Stockout Prediction in Multi Echelon Supply Chain using Machine Learning Algorithms

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Abstract

The main objective of a supply chain is to fulfil the customer demands in the right quantity at the right time. If an organization cannot meet the customer demand, stockout or out-of-stock situations happen. Inventory stockouts are costly to the organization and are very common in supply chains. It not only results in the loss of revenue but also affects the service level, which results in a loss of competitive advantage. Stockouts can be prevented by proper inventory planning and control. For any organization, it is crucial to maintain optimum inventory levels to ensure customer satisfaction. These days, technologies like Artificial Intelligence and Machine Learning give organizations the ability to foresee the future and proactively manage their inventory in the supply chain. This study investigates various supervised machine learning classifiers. It proposes the best machine learning stock out prediction model for each member of a four-stage divergent supply chain with eight members. Since the dataset for such a supply chain is not available, a supply chain operation simulation has been conducted under three distinct inventory replenishing policies such as Order-Up-To (OUT), Order-Up-To Smoothing (OUTS) and (s, S). Data generated from the simulation is divided into two sets, the train set and the test set. Various supervised machine learning algorithms are trained using training dataset. A five-fold cross-validation technique is adopted for the validation of the model. A random search cross-validation technique adjusts the hyperparameters of each classifier. The performance of the model is evaluated on the test dataset based on the assessment matrices, and it is found that boosting algorithms perform better than the other classifiers. This study proposes a meta-learning-based stacked ensemble model, using XG boost, Ada boost and random forest classifiers as the base model. The performance evaluation shows that for each supply chain member, the stacked ensemble model performs better than other classifiers, including boosting classifiers.

Keywords
Supply Chain, Inventory Policy, Stockout Prediction, Machine Learning Algorithms and Simulation.

1. Introduction

A supply chain is a network of nodes which aims to meet customers' demands (Kurian et al., 2020). It consists of various members, i.e., Supplier, Manufacturer, Distributor, Wholesaler, Retailer and Customers. For any supply chain, one of the most important assets is inventory, as it enables businesses to fulfil their customers' requirements in terms of quantity and time. A stockout, usually known as an out-of-stock (OOS), occurs whenever an organization cannot satisfy the customers' demand with their existing inventory. This stockout event is possible throughout the whole supply chain.

An investigation of the prevalence and scale of stockouts in supply chains and distribution systems was carried out by Gartner Inc. and is recognized as the preeminent research and advising for business worldwide. Non-promoted commodities and promoted items encounter between six and ten percent stockouts and between eighteen and twenty-four percent, respectively (Oroojlooyjadid et al., 2017).

The entire stockout rate in developed nations is estimated to be around 8 percent, according to one of the polls conducted by Gruen and Corsten (2007). The conclusions of the study, which was financed by P&G (Procter and Gamble), indicate that merchants are losing 4% of their yearly sales and that this is costing manufacturers an average of $23 million for every $1 billion in sales. These aspects demonstrate very clearly that stockouts are costly to the organization and may also result in a considerable loss of revenue and competitive disadvantage. Further, these aspects prompt the organizations to adequately plan and control their inventories to preserve the correct equilibrium of stocks and to avoid stockouts.

The rise in the application of artificial intelligence and machine leaning makes organizations prefer to make decisions based on data-driven insights instead of intuitions. As a result, this work investigates various supervised machine learning (ML) algorithms for predicting the periods with stockout and suggest appropriate machine learning prediction models for each stage of a four-stage divergent supply chain that operates under distinct inventory position-based inventory replenishing strategies, such as Order-Up-To (OUT), Order-Up-To Smoothing and (s, S). Also, this study proposes a Stacked Ensemble Model (SEM) for the stockout prediction.

The data for training the machine learning classifiers are generated through Python-based simulation. The effectiveness of the machine learning classifiers is assessed with the use of several different criteria for evaluation, and a stockout prediction model is utilised to solve an issue with order management.

1.1 Objectives

The main objective of this paper is to investigate the application of various supervised machine learning (ML) classifiers and propose an appropriate machine learning model to predict the stockout instances for each stage of a four-stage divergent type supply chain. It is assumed that the supply chain operates on various widely used inventory policies such as Order-up-to (OUT), OUT Smoothing, and (s, S) inventory policies. Supply chain operation simulation model are developed to generate the data required for training machine learning classifiers. The objective of this paper also includes the development of a Stacked Ensembled Model (SEM) for stockout instance prediction for each member of the supply chain.

