values.

In line with RMSE. The regression with the lowest mean MAE, GB Regression (1.37), is closely followed by RF Regression (1.47)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i| \quad (6)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (7)$$

$$\text{Accuracy} = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (8)$$

$$\text{Precision} = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (9)$$

$$\text{Recall (Sensitivity)} = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (10)$$

$$\text{F1} - \text{Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

where:
Y_i represents the actual value,
$\widehat{Y}_i$ represents the predicted value,
n represents the total number of observations.
Mean MSE: MSE in equation (7) quantifies the average squared difference between predicted and actual values. It penalizes larger errors more heavily than smaller ones.
As mentioned in Table 2, the two models with the lowest mean MSEs are RF Regression (3.3) and GB Regression (2.79).
The confusion matrices in Figure 5, show each model's performance, in summary, the logistic regression, decision tree and GB classifier models have varying degrees of success in predicting different delivery statuses. However, the SVM model struggles noticeably, misclassifying the majority of cases as 'late delivery'.
In addition, LR model perform less in term of mean RMSE in comparison to Decision Tree Regression, RF regression and GB regression, as in Figure 6. The models use the following hyperparameters:
Decision Tree Regression max_depth: [None, 10, 20, 30], min_samples_split: [2, 10, 20], min_samples_leaf: [1, 5, 10].
RF regression: n_estimators: [100, 200, 300], max_depth: [None, 10, 20, 30], min_samples_split: [2, 10, 20], min_samples_leaf: [1, 5, 10].
GB regression: n_estimators: [100, 200, 300], learning_rate: [0.01, 0.1, 0.2], max_depth: [3, 4, 5], min_samples_split: [2, 10, 20], min_samples_leaf: [1, 5, 10].
In order to find the optimal values for each regression model, these hyperparameters were tuned using GridSearchCV

