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A Voting-Based Hybrid Machine Learning Model for Predicting Backorders in the Supply Chain

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Abstract

Purpose: Backorder prediction is one of the most basic challenges in supply chains, which may have a direct impact on operational costs, inventory levels, and customer satisfaction. The main objective of this study is to come up with a voting-based hybrid Machine Learning (ML) model for the prediction of backorder that will enhance the accuracy of prediction.
Methodology: In this study, an attempt was made to use hard and soft voting models based on XGBoost, CatBoost, Random Forest, and LightGBM with model weights optimized through Optuna. The dataset used includes orders, inventory levels, supplier performance, and other related features. To reduce data imbalance, the ADASYN method was used, and also, optuna parameter tuning was used to find the optimal model settings. The RFECV method was also used to identify key features affecting backorders.
Findings: The soft voting model with an accuracy of 0.9524 yielded the best performance when predicting backorders over all other individual ML models considered in this study. Moreover, inventory level-related variables, supplier performance, and demand predictability were also identified as the most important in causing the occurrence of backorders. The proposed model was compared with other traditional methods, and it was found that by using robust models in a voting framework, the forecast accuracy can also be improved.
Originality/Value: The results indicate that the use of a voting-based hybrid ML model can be a suitable mechanism for enhancing backorder prediction. This model helps organizations manage order flow and their associated costs more accurately. Future research is suggested to use more advanced feature selection and optimization techniques, such as genetic algorithms and deep neural networks, to achieve better model performance.

Keywords: Machine learning, Backordering, Hybrid voting, Supply chain management, Demand forecasting.

1 | Introduction

Forecasting backorders is one of the crucial things in an organization and in companies with their complex supply chain. Management of these orders also ensures an increase in supply chain productivity, thereby preventing issues like increase in maintenance costs, reduction in customer satisfaction or occurrences of

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costs, supply and productions process [1–3]. As backorders are costly, there has become a scientific and practical necessity of developing intelligent methods to forecast backorders [4], [5]. High importance of the subject matter has prompted several of the studies on forecasting backlogs through traditional as well as artificial intelligence methods. It has been found previously that classical methods of time series model and statistical methods are unable to predict effectively in complex and dynamic supply chain [6].

However, Machine Learning (ML) and deep learning models are equipped with the capability to deal with an enormous amount of historical data in order to identify various patterns that enable the enhancement of forecast accuracy [7]. In particular, hybrid and voting based models have outperformed models which know only one variable [8]. Previous research has mainly concentrated in single models, and research of the use of hybrid models to increase the forecast accuracy is less investigated.

Unfortunately, this is one of the most important gaps in the research literature with respect to backorder prediction as there is no comprehensive review of voting based hybrid models in backorder prediction, not to mention a unified framework for selection of key features used in prediction. However, existing methods for handling data imbalance in backorder prediction have so far not been able to achieve the optimal [9].

However, in this study we used advanced ML models, that is, XGBoost, CatBoost, Random Forest, and light GBM for prediction in hybrid voting setup with aim of improving prediction accuracy. Additionally, we will use metamodel optimization methods such as Optuna for tuning the parameters of the models in order to achieve the best possible performance [10]. Therefore, the main question of this research is how the accuracy of backorder forecasting can be increased by utilizing voting-based hybrid models. The objectives of the research are to:

I. Design of a voting-based hybrid model for backorder forecasting.

II. Investigate the proposed model's performance with respect to feature selection and parameter tuning methods.

III. Compare the proposed model with other conventional backorder forecasting methods.

IV. The article offers a practical framework of companies to optimize the backorder management process.

It will be followed by structure of the paper: The second section will be reviewing the research background and theoretical foundation relating backorders and forecasting methods. In the third section, the work under this section will include description of the data, data processing processes, feature selection methods and design of hybrid models. The fourth section will report on the results of the experiments and model evaluation. The fifth section presents the discussion and conclusion of the research as well as some of the suggestions of future research.

2 | Theoretical Foundations and Research Background

2.1 | Backorders in the Supply Chain

One of the fundamental impacts of backorders on the overall supply chain. This generalized framework of inventory coordination in supply chains depends on fixed and linear backorder costs at the last downstream stage developed by Seliaman et al [11]. It shows that effective cost implications of backorders should be included in inventory strategies so that total operational costs may be minimized while demand is fulfilled [11]. Research also indicates, further, that proactive procurement and pricing strategies can alleviate risks of stockout in backorder systems [12]. In addition to inventory and facilities, technology is another important factor to consider within the context of a back order management system in the area of prediction and analytics. Ntakolia et al. [13] present a ML model to predict material backorders, where backorder implications play a role in production and inventory costs. Supply chain resilience is greatly reliant on this predictive capability because the lack of timely information about potential backorders can aggravate the supply chain disruptions [14]. ML techniques have been integrated in this thesis to identify possible backorder scenarios and this permits organizations to take preemptive actions to minimize their impact [15].

In addition, the structure of inventory policies matters a great deal in the manner inventory behaves. Jindal and Solanki [16] motivate an integrated inventory model that incorporates controllable lead times and backorder discounts to develop improved inventory management frameworks which may allow sales to be saved and service levels to be improved. It has also been studied how different types of compensation for back orders can be handled and what methods can partially handle back orders and sustain reasonable customer satisfaction [17]. Such studies point to the very fine balance of inventory management and customer demand that supply chains must operate under.

Another phenomenon related to backorders is the bullwhip effect. Iqbal et al. [18] describe how backorders can synergise demand variance in inventory levels to further up the supply chain, stressing the necessity for superior communication as well as coordination among supply chain partners to lessen variance and its associated costs [18]. Such an approach is also recommended by Choi et al. [19], who suggest that expected backorders need to be considered in the evaluation of supplier performance in case of vendor managed inventory programs. Finally, the theoretical background for backorders in supply chains is significant and covers various modern modeling methods, analytical models and processing real inventory policies. Frameworks and tools in these supply chain systems give the supply chain professionals the necessary information to be able to manage the backorders well in order to improve operational performance and customer satisfactions.

2.2 | Voting-Based Hybrid Machine Learning

With a vote based hybrid models, the major thing is that it can mix prediction from diverse algorithms. For example, Solomon et al. [20], comes up with an application of hybrid majority voting model of ML techniques for predicting obesity with an attainment of an accuracy of 97.16% based on various classifiers. It demonstrates that hybrid models can outperform the individual classifiers well, and the voting is robust. In addition, the task of Dengue fever classification and the way of algorithm combining, which is K nearest neighbors, Naive Bayes and decision tree to reach a hybrid accuracy rate of 95 % is also discussed by Rahman and Prasetiyowati [21].