2. Literature Review

The primary goal of any supply chain is to satisfy the requirements of the customers with the appropriate quantity at the appropriate time. It is essential to do a Predictive Inventory analysis to accomplish this objective. Even though stockout instance prediction is an interesting topic from the research perspective, only a small amount of research has been conducted in this field. According to a thorough study of the literature, investigations on stockout prediction in supply chains utilizing machine learning approaches are prevalent. Most of them have focused on forecasting customer demands and establishing an adequate quantity of safety stock. As a result, the scope of the literature review has been confined to the setting described above. There are many tools available for sales forecasting in the supply chain system; nevertheless, these tools have a lower level of accuracy for consumer demand prediction. Because of this, researchers are forced to find more precise methods to respond to uncertain demand in the traditional supply chain management system. In the end, with the advent of Artificial Intelligence systems, Machine Learning methods enable us to estimate relatively more accurate results in various aspects of the supply chain management system, such as customer demands, safety stock, lost sales, and out-of-stock events.

Researchers typically used machine learning to predict demand to improve inventory decision-making. Dong and Wen (2006) proposed a recurrent neural network-based demand forecast model for the supply chain. When the prediction results of multi-Layer feedback neural networks and recurrent neural networks are compared, the recurrent neural networks prediction model can aid in improving prediction accuracy. In another study, Mitrea et al. (2009) studied several forecasting approaches such as Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA) with Neural Networks (NN) models as Feed-forward NN and Nonlinear Autoregressive network with exogenous inputs (NARX). The results suggest that predicting with NN performs better than traditional approaches.

Bala (2010) proposed a Decision Tree based demand forecasting model for retail sales. The suggested forecasting model results in a significant decrease in inventory level and an increase in customer service level. Guo et al. (2014) focused on demand prediction for inventory optimization and employed a back propagation neural network to train the prediction model. Then based onthe forecast result, established one concise inventory policy. Following that, they compared the inventory cost of an established policy with the (s,S) inventory policy confronting demand normally distributed. The result reveals that the established inventory strategy outperforms the traditional (s,S) inventory strategy. A pharmaceutical corporation conducted empirical research on safety stock, considering demand forecasts and reorder points. This research is to minimise future shortages or surplus inventory (Mekel et al., 2014). This study employed quantitative methods to compute the forecasted safety stock level, and re-order point to predict when the firm needs to purchase and how much inventory to expect.

Machine learning algorithms have also been used in research to predict the desired level of safety stock on a periodical basis. Zhang et al. (2008) explored the possibility of utilising artificial neural networks to make predictions on safety stock. They created a three-level Back Propagation (BP) neural network based on the index system of safety stock to analyse the fundamental model and principle of safety inventory. They concluded that applying BP neural networks is an effective method to forecast safety stock. It can also be used to find the key factors for enterprises to improve their level of logistics management by using the samples to train and inspect the BP neural network. Similarly, Zhao and Liu (2010) observed that BP network enhancements, such as normalized input vectors, gradient descent momentum technique, and adaptive learning rate, can accurately forecast the safety stock value. Using K-means Clustering and Artificial Neural Networks (ANNs), Rezaei (2013) could accurately estimate safety stock levels and devise a novel approach to the issue of low accuracy and considerable variation in ANN target data. This approach implemented in MATLAB achieved better accuracy in forecasting the safety stock. Zhong and Zhang (2015) developed a combination forecasting model using a support vector machine (SVM) model and RBF neural network model. Agentic algorithm is used to calculate the weights of the variables in the model. The outcomes of the combination forecasting model have a high level of accuracy for the examples analysed.

When attempting to estimate the safety stock level and foresee the demand for stockout reduction, one restriction to keep in mind is that inventory tends to build up, which leads to a rise in the holding cost for the organisation. Recently, a few pieces of research that focus on predicting stockout status through machine learning classifiers have been recorded. To develop a prediction model for the imbalanced class problem, de Santis et al. (2017) used machine learning classifiers. This problem occurs when the frequency backorder is low compared to the frequency of no stockout. GBOOST achieved the greatest AUC score; however, BLAG fared better when considering precision-recall curves, processing costs, and enhancement capabilities. Prediction of stock-out in multi-echelon supply chain networks was examined by Oroojlooyjadid et al. (2017). Using classical inventory theory, it is possible to anticipate demand distributions in single-node networks. However, there is no way to foresee stock-outs in multi-tiered networks. To meet this demand, they devised a deep learning method. Three different methods were also introduced as a standard for stock-out prediction. Numerous numerical tests demonstrate that the Deep Neural Network (DNN) method outperforms the three naïve techniques in terms of performance.