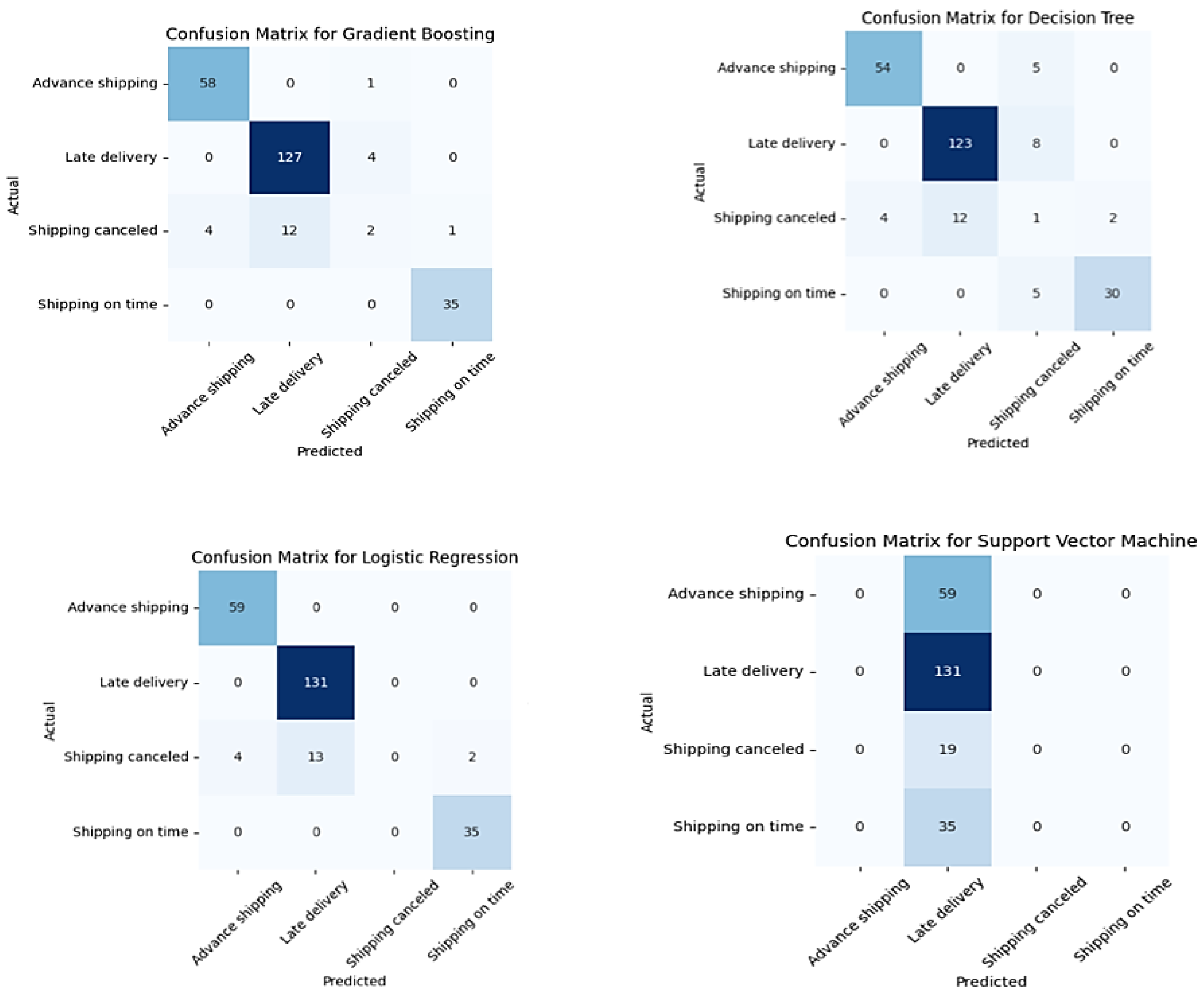

Fig. 5 confusion matrices for each classification models

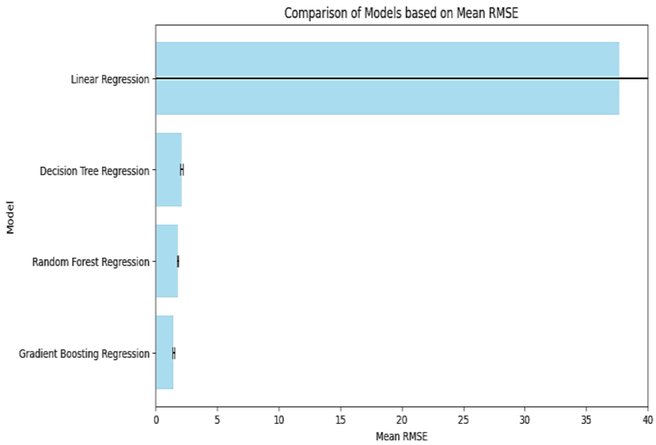

Fig. 6 Mean RMSE comparison of Regression Models

The classification report in Figure 7, provides performance metrics for each class (delivery status) predicted by four different models: Logistic Regression, Decision Tree, GB Classifier, and SVM.
For each class, the report includes precision, recall, and F1-score. Looking at the reports for each model, we can see that all models perform similarly across the classes, with precision, recall, and F1-score being low for all classes. This suggests that the models are mainly predicting late delivery, shipping on time, advance shipping well but struggling with shipping cancelled for all of the models except for GB classifier.
GBR and RF Regression surpass other commonly used regression models in predicting order delivery delay. The classification algorithms were advanced to anticipate the delivery status of orders by classifying them as either on-time or late. GB Classifier, Decision Trees, and Logistic Regression with the exception of SVM, classifiers are primarily forecasting Late delivery, Shipping on time, and Advance shipping. However, all models struggling in classifying shipping cancellations except for the GB classification. In both tasks, the GB classifier and regression perform better overall than other models.
Figure 8, indicates that Logistic Regression and GB outperform Decision Tree and SVM in terms of predictive accuracy. Logistic regression and GB models achieved the highest accuracy of 94%, implying that these models correctly predicted the outcome in 94% of cases. The Decision Tree model follows with an accuracy of 85%, indicating slightly lower predictive performance compared to logistic regression and GB. The SVM model achieved the lowest accuracy among the mentioned models, with an accuracy of 55%.