These give the principle that a quality can achieve good performance on several different algorithms, hence together giving superior overall performance. Ensemble methods with voting also handle diverse input data and avoid limited overfitting tendencies of the single model approach. Abro [22] points out that ensemble system based on voting works well in classification tasks and are robust in all kinds of scenario for classification. Gumilar et al. [23] in a work that studies the data imbalance apply hybrid methods like Voting and Stacking in rainfall classification as an example to support the idea that these techniques can manage the data variability as well as to boost the prediction accuracy. Rahman et al. [21] explore voting classifiers where voting classifiers can produce large gains in performance on complicated problems as in any ensemble methods.

Beyond majority voting (If the number of classes exceeds 2), soft voting is applied, which is based on weighted decisions of classifiers with confidence levels to improve model performance. Taha [24] in their research in the area of phishing website detection, puts emphasis in the advantage of a soft voting for better classification accuracy than classical voting schemes as there is always an improvement in confidence analysis. Overall, I was not able to find a reference for predicting specific heat capacities using ensemble methods as described in reference Mathur et al. [25], neither as the reference supports that. Thus, it's best to remove it. Finally, the hybrid models are taken together with modern computational techniques to the limit of their predictive ability. For instance, it enables a rich and algorithmic strength dominated exploration of algorithmic strengths with a significant reduction of algorithmic weaknesses. For instance, Cao et al. [26] proposed a Voting based Extreme Learning Machine (VELM), where in the ensemble nature of the frameworks enhanced the classification reliability on ML. The portrayed behavior showcases the behavior taken to aggregate the tracts of different ML methodologies and is consistent with current research efforts to improve ensemble learning.

In general, vote based hybrid ML encompasses the outcome of multiple algorithms achieved with the help of voting mechanisms ensuring improvement of prediction accuracy and model robustness. In several cases of specifying their practical applicability it has been proved that they are successful in all studies and it has established a basis for subsequent development in ML frameworks.

2.3 | Research Background

Given that, any prediction of that backorder is crucial to organizational effectiveness in supply chain management. Advanced ML techniques are required to tackle large scale datasets and complex relationship with traditional forecasting methods. In recent years models like hybrid quantum-classical neural networks, decision trees, gradient boosting machines, and Bayesian optimized algorithms have been explored for improving the predictive accuracy. The studies use datasets from benchmark datasets to historical supply chain records and pharmaceutical supply chains in times of crisis such as the COVID 19 pandemic. *Table 1* summarizes key studies in this domain in terms of their objective, methodology and findings.

Table 1. Research background.

Authors	Article Title	Goals	Model Used	Dataset	Conclusion
Jahin et al. [27]	QAmplifyNet: Pushing the boundaries of supply chain backorder prediction using interpretable hybrid quantum-classical neural network	Introduce a novel framework for backorder prediction using quantum-inspired techniques.	Hybrid Quantum-classical neural network (QAmplifyNet)	Benchmark dataset	QAmplifyNet outperforms classical models, effectively handling short and imbalanced datasets.
Jahin et al. [27]	QAmplifyNet: Pushing the boundaries of supply chain backorder prediction using interpretable hybrid quantum-classical neural network	Introduce a quantum-classical neural network for backorder prediction.	Hybrid Quantum-classical neural network (QAmplifyNet)	Benchmark dataset	Achieved 90% accuracy, outperforming traditional ML models and demonstrating potential for quantum computing in supply chain management.
Banik et al. [28]	A comparative analysis of ML algorithms to predict backorder in supply chain management	Compare ML algorithms for backorder prediction.	Random Forest (RF), extreme gradient boosting (XGBoost)	Kaggle competition dataset	XGBoost performed best with a ROC-AUC score of 95.93% on undersampled data.
Sani et al. [7]	Supply chain 4.0: A ML-based Bayesian-optimized lightgbm model for predicting supply chain risk	Optimizing Backorder Forecasting with a Hybrid Bayesian-LightGBM Approach	Bayesian-optimized LightGBM	SCM dataset with diverse risk factors	Model outperformed traditional approaches, improving computational efficiency and prediction accuracy.
Iqbal et al. [6]	Classification and regression tree model to predict the probability of a product being backordered in supply Chain	Use decision tree models to predict backorders.	Classification and regression tree (CART)	Historical supply chain dataset	CART effectively predicted backorders, demonstrating its usefulness for supply chain risk management.

Table 1. Continued.

Authors	Article Title	Goals	Model Used	Dataset	Conclusion
Li et al. [29]	Explainable ML for drug shortage prediction in a pandemic setting	Develop explainable ML techniques for backorder prediction in pharmaceutical supply chains.	Decision Tree	Pharmaceutical supply chain dataset during COVID-19	Decision Tree performed best, providing interpretable insights into supply chain risks.
Maitra and Kundu [4]	Ackorder prediction in inventory management: Classification techniques and cost considerations	To evaluate classification techniques for backorder prediction and their cost implications	Classification techniques	Kaggle competition dataset	The model demonstrated a low number of false positives, indicating effective backorder prediction
Malviya et al. [30]	Backorder prediction in the supply chain using ML	Analyze ML algorithms for identifying parts with shortages.	Various ML algorithms	Previous sales and forecasting data	ML algorithms effectively identify parts with high shortage probabilities.
Ntakolia et al. [13]	An explainable ML Model for material backorder prediction in inventory management	Develop interpretable models for backorder prediction.	Random Forest (RF), XGBoost (XGB), LightGBM (LGBM), Balanced Bagging (BB)	Publicly available dataset	LGBM model, calibrated with Isotonic regression, achieved highest AUC score of 0.95.
Islam and Amin [15]	Prediction of probable backorder scenarios in the supply chain using Distributed Random Forest and Gradient Boosting ML techniques	Predict backorders to enhance business decision processes.	Distributed random forest (DRF), Gradient boosting machine (GBM)	Company inventory data	Ranged approach improves model performance by 20% in biased datasets.

3 | Research Methodology

The goal of this research is to predict backorder occurrence in the supply chain. The major objective of this research is therefore to develop a hybrid ML model that is really effective in the prediction of occurrence of backorders with high accuracy against the evaluation criteria and better balancing. In order to achieve this goal, the BackOrders dataset from Kaggle that is available is used. The inventory banks containing inventory levels, sales volume, product delays, demand forecasting and supplier performance are available in this dataset. The target variable 'went_on_backorder' is a binary variable (value = 1 for a backorder and value = 0 for no backorder). And through this, some amount of data preprocessing has been done in this research in order to improve the data quality. In this research ADASYN was used to balance unbalanced data and improve minority class samples.

A general problem but still very important is that this method overcomes the classes balance and increases the performance of ML models using few synthetic examples out of few classes [31], [32]. The Random Forest model optimized by Optuna was used with the Recursive Feature Elimination with Cross-Validation (RFECV) to select the most important variables, to remove the less important features and finally 17 key features were selected with for the modeling.