Hajek and Abedin (2020) developed inventory models based on big data-driven backorder prediction, presenting a machine learning model with an under-sampling technique to optimise the anticipated profit of backorder selections. They proved that the proposed inventory backorder prediction model outperforms traditional machine learning algorithms applied to vast imbalanced data in terms of prediction and profit function. Islam and Amin (2020) employed machine learning models in the business decision process to anticipate product backorders while offering flexibility to the decision authority, improved process clarity, and higher accuracy. They discovered that when the dataset is substantially skewed with random error, this ranging technique improves the performance of machine learning models by 20%. To examine the effects of the ranging method, a decision tree from one of the produced models is evaluated.

Kurian et al. (2020) investigated a variety of machine learning classifiers to predict stockouts and provide suitable classifier models for each member of a four-stage serial supply chain. Based on the findings of the performance evaluation, it has been determined that the boosting classifiers of ensemble learning perform better at each level. Malviya et al. (2021) studied backorder predictions using a variety of machine learning classifiers so that inventory management may be more effectively controlled. According to the findings, backorder is infrequent in comparison to no backorders. To overcome the problem of out-of-stock, Andar et al. (2021) performed a case study on the retail packaged products manufacturing business in Latin America. They developed two ML models to identify OOS conditions. The first model was based on Random Forest, whereas the second was developed using an ensemble model comprising six distinct machine learning classifiers. They increased the system's predictive performance by including more predictive factors in their ML models. According to their findings, the Random Forest classifier had the best real-world performance, recognising 68 percent of OOS events with a precision of 72 percent.

Ntakolia et al. (2021) examined several machine learning models for handling the binary classification issue of backorder prediction. The Area Under Curve (AUC) score for the Random Forest (RF), Extreme Gradient Boosting (XGB), Light Gradient Boosting Machine (LGBM), and Balanced Bagging (BB) models was 0.95, with the LGBM model performing best following calibration with the Isotonic Regression approach. The explain ability study revealed that a product's inventory supply, the number of items that can be supplied, the immediate demand, and the precise prognosis of future demand might all significantly contribute to the proper prediction of backorder.

Even though stockout prediction is an important research area, relatively few studies have been done on stockout instance prediction. In most studies, a single echelon structure is considered with the real-world data for training and testing the model, due to which inventory policies are not specified. A few studies have been conducted on the serial supply chain structure, irrespective of the fact that most real-world supply chain structures are divergent. Also, experimental researchers didn't consider the stacking technique for developing a stockout prediction model, as it can perform better on time series data than machine learning classifiers.

3. Methods

The main objective of this study is to propose a suitable machine learning technique for predicting the stockout occurring at each member of the four-stage, divergent supply chain under distinct inventory replenishing policies. Since there is no publicly available data for such a supply chain network, a simple type of supply chain structure was identified, and simulation experiments were carried out to generate the required data for training the classifiers. The dataset generated by simulation is used to train machine learning classifiers to develop a prediction model. A suitable machine learning technique can be identified by comparing the performance measures of machine learning models. This predictive model can be used for inventory planning and control to improve the overall performance of the supply chain. The methodology of the study can be understood from Figure 1.

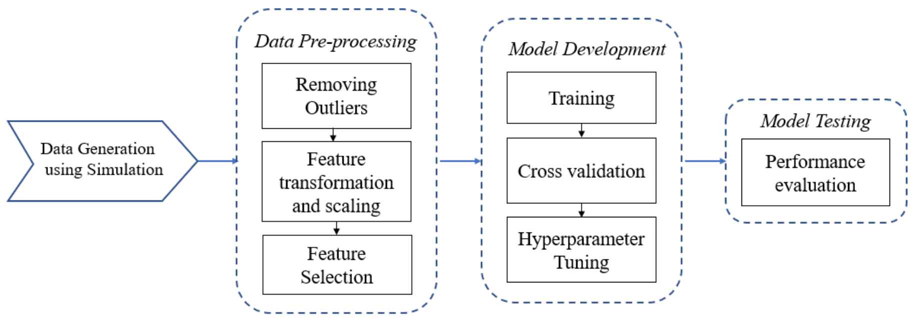


Figure 1. Flowchart of methodology

3.1 Data Generation using Simulation

In this study, a single product divergent supply chain with four-stage and eight members is considered (Pamulety et al., 2017) and is shown in Fig. 4.1. Where *i* represents a stage and *j* represents amember. The names of the stages are retailer(s) (i = 1), wholesaler(s) (i = 2), distributor (i = 3) and factory (i = 4). Each node of the supply chain serves as either supplier or customer to the other except in factory that is a supplier to the distributor.