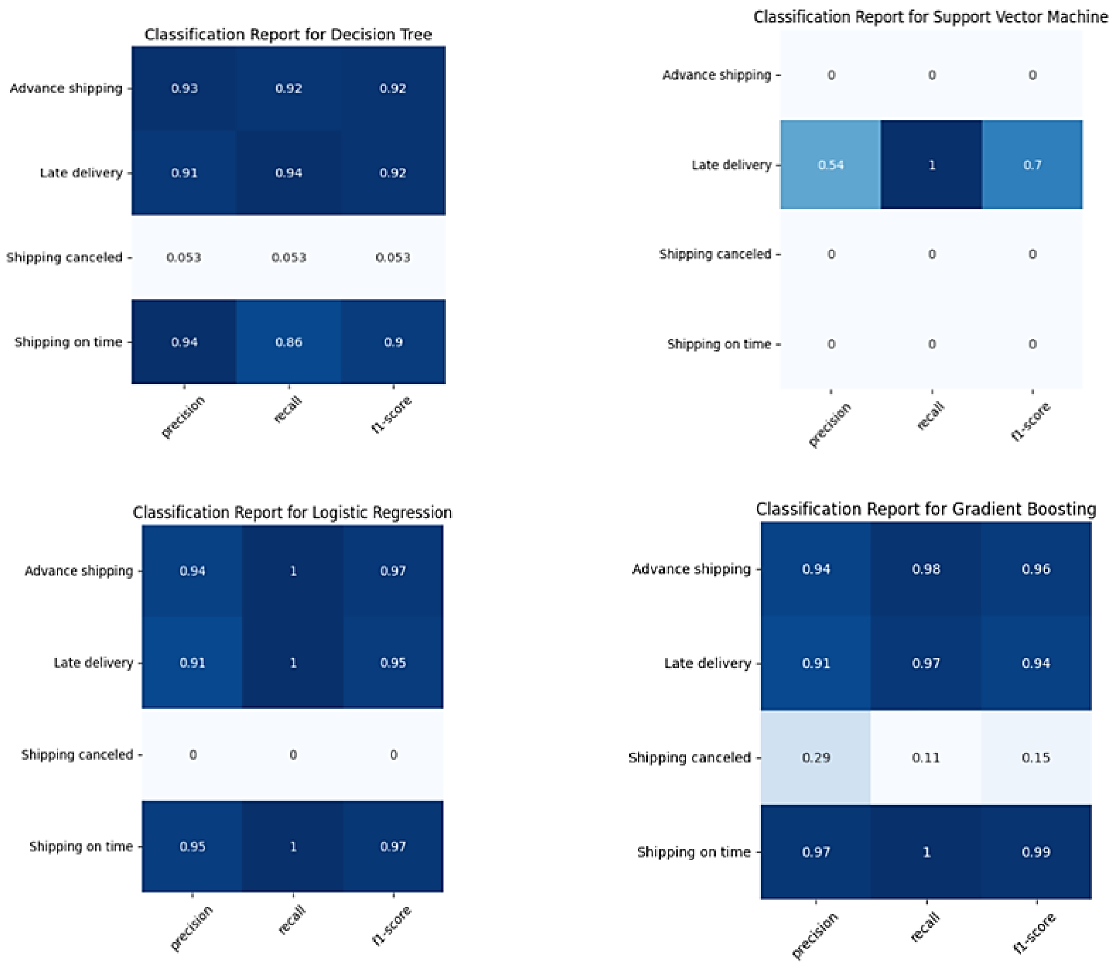

Fig. 7 Performance metrics for delivery status class by classification models

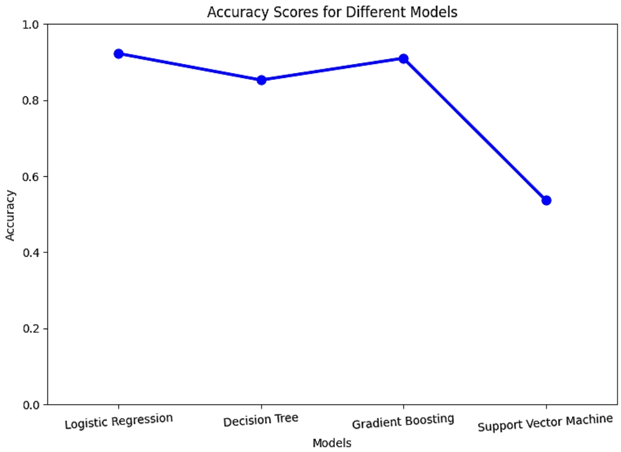

Fig. 8 Accuracy Scores for Classification Models

The GridSearchCV was used to find the optimal hyperparameters for each classifier, as the following:

Logistic Regression: C: [0.01, 0.1, 1, 10, 100], penalty: ['l1', 'l2', 'elasticnet', 'none'], solver: ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']

Decision Tree:max_depth: [None, 10, 20, 30], min_samples_split: [2, 10, 20], min_samples_leaf: [1, 5, 10], criterion: ['gini', 'entropy']

Gradient Boosting: n_estimators: [100, 200, 300], learning_rate: [0.01, 0.1, 0.2], max_depth: [3, 4, 5], min_samples_split: [2, 10, 20], min_samples_leaf: [1, 5, 10]

Support Vector Machine: C: [0.1, 1, 10, 100], kernel: ['linear', 'poly', 'rbf', 'sigmoid'], gamma: ['scale', 'auto', 0.01, 0.1, 1, 10].

The grid-search cross-validation approach was used to identify the number of decision trees in the forest and the maximum number of levels in each decision tree in order to optimize the performance of the RF model. A model with 800 trees and a maximum depth of 25 was developed based on the cross-validated gridsearch findings for the optimal number of trees and the optimum maximum depth of each tree.