In order to analyze the features, Random Forest model was used to carry out the correlation analysis and feature importance method. Then, after the process of feature selection, a hybrid model of hard voting and soft voting was developed and implemented out of four robust models: XGBoost, CatBoost, Random Forest and LightGBM. Based on the optimization results obtained from Optuna with 50 trials for each of the hard and soft voting approaches, optimal weights were assigned to each base model. Specifically, for the hard voting model, optimal weights were identified as follows: XGBoost (7), CatBoost (3), Random Forest (4), and LightGBM (4). In the Soft Voting model, optimal weights were set as XGBoost (10), CatBoost (6), Random Forest (5), and LightGBM (4).

Furthermore, each base model's hyperparameters were tuned meticulously using Optuna to ensure the highest possible predictive performance. Both hard and soft voting approaches were investigated here for accuracy of estimation of performance of various model combination methods on forecasting. Here 16 ML models were independently run and optimized to predict backorders and this can be used to compare the performance of the combined model. The model types considering these were Logistic Regression, Decision Tree, Random Forest, Extra Trees, Gradient Boosting, AdaBoost, XGBoost, LightGBM, CatBoost, KNN, SVM, Naive Bayes, QDA, LDA, MLP, and SGD. GridSearch CrossValidation was used to optimize all these models and the evaluation was done considering four main metrics–accuracy, precision, recall, and F1 score. The analysis and modeling steps were performed using the Python programming language with its related tools.

3.1 | Features Description

In this study we had used the dataset downloaded from the Kaggle website which consists of the information about backorders from the supply chain. They have aimed to publish this dataset in order to help data analysts and ML experts to predict backorders. Features used for the data used on the supply chain process including inventory, supplier performance, forecasted demand, etc are included. It includes 22 independent variables and a target variable (went_on_backorder) indicating whether a product will be backordered later. *Table 2* provides a description of the variables.

Table 2. Variables description.

Feature Name	Description	Data Type
Sku	Unique identifier for the product (SKU code)	Categorical
National_inv	Current inventory level of the component	Numerical
Lead_time	Estimated lead time for replenishment (In days)	Numerical
In_transit_qty	Quantity of the product currently in transit	Numerical
Forecast_3_month	Forecasted sales for the next 3 months	Numerical
Forecast_6_month	Forecasted sales for the next 6 months	Numerical
Forecast_9_month	Forecasted sales for the next 9 months	Numerical
Sales_1_month	Actual sales for the past 1 month	Numerical
Sales_3_month	Actual sales for the past 3 months	Numerical
Sales_6_month	Actual sales for the past 6 months	Numerical
Sales_9_month	Actual sales for the past 9 months	Numerical
Min_bank	Minimum desired inventory level	Numerical
Potential_issue	Indicator variable noting potential issue with the item (Yes/No)	Categorical
Pieces_past_due	Number of overdue parts from the supplier	Numerical
Perf_6_month_avg	Average supplier performance over the past 6 months	Numerical
Perf_12_month_avg	Average supplier performance over the past 12 months	Numerical
Local_bo_qty	Number of backorders at the local level	Numerical
Deck_risk	Risk associated with storage location (Yes/No)	Categorical
Oe_constraint	Constraint related to original equipment manufacturer (OEM) orders (Yes/No)	Categorical
Ppap_risk	Risk associated with production part approval process (PPAP) (Yes/No)	Categorical
Stop_auto_buy	Flag indicating whether automatic buying is stopped (Yes/No)	Categorical
Rev_stop	Flag indicating a revenue stop (Yes/No)	Categorical
Went_on_backorder	Target variable: Indicates whether the product went on backorder (1: Yes, 0: No)	Categorical

3.2 | Data Preprocessing and Correlation Analysis

After completing the cleaning and preparing processes, the dataset is of high quality to be used in this study. In the preprocessing stage data was checked very carefully and missing or invalid values were found out and must be removed. The rows containing -99 in the variables perf_6_month_avg and perf_12_month_avg were treated as invalid data and eliminated specifically. In addition, rows in the variables national_inv and lead_time were dropped containing missing values.

After performing the cleaning processes, the dataset contained 61,589 records initially, which ended up being 57,246 records. Such measures improved the quality of data and prediction accuracy of the prediction models. The sku attribute is a unique id for each product and so, it was removed in the preprocessing phase.

However, this feature had no useful information to predict backorders and was just a numerical identifier that could not be used in ML modeling, so this feature was removed right away in the beginning of the data processing process to not affect the model performance negatively. Data imbalance was one of the fundamental challenges when modeling the backorder prediction problem. When sample distribution is examined, it is found that the initial data set contains 46,383 samples with class 0 (No backorder occurred) and just 10,863 samples with class 1 (Backorder occurred).

Such a severe imbalance can bias the ML model to focus the majority class, resulting in poor performance of the model in identifying the occasions when backorders happen. To improve the model performance and to balance the data, Adaptive Synthetic Sampling (ADASYN) method is used.

The chosen method, ADASYN, is a data balancing method based on synthetic sampling and it has a special focus on generating new samples for the minority class. In contrast to usual techniques like SMOTE which create brand new information impartially, ADASYN moves closer to occupying an area with less density (i.e more of synthetic information in the minority class information portion) but by thinking about the weighted density of the minority class data. In the ADASYN method, the number of new samples according to the following formula are decided.

$$G = \left(\bar{d} \times (N_1 - N_0)\right), \quad (1)$$

where:

I. G is the number of new samples to be created.

II. d¯ is the ratio of the average neighborhood of the minority class to the total data of the minority class.

III. N1 is the number of samples of the majority class.

IV. N0 is the number of samples of the minority class.

Artificial samples are created as follows:

$$X_{new} = x_i + \lambda \times (x_j - x_i). \quad (2)$$

I. xi is an instance of the minority class.

II. xj is one of its nearest neighbors.

III. λ is a random value in the interval [0,1].

Once ADASYN has been applied, there is a more balanced data distribution and a higher number of class 1 samples relative to before (10,863 class 1 samples became 47,605 upon applying ADASYN) with no change in the number of class 0 samples. This alteration also improved the ML model's ability to learn from future data, as well as helped the model not get affected by data imbalance [33].