In this supply chain, only the most downstream member, i.e., the Retailer(s), faces the customer demand, which is stationary and stochastic (Kurian et al., 2020). Every member is allowed to place an order to one corresponding upstream member. Here, retailers place orders to the wholesaler (R1,1 and R1,2 place orders to W2,1; R1,3 and R1,4 place orders to W2,2). Wholesalers place orders to the distributor (W2,1 and W2,2 place orders to D3,1). The distributor places an order with the factory (F4,1), and finally, the factory places an order for production (Pamulety et al., 2017). The inventory of each stage is reviewed periodically and the decision regarding when and how much to order for any member depends on the inventory policy followed by respective members (Lau et al., 2004). Three distinct inventory-position based inventory policy has been used in this study, which are Order up to (OUT), Order up to smoothing (OUTS) and (s, S) inventory policy.

In OUT, whenever the inventory position is less than the Order up to level (S) an order will be placed, which size is equal to the difference between the inventory position and S. Whereas, OUTS inventory policy is modified version of OUT which include net-stock smoothing parameter (β) and on-order inventory smoothing parameter (γ). Therefore, the complete gap between the OUT level and inventory position is not filled. Here, β and γ are set to 0.5. (Pamulety et al., 2017). In (s, S) inventory policy the when to place an order differs from the OUT policy, but the order quantity remains the same. For each review period, an order is placed if the inventory position is less than or equal to the reorder level.

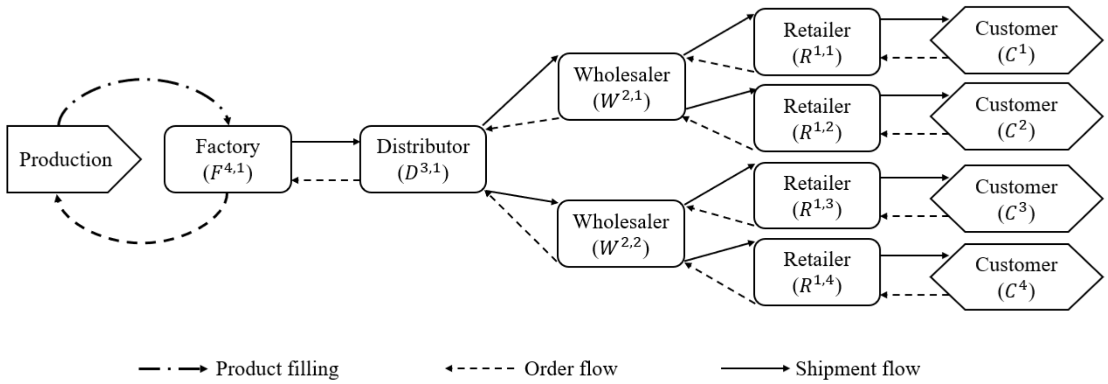


Figure 2. Divergent supply chain structure

In Figure 2, the symbol $R^{i,j,}$ represents jth retailer of ith stage. For example, symbolic representation of the first retailer will be $R^{1,1}$, whereas for second retailer it will be $R^{1,2}$ and so on.

Customer demand which is stationary and stochastic arises at retailers end only and independent from other retailers. Each member of supply chain receives replenishment quantity from upstream member at the beginning of a period. While order arouses at the beginning of a review period. Available quantities are allocated at the beginning of the week, whereas each stage places order to immediate upstream stage at the end of review period. At each level of the supply chain, there are no capacity and no storage space constraints (George and Pillai, 2014; Kurian et al., 2020). The factory possesses an unlimited capacity for producing products and has an adequate supply of raw materials. No safety stock exists at any point in the supply chain. Demand not met in any stage is considered as lost sales (George and Pillai, 2014; Kurian et al., 2020; Pamulety et al., 2017).

Within the context of the divergent supply chain, there may be times when the available stock held by a member of a stage is insufficient to satisfy the demand of respective members of its downstream stage. In these kinds of circumstances, proportionate allocation rule can be applied, which explains the process of dividing up the available inventory among the related members in the downstream (Pamulety et al., 2017). This rule has been implemented to the members of second and third stages. No back orders are allowed (George and Pillai, 2014; Kurian et al., 2020; Pamulety et al., 2017).In order to create the data required for training the machine learning classifiers, a series of simulation experiments are carried out. The Python programming language is used to simulate the operations of a four-stage divergent supply chain in which each member adheres to inventory policy. Each experiment is simulated for a length of 120 periods (weeks). Out of which, data generated for first 52 periods is considered as warm up period and data from period 53 to period 104 is considered for evaluation and rest periods are not considered to avoided period effect. Similarly, 100 simulation instances are run, and 5200 (100 × 52 weeks) observations are compiled for each member of the identified divergent supply chain. Simulation details are provided in Table 1.