For the k-NN model, the Euclidean distance implementation was used, and grid-search cross-validation was used to maximize the number of neighbors, or kvalue. The best value for our k-NN model's neighbors is k = 5.

Figure 9, shows values for all metrics (RMSE, MAE, and MSE) for all models. Moreover, RF Regression outperforms GB in every metric, albeit little higher. With noticeably higher mean RMSE, MAE, and MSE values, which indicate less predictive ability, linear regression performs less. When compared to RF and GB, Decision Tree Regression exhibits superior performance in terms of mean RMSE and MAE, however, its mean MSE is marginally higher. In predicting order deliver delay GB regression and RF Regression are outperforming the other regression used models.

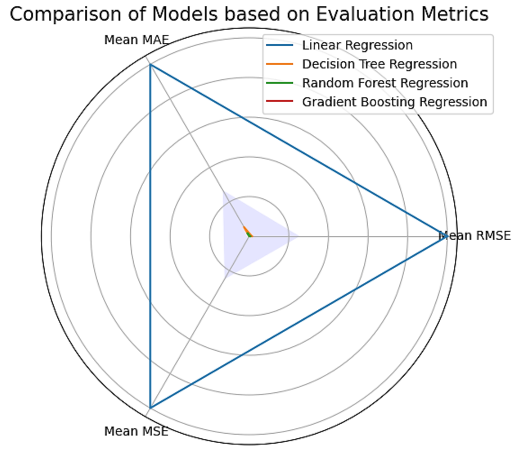

Fig. 9 Comparison of models based on Evaluation Metrics (Mean MAE, Mean MSE, Mean RMSE)

Cluster analysis for supplier performance analysis results

We employ a clustering technique to group suppliers based on similarities in their delivery patterns (on time delivery, average delay time, and delivery lead time), enabling the manufacturer to prioritize high-performing suppliers and mitigate risks associated with under performing ones.