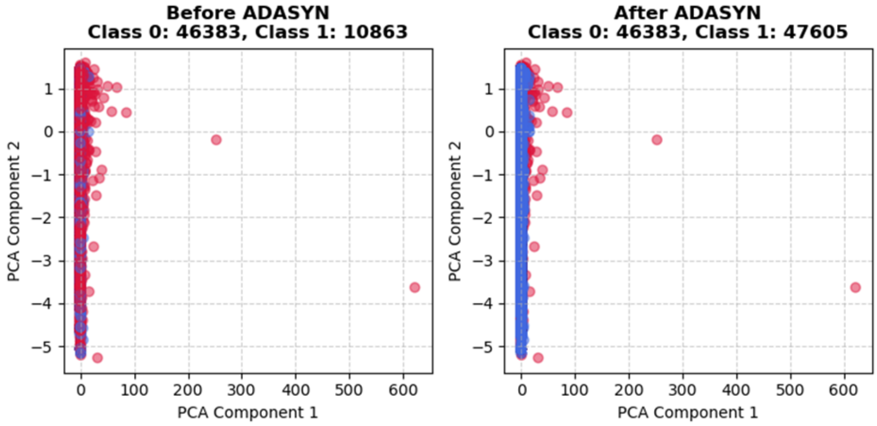

Fig. 1. Impact of ADASYN on class distribution visualized with PCA.

In *Fig. 1*, PCA is performed to show a 2D visualization of data after data balancing using ADASYN; it shows that the density of class 1 samples has increased with the use of ADASYN where the data is more balanced. Therefore, this change shows that data created by ADASYN has the correct distribution in the low density areas of the minority class and hence improving the results of ML models in identifying backorders [34].

Standard Scaler was also used in order to scale the data. All of the variables were transformed as being on average of zero, and with a standard deviation of one. The data of this study was divided into two parts, so 80% data was used for model training and 20% for model evaluation. Correlation analysis was carried out in order to analyze the relationships between the variables in the data set.

The objective was attempting to identify which variables have the largest influence in creating backorders. For this study, a correlation matrix was used alongside Heatmap chart to visualize the relationship between variables [35]. *Fig. 2* illustrates this.

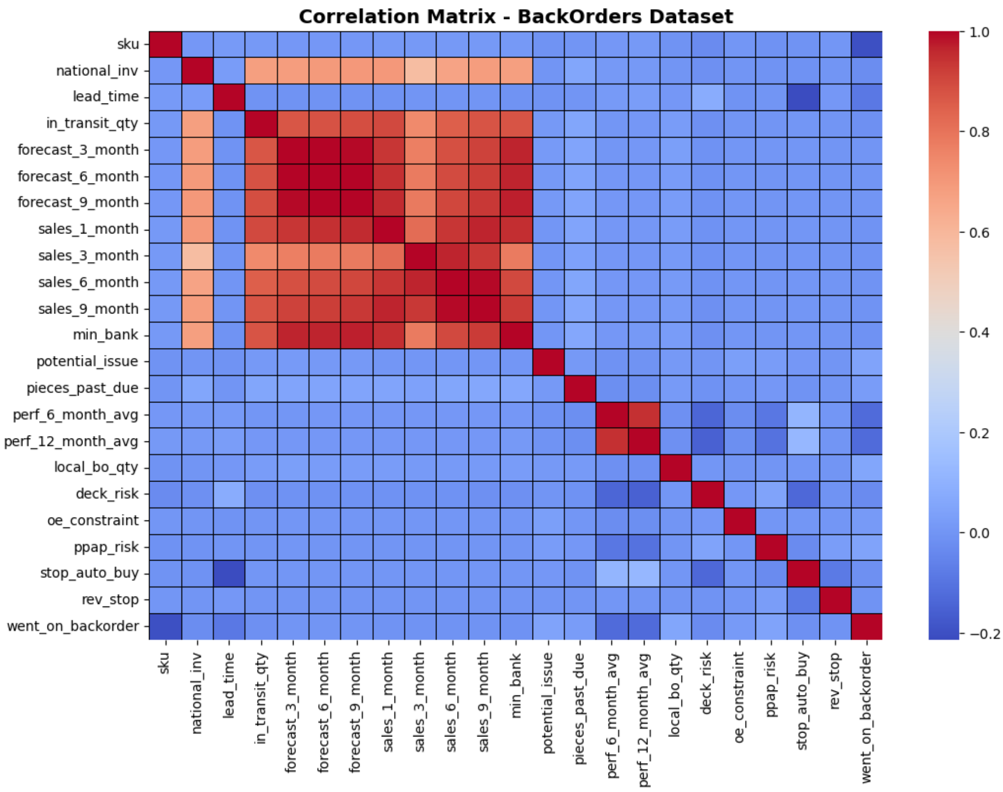

Fig. 2. Correlation heatmap.

Analysis of the results indicates that the variables selling sales in the coming months (Forecast_3_month, forecast_6_month, forecast_9_month) and actual sales in previous periods (Sales_1_month, sales_3_month, sales_6_month, sales_9_month) have a high correlation with each other. This implies that with the sales volume in the past, demand can be predicted in the future. In addition, variable national_inv (Total inventory) is moderately negatively correlated with other sales and sales forecast variables, meaning that changes in sales volume is negatively related to changes in inventory level in warehouse. Finally, concerning variables, related to supply chain risk, deck_risk, ppap_risk, and oe_constraint are correlated between them and without a notable effect on the target variable; however, they are correlated to each other. This implies that there may be supplier and supply chain performance related factors that are indirectly responsible for backorders.

3.3 | Importance of Features and Feature Selection

The model Random Forest after tuning for hyperparameters was optimized through Optuna to investigate the effects of several features that cause backorders. Using this honed model after it becomes optimal, feature importance was evaluated and the most important determinants for backorders were pinpointed [36].

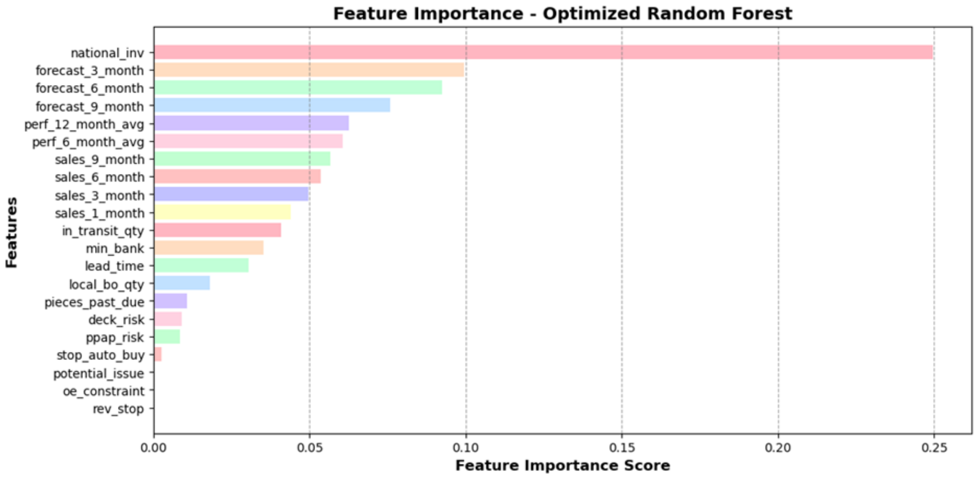

Fig. 3. Feature importance.