The customer demand which arouses at retailer end is considered as normally distributed with mean 100 units and standard deviation of 25 units and independent from other retailers (Kurian et al., 2020). Customer demand related details are provided in Table 2. Inventory at each stage is reviewed periodically. Here, review period is considered as one week. Every stage of a supply chain has a one-week lead time. This lead time is calculated by adding the time it takes to transmit an order and the time it takes to ship it. The order transmission time to the immediate upstream stage is zero weeks, whereas the delivery time to downstream stage is one week (George and Pillai, 2014). Time related details are provided in Table 3. The initial period inventory of each supply chain member is determined by the total number of end customers' demand to be satisfied by that specific member (Pamulety et al., 2017) and can be calculated by multiplying the expected demand per period of end customer, No. of end customers and No. of week for which inventory must be carried. For example, initial inventory for a wholesaler, W2,1 is equal to 40 units (20 units × 2 end customers × 2 weeks) (Table 1-5). Likewise, initial period inventory for each member of the divergent supply chain is calculated and is provided in Table 4. For forecasting the expected demand, simple exponential smoothing method is used with smoothing constant (α) of 0.1 (equivalent to 20 periods moving average). Forecasting related details are mentioned in Table 5.

Table 1. Demand Details

Length of simulation (N)	120 weeks
Warm-up period (W)	Period 1 to 52 (52 weeks)
Period considered for evaluation	Period 53 to 104 (52 weeks)
No. of Replication (R)	100
No. of observations generated	52 weeks x 100 = 5200

Table 2. Demand Details

Demand Distribution	Normal
Mean	80
Standard Deviation	10

Table 3. Time Parameter

Parameter	Periods
Review Period (*T*)	1 week
Order Lead Time (*K*)	0 week
Delivery Lead Time (*L*)	1 week

Table 4. Beginning period inventory

Stage	Calculation	BI_0
Retailer	80 × 2 × 1	160 units
Wholesaler	80 × 2 × 2	320 units
Distributor	80 × 2 × 4	640 units
Factory	80 × 2× 4	640 units

Table 5. Forecasting details

Forecasting Technique	Exponential smoothing method
Exponential smoothing constant (α)	0.1

The dataset generated by simulation is useful for building stockout prediction model by using machine learning technique. Since there are total eight members in the supply chain, result of the OUT-level inventory policy-based supply chain inventory simulation have eight datasets (distinct dataset for every member). In this study, three distinct inventory policies have been considered, thus, a total of 24 Datasets (8 members × 3 inventory policy) are there.

3.2 Data Pre-processing

Each data set is split into two parts, training and test sets, using the train-test ratio of 0.8:0.2. As a result, the data set is divided into 4,160 and 1,040 observations corresponding to training and test sets, respectively. The training set is used for training the classifier models, and the test set is used for testing the trained model. After splitting, the size of the training dataset is (4160, 14), while the size of the test dataset is (1040, 14). Hence, all the machine learning techniques are trained to develop a prediction model using the training dataset.

In this study, the target feature 'stockout' is a categorical variable with classes YES and NO. In the training dataset, out of the 4160 data points, only 1066 have stockout instances (minority class), whereas 3094 datapoints have no stockout (majority class). The minority class is 25.625 percent of majority class, indicating a class imbalance in dataset. The synthetic minority oversampling technique (SMOTE) has been used to deal with the problem of class imbalance. Also, power transformation (Yeo-Johnson) has been used to transform the skewed data. By plotting the correlation heatmap and checking the values of the variable inflation factor (VIF), we can say that dataset has the problem of multicollinearity. The problem of multicollinearity has been solved using Principal Component Analysis (PCA) (Lafi and Kaneene, 1992).

3.3 Model Development

For training the classifiers various supervised machine learning methods are considered: logistic regression, decision tree, gaussian naïve Bayes, k-nearest neighbours, support vector classification, bagging classifiers, random forest, adaptive boosting, gradient boosting, XG boost, categorical boosting, and artificial neural network are trained using train dataset.

Machine learning algorithms are trained using the training dataset. K-fold cross-validation with the value of k equal to five is used to validate the model. The performance measure reported by k-fold cross validation is the average of the values computed in the loop. Based on the performance of the cross-validation results, it is found that boosting algorithms overperform other classifiers. In order to improve the performance of each model, hyperparameter tuning is performed using the Random Seach CV technique. A Stacked Ensemble Model (SEM) has been developed to achieve the best prediction model, using the top three best classifiers, which are XG Boost, Random Forest and Adaptive Boosting classifiers as the base model. The stack ensemble model uses a meta-learning technique to lean; hence it overperforms other classifiers. Successful completion of model training and prediction is evaluated based on the performance on test data. F1-Score and AUC Score are used to measure and compare the performance of the developed model. The process of model development using various machine learning algorithms can be better understood by schematic diagram provided in Figure 3.