The Figure 10 provides a comprehensive view of supplier performance trends and allows for comparisons between different groups of suppliers.

By visualizing these metrics in clusters, including:

On-time delivery rate cluster: Suppliers are grouped based on their on-time delivery rates, with clusters indicating similar performance levels.

Average delay time cluster: Similar to the on-time delivery rate, suppliers are clustered based on their average delay times.

Delivery lead time cluster: This aspect likely shows how suppliers are grouped based on their average lead times.

By utilizing these objectives, the manufacturer can prioritize resource allocation and develop backup strategies to be able to minimize the repercussions of potential delays, identify groups of suppliers with similar performance characteristics, which will aid the manufacturer in strategic decision-making such as supplier selection, and supplier risk management. This enables the manufacturer to fulfill customer demands more effectively.

In the classification provided in Figure 10, the numbers 0, 1, and 2 correspond to the class labels assigned to the suppliers, each class label represents a specific cluster into which the suppliers have been classified based on their performance metrics (On-time delivery rate, average delay time, and delivery lead time).

Class 0, 1, and 2 denote suppliers with varying degrees of performance, ranging from the lowest to moderate to the best, respectively.

In KNN classification, the algorithm assigns each supplier to the nearest cluster based on their performance metrics. Therefore, we identify the performance metrics associated with each class label in Figure 11.