The importance of the features are shown in *Fig. 3*. An analysis of the results in this case demonstrates that there is the maximum impact of variable national_inv (The total inventory in the warehouse) on backorders forecast. All this seems reasonable, however, since the biggest supplier of customer orders is the inventory level, its lowering increases the likelihood of backorders. After that, the most important influential factors were found to be related to future sales forecasting, variables such as forecast_3_month, forecast_6_month, and forecast_9_month. These variables have a direct relationship to the forecasted demand and hence will help in making decisions about how much is to be supplied and how to prevent the backorders. Moreover, supplier performance related variables, like perf_12_month_avg and perf_6_month_avg were also found to have a significant impact on the forecast of backorders.

This suggests that performance delays and fluctuations by suppliers increases the chances of supply chain problems. Features such as deck_risk, ppap_risk, stop_auto_buy, rev_stop related to supply risk and production approval processes were less important than other features, however, they may still be used in management decisions. Overall, the feature importance analysis indicates that an inventory, a demand forecast, a supplier performance, and potential delays are most influential in occurrence of backorders. Such finding can be used to enhance supply chain management strategy and avoid potential delay.

However, in this study Recursive Feature Elimination with Cross Validation (RFECV) is used to optimize feature selection, to remove features that have insignificantly impact over backorder forecasting [37]. It is a method based on recursive feature elimination in which the ML model is trained for several times and the least important features are deleted at each step to find the best set of effective variables.RFECV was employed as an estimator in RFECV using this study's Random Forest model optimized with Optuna [38].

We conducted the feature selection through following steps: First, all the features are included in the model, and by the different stages, less impacting features are removed. In this process the main criterion was to increase the performance of a model by the accuracy value on the cross-validation step. The feature selection made using RFECV resulted in a set of 17 key features which achieved the greatest impact in predicting the backorders. Some of these features include national_com_i (Inventory level variables), lead_time (Supply time) and in_transit_qty (Number of goods in transit) that are the main players in supply chain management. Additionally, sales forecast in various time periods (Forecast_3_month, forecast_6_month and forecast_9_month) and actual sales for the past months (Sales_1_month, sales_3_month, sales_6_month, and sales_9_month) other such features identified, which clearly has an indirect or direct effect of demand and sales cases on the instances of backorders.

In addition, inventory management and supply problem identification also involves min_bank (Minimum required inventory) and pieces_past_due (Number of pieces overdue from the supplier). And moreover, supplier performance during past 6 and 12 months (Perf_6_month_avg and perf_12_month_avg) are deemed relevant factors for evaluating the quality and stability of a supplier. The list of selected features also includes variables related to the risk in the supply chain process, such as local_bo_qty (Local backorder quantity), deck_risk (Warehouse storage risk), and ppap_risk (Supplier production approval risk).

In this study, RFECV has made the model more easier to interpret, the model more efficiency, and more forecast accuracy. Furthermore, this method has gotten rid of unnecessary variables and reduced the influence of correlated variables on the final model, which then improved the model's interpretability and decreased processing time [39].

3.4 | Modeling with Voting-Based Crowd Learning Method

Here, a voting based ensemble model was designed and implemented to predict the backorder occuring. The ensemble model is built with many ML algorithms trained simultaneously and finally applying voting where the final decision is made by weighted voting. The use of this method is to increase the prediction accuracy and enhance the model performance in the problems of the data, such as class imbalance. For this approach, the base models were selected from four robust algorithms, i.e. XGBoost, CatBoost, Random Forest, LightGBM.

The high pattern identification and refusal to unbalanced data and high classification accuracy of these algorithms made it one of the best suitable algorithms. The random forest model is dependent on a set of random decision trees which help to reduce the variance in the model and to stabilize it [40]. XGBoost is the optimized and more efficient version of the gradient boosting, it enhance the accuracy and speeds up the models and training using the technique like pruning, regularization, parallelization [41]. On categorical variables, it is optimal in dealing with batch data and lack of such process as one hot encoding.

In this research another model used is lightgbm which is faster than other model and uses less memory as the decision trees are built leaf-wise instead of level-wise. Hyperparameter optimization with Optuna was conducted to improve the performance of each model [42]. This process helped us to find the best settings for each model, in turn improving the prediction accuracy of each model by itself as well as that of an aggregated model containing all models. We implemented two types of voting after optimization: Hard voting and soft voting.

In the hard voting method, each model outputs not an individual class, but a class itself, and the class with the highest vote count wins [43]. However, in the soft voting method, instead of directly selecting a class, different models approximate the probability of a sample belonging to each class, which is then combined by a weighted average to decide the final class [44]. Specific weights were optimized for each of the base models using Optuna with 50 trials for the soft voting and 50 trials for the hard voting frameworks, combined with 5-fold cross-validation to ensure robust results.

The weight search range was set between 1 and 10 to identify the optimal contribution of each model. Consequently, the optimal weights obtained for the hard voting model were XGBoost (7), CatBoost (3), Random Forest (4), and LightGBM (4), while the optimal weights for the soft voting model were XGBoost (10), CatBoost (6), Random Forest (5), and LightGBM (4). Assigning these optimized weights significantly enhanced the accuracy of the ensemble models, allowing the hybrid approaches to achieve superior predictive performance compared to individual classifiers. *Fig. 4* illustrates the workflow of the voting classifier.

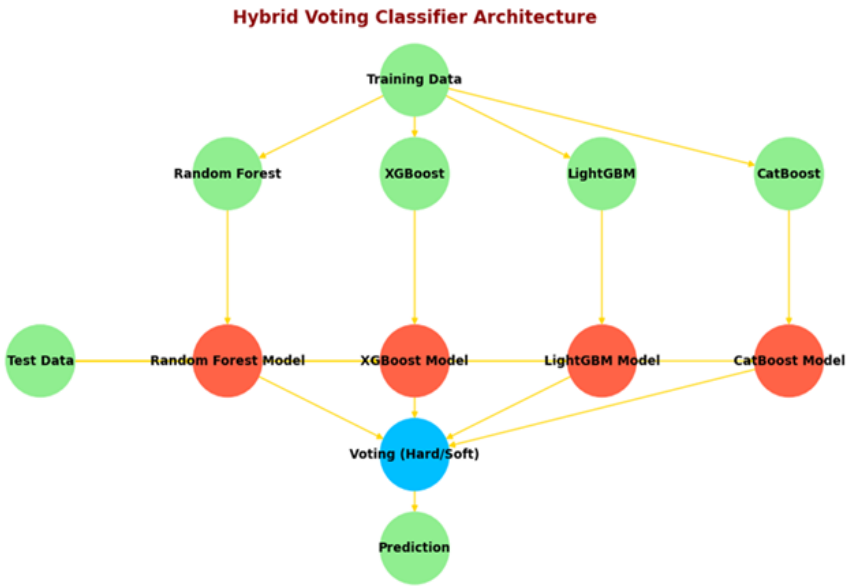

Fig. 4. The workflow of the voting classifier.