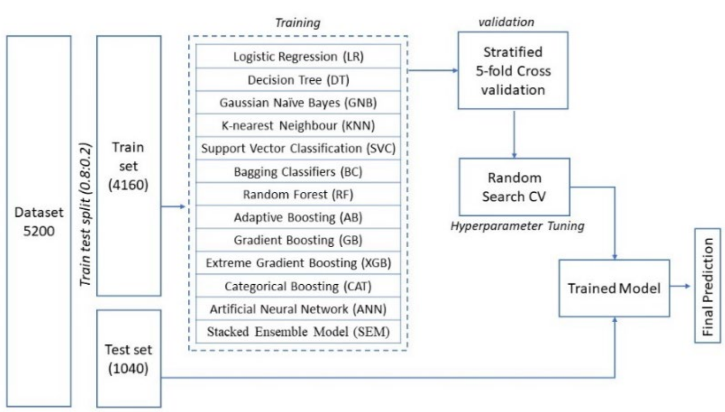


Figure 3. Schematic diagram of the model development

4. Results and Discussion

4.1 Numerical Results

This section consists of the final performance measures of each ML classifier model on the test sets for all eight supply chain members (retailers, wholesalers, distributors and factory) following distinct inventory-position based inventory policies, i.e., OUT, OUT smoothing and (s, S). Here, we infer the stockout prediction model after cross-validation and hyperparameter tuning. To compare the performance of different models, it is difficult to keep an eye on every performance measure, i.e., Accuracy, Precision, Recall, F1-score, and AUC score.In this study, F1-Score and Area under the ROC curve (AUC Score) are used to evaluate and compare the classifiers and to identify the best classifier for each member of the supply chain under distinct inventory policies (Kurian et al., 2020; Ntakolia et al., 2021; Malviya et al., 2021).AUC Score and F1 Score of machine learning classifiers for various supply chain members following OUT, OUT Smoothing and (s, S) inventory policies are shown in Tables 6, 7 and 8, respectively. Table 9 provides the best machine learning classifiers for each supply chain member under distinct inventory policies. Whereas Table 10 provides the performance matrices of the developed stacked ensemble model for each supply chain member.

Table 6. Performance measure of supply chain members operating under OUT inventory policy

Member	***Measure***	***Machine Learning Algorithms***												
		LR	***DT***	***GNB***	***KNN***	***SVC***	***BC***	***RF***	***AB***	***GB***	***XGB***	***CAT***	***ANN***	***Stack***
R^{11}	*F1 Score*	0.8585	0.8585	0.8280	0.7715	0.7456	0.8782	0.8932	0.9018	0.8926	0.8932	0.8758	0.8951	0.9089
	AUC	0.8463	0.8463	0.7996	0.7617	0.7299	0.8616	0.8773	0.8929	0.8834	0.8816	0.8499	0.9099	0.9201
R^{12}	*F1 Score*	0.8692	0.8418	0.8190	0.7873	0.7279	0.8866	0.8919	0.8769	0.8581	0.8932	0.8758	0.8369	0.8945
	AUC	0.8651	0.8399	0.7918	0.7883	0.7159	0.8708	0.8767	0.8697	0.8482	0.8816	0.8522	0.835	0.9111
R^{13}	*F1 Score*	0.8923	0.8593	0.8307	0.8028	0.7822	0.8805	0.8952	0.873	0.8769	0.8923	0.9001	0.9027	0.9132
	AUC	0.8846	0.8532	0.8028	0.8068	0.7724	0.8613	0.8799	0.8622	0.8696	0.8846	0.8741	0.9193	0.9207
R^{14}	*F1 Score*	0.8476	0.8269	0.7731	0.7633	0.7755	0.8534	0.8676	0.8641	0.8589	0.8722	0.8446	0.856	0.8857
	AUC	0.8413	0.8230	0.7442	0.7643	0.7673	0.8319	0.8469	0.857	0.852	0.8628	0.8154	0.8482	0.8862
W^{21}	*F1 Score*	0.8672	0.8546	0.8451	0.7932	0.8344	0.8692	0.8877	0.8639	0.8785	0.8722	0.8793	0.7998	0.8966
	AUC	0.8704	0.8481	0.8352	0.7955	0.8337	0.8604	0.8805	0.8611	0.8705	0.8628	0.8705	0.8191	0.8977
W^{22}	*F1 Score*	0.8754	0.8608	0.8402	0.7695	0.7736	0.8900	0.8878	0.8734	0.8966	0.8956	0.8945	0.8458	0.9019
	AUC	0.8790	0.8612	0.8334	0.7749	0.7732	0.8827	0.8836	0.8707	0.8933	0.8926	0.8913	0.8283	0.9076
D^{31}	*F1 Score*	0.8446	0.8352	0.7829	0.7360	0.6978	0.8723	0.8756	0.8677	0.8636	0.8771	0.8779	0.7237	0.8827
	AUC	0.8449	0.8332	0.7907	0.7404	0.6929	0.8650	0.8683	0.8644	0.8603	0.8739	0.8687	0.7326	0.8841
F^{41}	*F1 Score*	0.7394	0.8802	0.7893	0.7883	0.7822	0.8943	0.9126	0.8979	0.9068	0.908	0.9134	0.7252	0.9285
	AUC	0.7471	0.8774	0.8004	0.7966	0.7919	0.8906	0.9091	0.9003	0.9044	0.9065	0.9087	0.7181	0.9287