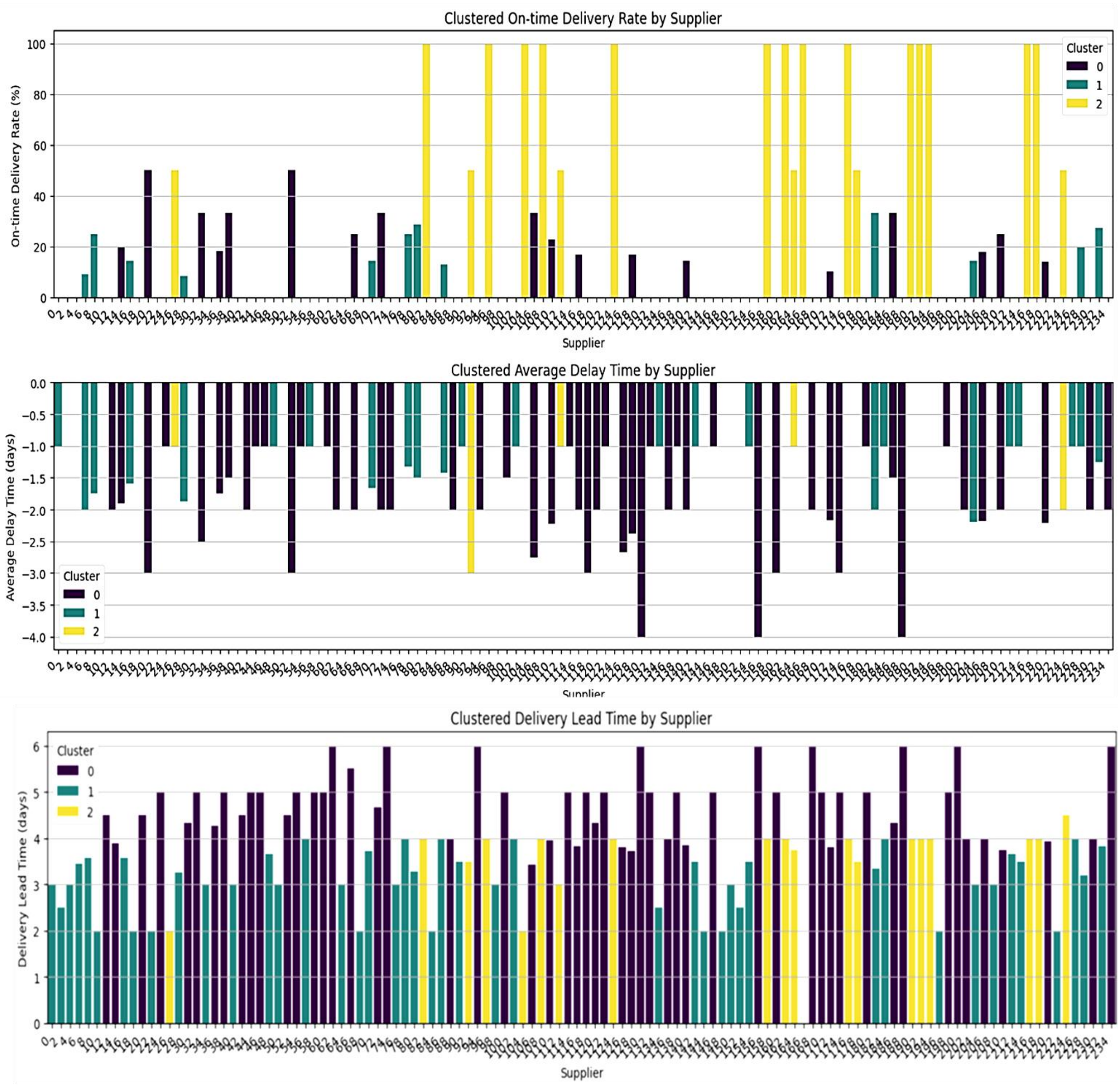

Fig. 10 On-time delivery rate, average delay time, and delivery lead time clustering

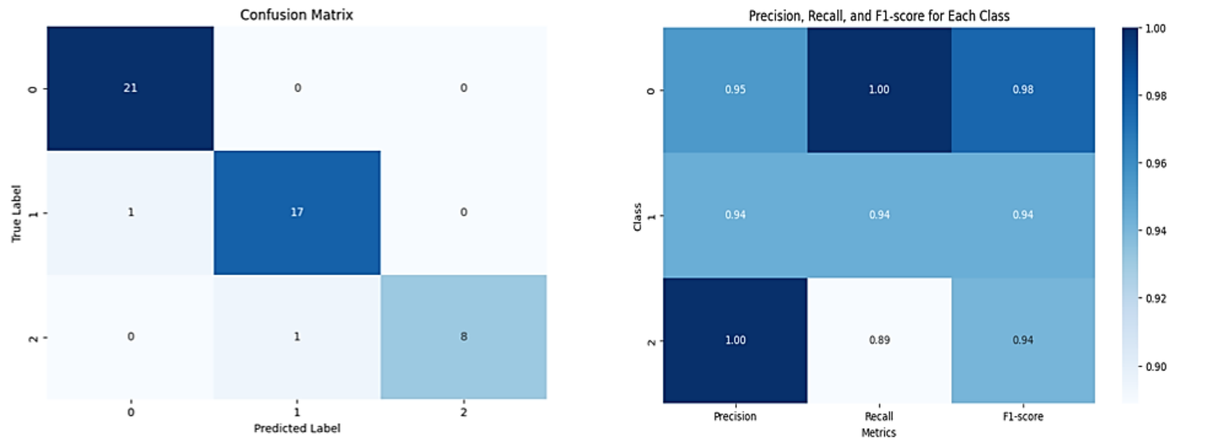

Fig. 11 Confusion matrix and Performance metrics of each class for the KNN

The KNN model's high accuracy and solid performance across precision, recall, and F1-score measures for all classes proved how effective it was at classifying the data.

While ML models learn their parameters through training, their hyper-parameters are typically determined empirically or from prior knowledge of the data. Nonetheless, a number of studies suggest searching techniques to determine the ideal hyper-parameter value. Grid-search cross-validation approach to modify the machine learning models' critical hyper-parameters. In essence, a grid search creates an entire factorial design of experiments taking the specified hyper-parameters into account. Cross-validation is used to assess the model's performance over the whole training data set at each grid node. A 10-fold cross-validation design with 30 repetitions was devised for this investigation.