Selecting appropriate values for hyperparameters helps to improve the performance of ML models, an important part of the process. To improve the accuracy and efficiency of the models, the Optuna-based optimization method is used to tune hyperparameters in this study. Optuna is a directed random search that can find the optimal parameter values, while reducing computation time compared to conventional methods like grid search. In each model, we determine a range of adjustable values, and Optuna selects the optimal value found for that model during the model training process. Each hyperparameter is searched over a range whose extreme values are those common and recommended within the research literature. After hyperparameter tuning, *Table 3* shows the optimized values for each model.

Table 3. Hyperparameter tuning summary.

Algorithm	Hyperparameters	Search Range	Best Hyperparameter
XGBoost	N estimators	[100, 300] (Step=50)	265
	Max depth	[3, 10]	10
	Learning rate	[0.01, 0.3]	0.251592684969262
	Subsample	[0.6, 1.0]	0.905982896665368
	Weight in soft voting	[1, 10]	10
	Weight in hard voting	[1, 10]	7
CatBoost	Iterations	[100, 300] (Step=50)	237
	Depth	[3, 10]	10
	Learning rate	[0.01, 0.3]	0.291888424951622
	Weight in soft voting	[1, 10]	6
	Weight in hard voting	[1, 10]	3

Table 3. Continued.

Algorithm	Hyperparameters	Search Range	Best Hyperparameter
Random Forest	N estimators	[100, 300] (Step=50)	133
	Max depth	[3, 20]	20
	Min samples split	[2, 10]	2
	Weight in soft voting	[1, 10]	5
	Weight in hard voting	[1, 10]	4
LightGBM	N estimators	[100, 300] (Step=50)	297
	Max depth	[3, 10]	9
	Learning rate	[0.01, 0.3]	0.279538260439088
	Weight in soft voting	[1, 10]	4
	Weight in hard voting	[1, 10]	4

3.5 | Comparing the Hybrid Model with other Machine Learning Methods

Its results were compared with 16 ML models in order to evaluate the performance of the voting based ensemble models. Logistic regression, Decision Tree, Random Forest, extra trees, gradient boosting, AdaBoost, XGBoost, LightGBM, CatBoost, k-nearest neighbors, support vector machine, Naive Bayes, quadratic discriminant analysis, linear discriminant analysis, multilayer perceptron, and stochastic gradient descent were the included models. Each of these models was fed to the dataset independently and the results of this prediction of backorders were presented. For these models optimum performance, their hyper parameters were tuned using grid search cross validation method.

This method goes through all possible actions of the specified hyperparameters and chooses the best value in accordance with the model evaluation criteria. This gives models the chance to have the most optimal performance, avoiding overfitting and increasing model's generalization. A large variety of classical ML algorithms including tree based, boosting models and neural network based models, as well as support vectors constitute the model set used. They have high ability to understand complex pattern, deal with unbalanced data and extract important features, which are the reasons why being used so popularly in classification problem. On the other hand, instead linear models such as logistic regression, LDA, and QDA are more used to study the correlation between variables and can be more interpretable. Another included SVM and MLP, based on the support vectors and neural networks, respectively, have high performance in processing the complex data. Each model is explained briefly in *Table 4*.

Table 4. Other ML methods for comparison.

Model	Description	Best Hyperparameters	Reference
Logistic regression	A linear model for classification that calculates the probability of samples belonging to classes.	{'C': 10}	[45]
Decision Tree	A tree-based algorithm that makes decisions based on data characteristics.	{'max_depth': 20, 'min_samples_split': 2}	[46]
Random Forest	A model consisting of multiple decision trees used to reduce variance and increase accuracy.	{'max_depth': 20, 'n_estimators': 100}	[40]
Extra Trees	Similar to Random Forest but without resampling, which reduces the impact of outliers.	{'max_depth': 20, 'n_estimators': 200}	[47]
Gradient boosting	A reinforcement method that strengthens weak models and improves performance at each stage.	{'learning_rate': 0.1, 'n_estimators': 200}	[48]
AdaBoost	A method based on incremental reinforcement that combines weak models to increase accuracy.	{'learning_rate': 0.1, 'n_estimators': 100}	[49]

Table 4. Continued.

Model	Description	Best Hyperparameters	Reference
XGBoost	An optimized version of Gradient Boosting that uses parallelization techniques to improve efficiency.	{'max_depth': 10, 'n_estimators': 200}	[41]
LightGBM	A reinforcement model that processes data leaf-wise and increases learning speed.	{'learning_rate': 0.1, 'n_estimators': 200}	[42]
CatBoost	A boosting model that is optimized for categorical data and does not require additional preprocessing.	{'depth': 10, 'iterations': 200}	[50]
KNN	A nearest neighbor model that classifies new data based on similar examples.	{'n_neighbors': 3}	[51]
SVM	A support vector-based model that determines decision boundaries in feature space.	{'C': 10, 'kernel': 'linear'}	[52]
Naive Bayes	A probabilistic model that calculates the probability of data belonging to classes based on Bayes' rule.	Default Hyperparameters	[53]
QDA	A model that identifies nonlinear boundaries and improves class separation.	Default Hyperparameters	[54]
LDA	A statistical method for dimensionality reduction and classification of data that uses the covariance matrix.	Default Hyperparameters	[55]
MLP	A neural network model that uses multiple hidden layers to learn complex relationships.	{'alpha': 0.0001, 'hidden_layer_sizes': (64, 32), 'learning_rate': 'adaptive'}	[56]
SGD	A linear learning model that uses stochastic gradient descent for optimization.	{'alpha': 0.0001, 'penalty': 'l1'}	[57]

Four main indicators for evaluating the performance of ML models on predicting backorders namely accuracy, precision, recall, and F1 score are used. The metrics for above are calculated based on the concepts of True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN).

TP here is the number of people for whom the model predicts that they will be backordered while the true number is actually backordered, and TN is the count of people for whom the model predicts they will not be backordered when actually they are not backordered.

FN is the number of instances, when the order would have backordered had the market still been down but the model predicted that is would not backorder. Furthermore, the number of instances in which the model erroneously indicated that the order would be not backordered, when matters really were backordered, is known as FN.

For a better evaluation (And less dependence) to the data distribution, the cross validation was employed with K=5. It uses this method which would split the data into 5 parts and train and evaluate the model 5 times that each time one part is used for evaluating (Validation) and other four part is utilized for training (Training). By doing this, the generalizability of the models increased and the model does not depend on a certain distribution of the data. *Table 5* presents evaluation indicators for ML models.