Table 7. Performance measure of supply chain members operating under OUTS inventory policy

Member	***Measure***	***Machine Learning Algorithms***												
		LR	***DT***	***GNB***	***KNN***	***SVC***	***BC***	***RF***	***AB***	***GB***	***XGB***	***CAT***	***ANN***	***Stack***
R^{11}	*F1 Score*	0.7429	0.8217	0.7123	0.7573	0.6138	0.8352	0.8589	0.869	0.8217	0.8523	0.8402	0.7336	0.8823
	AUC	0.8497	0.8140	0.7008	0.7635	0.5929	0.8113	0.8435	0.8602	0.814	0.843	0.8069	0.8421	0.9287
R^{12}	*F1 Score*	0.7246	0.7848	0.6825	0.7078	0.6057	0.8021	0.8237	0.858	0.8059	0.84436	0.8478	0.7246	0.9011
	AUC	0.8057	0.7757	0.6532	0.7125	0.5857	0.7851	0.8125	0.8651	0.7969	0.8445	0.8392	0.8057	0.9341
R^{13}	*F1 Score*	0.7246	0.8395	0.7133	0.7562	0.6323	0.8471	0.8705	0.9001	0.8515	0.8929	0.8769	0.7273	0.903
	AUC	0.8057	0.8459	0.6915	0.7607	0.6065	0.8411	0.8677	0.906	0.8472	0.8988	0.8769	0.8353	0.9371
R^{14}	*F1 Score*	0.7376	0.8416	0.7246	0.7804	0.6783	0.8566	0.8823	0.9083	0.8543	0.8965	0.8719	0.7376	0.8863
	AUC	0.8313	0.8272	0.7104	0.7849	0.6503	0.8391	0.8652	0.9019	0.8519	0.8788	0.8332	0.8313	0.9055
W^{21}	*F1 Score*	0.7559	0.7788	0.7602	0.7995	0.7200	0.7953	0.8076	0.7976	0.8029	0.8083	0.8031	0.7169	0.846
	AUC	0.8062	0.7796	0.7463	0.8085	0.6976	0.7879	0.8033	0.8038	0.8043	0.8049	0.7983	0.7463	0.8671

W^{22}	*F1 Score*	0.7666	0.8274	0.7708	0.8125	0.5405	0.8299	0.834	0.8258	0.8195	0.8328	0.842	0.7809	0.8413
	AUC	0.8094	0.8331	0.7587	0.8210	0.5473	0.8191	0.82	0.8131	0.811	0.8244	0.8176	0.7624	0.8671
D^{31}	*F1 Score*	0.7499	0.8271	0.8097	0.7987	0.7660	0.8513	0.8546	0.8177	0.8432	0.8397	0.8552	0.8174	0.8829
	AUC	0.7897	0.8306	0.8007	0.8095	0.7508	0.8456	0.8504	0.8264	0.8472	0.8413	0.8585	0.8306	0.8933
F^{41}	*F1 Score*	0.7546	0.8342	0.7993	0.8206	0.6820	0.8875	0.8914	0.8114	0.8811	0.909	0.8877	0.7742	0.9119
	AUC	0.7773	0.8271	0.7824	0.8432	0.6639	0.8824	0.8867	0.811	0.8838	0.9095	0.8878	0.7615	0.9144

Table 8. Performance measure of supply chain members operating under (s, S) inventory policy