This means that the entire data set was randomly divided into 10 parts for each repeat. The model was then iteratively trained using seven of the parts (i.e., 70% of the data) and tested using the remaining part (i.e., 30% of the data), ensuring that every data point was utilized only once for testing.

The absence of works with similar combinations of ML approach, stated goals, and different learning algorithms for delayed demand and suppliers' performance evaluation process in the automotive industry make it difficult to evaluate the performance of our proposed models with other studies. A further challenge is the lack of real-world datasets comparable to ours for comparing cutting-edge research.

DISCUSSION AND CONCLUSIONS

As the role of ML technology continues to expand in SC management, the integration of data-driven strategies and advanced analytics will be vital in effectively addressing delayed demand and enhancing overall SC resilience. By harnessing the power of data and ML, companies can create more agile, responsive, and efficient SCs to meet the evolving demands of the market.

In this study, various regression and classification models were employed to address different aspects of the forecasting and categorization tasks related to delivery delays and supplier performance. These models attempted to track the progress of order deliveries, forecast future delivery delays, and categorize suppliers according to their delivery performance.

According to the study's computational studies, the algorithms for RF Regression and GB produced the most accurate forecasts of delivery delays. These algorithms scored better at minimizing test error than other regression models, suggesting that they are useful for forecasting delivery delays in the future.

Furthermore, in the classification task, the study found that the GB Classifier and logistic regression exhibited superior performance compared to other classification methods. These models demonstrated their ability to accurately categorize suppliers based on their delivery performance, suggesting their suitability for tracking and evaluating supplier performance.

The superior performance of RF Regression and GB in forecasting delivery delays, and GB Classifier and Logistic Regression in classification tasks can be attributed to these strengths including the ability to handle different types of data, reduce overfitting, manage noise and outliers, capture complex relationships, and balance bias and variance effectively. Each of these models has strengths that make them especially suitable for the particular nature of the tasks described in the study.

The tools and methodologies developed in our study serve as invaluable resources for SC managers. Maintaining operational efficiency and customer satisfaction in today's dynamic business climate requires the ability to accurately estimate delivery delays and assess supplier delivery performance.

The reliance on data from a particular automotive company provides a robust foundation for our study, especially within the automotive sector. The specificity and relevance of the data ensure that the models developed are tailored to the intricacies and challenges prevalent in this industry. This targeted approach enhances the accuracy and applicability of the models when applied within similar automotive SC contexts. However, it is important to note that the study does not specify the diversity of the dataset, Due to its dependence on data from a single automotive company means that the dataset may not encompass the wide range of scenarios, practices, and conditions present in other industries. This constraint may have an impact on the conclusions' generalizability

as the models developed might be highly specialized for the specific context of the studied company. Consequently, their applicability and effectiveness in different industrial settings may be restricted.

In summary, the incorporation of data from a specific automotive company enhances the study's significance within the automotive sector, nevertheless, it may restrict the generalizability of our findings to other industries or SC situations. The limitations of our study must be taken into account when interpreting and applying the results in different settings. Because different sectors are affected by different external influences, SC dynamics, and operational processes, the conclusions may not apply directly to other industries or SC environments.

In subsequent work, we intend to expand the feature set by obtaining information from many sources, such as economic research, consumer trends, social media, social gatherings, and retail demographics depending on geography. It is possible to see new types of data sources contributing to deep learning. To find the deep learning algorithm's hyperparameters, more research can be done. Furthermore, we intend to employ deep neural networks, recurrent neural networks, and convolutional neural networks as learning algorithms, among other deep learning techniques.

Furthermore, in a later investigation, it would be fascinating to explore the findings in more detail and include them into a mathematical optimization model in order to develop customer lead times that account for supplier delivery performance.

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