Table 5. Evaluation indicators for ML models.

Index	Definition	Formula
Accuracy	The proportion of all correct predictions (Both positive and negative) out of the total samples.	$\frac{TP + TN}{TP + FP + FN + TN}$
Precision	The proportion of correctly identified positive instances out of all instances predicted as positive.	$\frac{TP}{TP + FP}$
Recall	The proportion of correctly identified positive instances out of all actual positive instances.	$\frac{TP}{TP + FN}$
F1 score	The harmonic mean of precision and recall offers a balance between these two metrics.	$\frac{2 \times Precision \times Recall}{Precision \times Recall}$

4 | Findings

In this section, the performance of the models is analyzed. The study was conducted using the Python programming language, with all models executed on a system equipped with an intel core i7-13700H processor, 16 GB of RAM, and Python version 12.3. The detailed performance results of the models are summarized in *Table 6*.

Table 6. Performance results of the models.

Model	Accuracy	Precision	Recall	F1 Score
Logistic regression	0.6760	0.6593	0.7039	0.6807
Decision tree	0.9043	0.9076	0.8972	0.8997
Random forest	0.9412	0.9296	0.9529	0.9405
Extra trees	0.8423	0.8531	0.8204	0.8364
Gradient boosting	0.9004	0.9036	0.8935	0.8965
AdaBoost	0.8634	0.8481	0.8798	0.8635
XGBoost	0.9414	0.9464	0.9348	0.9371
LightGBM	0.9197	0.9313	0.9045	0.9131
CatBoost	0.9362	0.9434	0.9268	0.9312
KNN	0.8769	0.8453	0.9172	0.8797
SVM	0.6940	0.6383	0.8715	0.7367
Naive Bayes	0.5125	0.5021	0.9866	0.6655
QDA	0.5214	0.5068	0.9797	0.6680
LDA	0.5828	0.5942	0.4762	0.5287
MLP	0.8636	0.8579	0.8663	0.8619
SGD	0.6903	0.6480	0.8207	0.7205
Hard voting	0.9515	0.9400	0.9636	0.9512
Soft voting	0.9524	0.9409	0.9645	0.9519

Clearly, the evaluation results demonstrate that the two hybrid ensemble models; hard voting and soft voting always outperformed all individual ML models that the study considered in its evaluation. In particular, our proposed model outperformed all other models in terms of key evaluation metrics with an Accuracy of 95.24%, precision of 94.09%, recall of 96.45%, and an F1 score of 95.19%.

As in the case of the hard voting ensemble, the hard voting ensemble achieved similar but slightly lower and highly competitive results with accuracy of 95.15%, precision of 94.00%, recall 96.36%, and F1 score 95.12%. These voting-based ensemble models achieve superior performance because they have already combined the predictive strengths of several robust classifiers (Such as Random Forest, XGBoost, CatBoost, and LightGBM) yet cased for the biases and variances.

Through the use of weighted contributions of these high performing base learners, the voting ensembles accurately predict, generalize better, and balance between precision and recall are all better than single classifiers.

For instance, XGBoost, with an Accuracy of 94.14% and an F1 Score of 93.71% was the strongest individual model; Random Forest got 94.12% / 93.71% while CatBoost reached 93.61% / 93.57%. While the specific tree based and boosting methods work quite well independently, their stand alone results were always bad, always below the voting ensemble models.

On the other hand, classical statistical or linear methods such as Logistic Regression (Accuracy: 67.60%), SVM (Accuracy: 69.40%), Naive Bayes (Accuracy: 51.25%), and QDA (Accuracy: 52.14%) had much more lower accuracy and precision and were highly unsuccessful in capturing complex patterns within the dataset. Moreover, neural network methods such as MLP (Accuracy: 86.36%) and proximity based approaches such as KNN (Accuracy: 87.69%) proved to be relatively outdated adding quite a lot behind the very modern ensemble and boosting algorithms.

However, the Soft Voting ensemble model is very strongly recommended for the prediction of backorders in supply chain management scenarios in the research as it has an excellent predictive performance with the consistent ability to outperform individual classifiers on all key evaluation metrics.

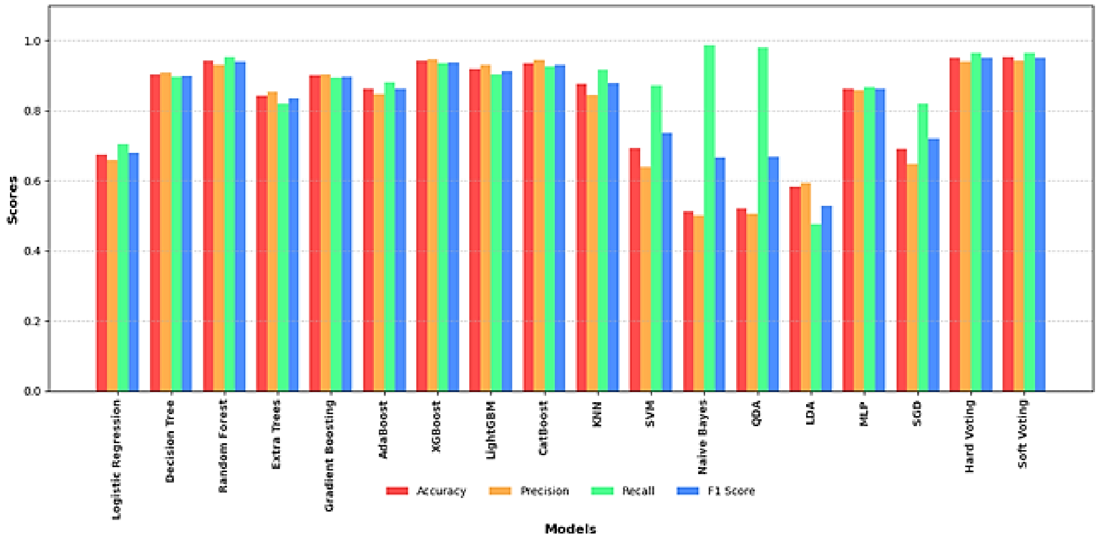

Fig. 5. Comparison of models based on performance metrics.

Fig. 5 illustrates the performance of individual ML models as well as the hybrid voting models, based on four main indicators–accuracy, precision, recall, F1 score. The results of this work demonstrate that the hybrid models have been able to develop a superior prediction compared to the individual models. Based on our highest accuracy and balance of the evaluation criteria shown in this study, the best model proposed is soft voting. Providing such an ability for this model to identify complex patterns in the data and also acting as an efficient solution for similar problems in forecasting backorders in the supply chain is the contribution of this model.

5 | Conclusion

In this study, voting-based hybrid ML models were used to enhance the accuracy of backorder prediction. The obtained results indicated that hybrid voting models, combining XGBoost, CatBoost, Random Forest, and LightGBM, significantly outperformed all single models in both hard and soft voting frameworks. Specifically, the soft voting model, our proposed model in this study, achieved the best performance with an accuracy of 0.9524, precision of 0.9409, recall of 0.9645, and F1 score of 0.9519.

These results demonstrate a clear improvement over the best-performing individual models, such as XGBoost and Random Forest, highlighting the advantage of employing a weighted combination of multiple robust classifiers for superior predictive performance. This means that by stacking multiple robust models, backorder prediction accuracy can be improved and the results are more impressive than traditional methods only based on one specific model. An object of the study was to assess the effect of feature selection and parameter tuning method on performance of the proposed model.

It was found that the use of the RFECV method to select features, as well as to perform the parameter optimization using Optuna, reduced the difficulty of the model and improved its prediction accuracy. With 17 key variables being selected to have the most impact towards the forecast of backorders from the 22 initial variables. The most important variables related to inventory levels, supplier performance and demand forecasting in causing backorders were those variables. The findings of this study compared to other studies show that the use of voting based hybrid models can increase the prediction accuracy to a great extent.

For instance, studies of Iqbal et al. [6] indicate that CART type models can achieve a competitive performance for predicting backlogged orders, but their impunity worsens our understanding of the complexities of the supply chain. However, we were able to overcome this limitation provided our proposed model was able to combine several robust models and increased the prediction accuracy.

Furthermore, the study of Sani et al. [7] in which the LightGBM model of supply chain risks was optimized provided that the optimization methods such as Bayesian optimization enhance the performance of the model. By performing Optuna on the parameters of the hybrid model, this study found large improvement in the accuracy of the hybrid model. Shukla and Pillai [9] also showed that data imbalance is one of the fundamental challenges of predicting backlogged orders. A solution to this problem in this study is through the ADASYN method, results were found that when applying this method the models were better able to predict backlogged orders and there were improvements in the accuracy of the models.

Also this study is very important in supply chain management process improvement. Predicting backorders with more accuracy assists companies to make better decisions on inventory management and supply chain management. Therefore, this model will help mainly in manufacturing, retail and logistics fields to avoid stockouts and raise the holding costs. This model in the other hand permits analysis of historical data so that managers can utilize past trends in order to design strategies for managing backorders more effectively.

The results of the study also indicate that, when there is unbalanced observed data on backorders, hybrid models perform better than single models. Thus, it appears that hybrid learning methods can be useful in case of the number of data obtained from different classes is imbalanced because it reduces prediction error with a prediction accuracy increase. Overall, this study identifies that voting based hybrid models used during forecasting can improve the accuracy of backorder forecasting and are superior to conventional models like statistical models and linear methods.

Future studies are therefore suggested to employ more advanced feature selection and optimization methods, for example genetic algorithms and deep neural networks, to improve the accuracy of the forecasting. Examining the effect of the environment and economy on the backorders occurrence should further build comprehensive models. In the end, joining ML methods with intelligent decision making systems can result in improvement of supply chain management systems and help in better managing forecast trends. The hybrid models can be tested with newer data and more recent external factors, such as economic changes, global crises and price fluctuations can be considered as future research suggestions to examine their impact on the models performance. Furthermore, the methods to increase the explainability of ML models are applicable to understand what the models and methods decide. Finally, a valid solution to improve forecast efficiency is to combine ML models with multi-objective optimization algorithms.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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نوع مقاله: پژوهشی

یک مدل یادگیری ماشین ترکیبی مبتنی بر رای‌گیری برای پیش‌بینی سفارش‌های معوق در زنجیره‌تامین

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چکیده

هدف: پیش‌بینی سفارش‌های معوق یکی از اساسی‌ترین چالش‌ها در زنجیره‌های تامین است که می‌تواند تاثیر مستقیمی بر هزینه‌های عملیاتی، سطح موجودی و رضایت مشتری داشته باشد. هدف اصلی این مطالعه، ارایه یک مدل یادگیری ماشین ترکیبی مبتنی بر رای‌گیری برای پیش‌بینی سفارش‌های معوق است که دقت پیش‌بینی را افزایش می‌دهد.

روش‌شناسی پژوهش: در این مطالعه، تلاش شد تا از مدل‌های رأی‌گیری سخت و نرم مبتنی بر *XGBoost*، *CatBoost*، جنگل تصادفی و *LightGBM* با وزن‌های بهینه‌شده از طریق *Optuna* استفاده شود. مجموعه داده‌های مورد استفاده شامل سفارشات، سطوح موجودی، عملکرد تامین‌کننده و سایر ویژگی های مرتبط است. برای کاهش عدم توازن داده‌ها، از روش *ADASYN* استفاده شد و همچنین از تنظیم پارامتر *optuna* برای یافتن تنظیمات بهینه مدل استفاده شد. روش *RFECV* نیز برای شناسایی ویژگی‌های کلیدی موثر بر سفارشات معوقه استفاده شد.

یافته‌ها: مدل رای‌گیری نرم، با دقت ۰/۹۵۲۴، بهترین عملکرد را در پیش‌بینی سفارش‌های معوق نسبت به سایر مدل‌های یادگیری ماشینی منفرد مورد بررسی در این مطالعه داشت. علاوه بر این، متغیرهای مرتبط با سطح موجودی، عملکرد تامین‌کننده و قابلیت پیش‌بینی تقاضا نیز به عنوان مهم‌ترین عوامل در ایجاد سفارش‌های معوق شناسایی شدند. مدل پیشنهادی با سایر روش‌های سنتی مقایسه شد و مشخص شد که با استفاده از مدل‌های استوار در یک چارچوب رای‌گیری، می‌توان دقت پیش‌بینی را نیز بهبود بخشید.

اصالت/ارزش افزوده علمی: نتایج نشان می‌دهد که استفاده از یک مدل یادگیری ماشین ترکیبی مبتنی بر رای‌گیری می‌تواند مکانیزم مناسبی برای بهبود پیش‌بینی سفارش معوق باشد. این مدل به سازمان‌ها کمک می‌کند تا جریان سفارش و هزینه‌های مرتبط با آن را با دقت بیشتری مدیریت کنند. پیشنهاد می‌شود در پژوهش‌های آتی از تکنیک‌های پیشرفته‌تر انتخاب ویژگی و بهینه‌سازی، مانند الگوریتم‌های ژنتیک و شبکه‌های عصبی عمیق، برای دستیابی به عملکرد بهتر مدل استفاده شود.

کلیدواژه‌ها: یادگیری ماشین، سفارش معوق، رای‌گیری ترکیبی، مدیریت زنجیره‌تامین، پیش‌بینی تقاضا.