Member	***Measure***	***Machine Learning Algorithms***												
		LR	***DT***	***GNB***	***KNN***	***SVC***	***BC***	***RF***	***AB***	***GB***	***XGB***	***CAT***	***ANN***	***Stack***
R^{11}	*F1 Score*	0.9173	0.9031	0.9198	0.9142	0.9206	0.8950	0.9138	0.9191	0.9179	0.9191	0.9228	0.9192	0.9189
	AUC	0.9212	0.9045	0.9269	0.9173	0.9267	0.8955	0.9203	0.9286	0.926	0.9286	0.9308	0.9225	0.9288
R^{12}	*F1 Score*	0.9122	0.9017	0.9126	0.9115	0.9143	0.9022	0.9379	0.9055	0.9359	0.9099	0.9113	0.914	0.9428
	AUC	0.9182	0.9047	0.9213	0.9197	0.9214	0.9078	0.9454	0.9195	0.9426	0.9208	0.9244	0.926	0.9494
R^{13}	*F1 Score*	0.9362	0.9289	0.9364	0.9285	0.9352	0.9323	0.9431	0.9342	0.9319	0.9409	0.9364	0.9348	0.9539
	AUC	0.9394	0.9305	0.9415	0.9343	0.9391	0.9367	0.9459	0.9371	0.9337	0.9426	0.9415	0.9428	0.9558
R^{14}	*F1 Score*	0.9269	0.9186	0.9203	0.9187	0.9231	0.9016	0.9216	9180	0.8976	0.9254	0.9227	0.9223	0.9254
	AUC	0.9326	0.9216	0.9277	0.9219	0.9290	0.9036	0.9282	0.9231	0.8993	0.9337	0.9263	0.9298	0.9337
W^{21}	*F1 Score*	0.7494	0.8642	0.7574	0.8838	0.8577	0.8678	0.8642	0.8642	0.8709	0.8917	0.8901	0.8539	0.8829
	AUC	0.7557	0.8637	0.7647	0.8831	0.8614	0.8668	0.8637	0.8637	0.8702	0.8909	0.8908	0.8622	0.8982
W^{22}	*F1 Score*	0.7123	0.8473	0.7292	0.8583	0.8604	0.8491	0.8473	0.8697	0.8473	0.8483	0.8571	0.8607	0.8749
	AUC	0.7179	0.8475	0.7368	0.8592	0.8651	0.8486	0.8475	0.8729	0.8475	0.8486	0.8572	0.8668	0.8759
D^{31}	*F1 Score*	0.6002	0.6272	0.5992	0.6166	0.5981	0.8605	0.8853	0.8739	0.8793	0.8303	0.7673	0.5931	0.9448
	AUC	0.6000	0.6327	0.6005	0.6173	0.6004	0.8583	0.8853	0.8747	0.8789	0.8291	0.7759	0.5989	0.9468
F^{41}	*F1 Score*	0.8856	0.8989	0.8847	0.9241	0.8847	0.9031	0.8989	0.9276	0.8989	0.8989	0.9244	0.8837	0.9217
	AUC	0.9045	0.8996	0.9037	0.9308	0.9042	0.9045	0.8996	0.9386	0.8996	0.8996	0.9335	0.9029	0.9325

Table 9. Best machine learning classifier for each supply chain member

Members	***OUT***	***OUTS***	***(s, S)***
R^{11}	ANN	AB	CAT
R^{12}	XGB	AB	RF
R^{13}	ANN	AB	RF
R^{14}	XGB	AB	XGB
W^{21}	RF	XGB	XGB
W^{22}	GB	XGB	AB
D^{31}	XGB	CAT	RF
F^{41}	RF	XGB	AB

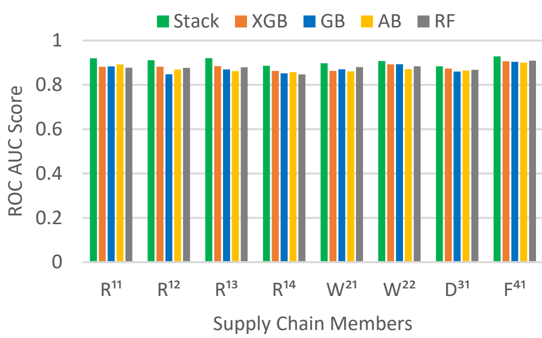
Table 10. Performance assessment of best ML model (SEM)

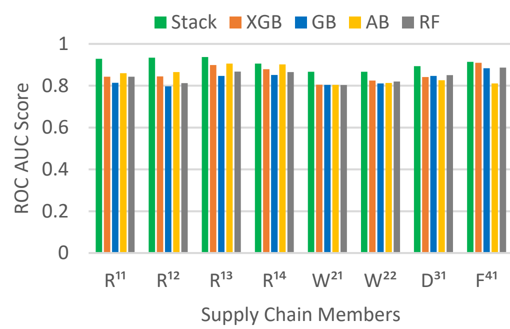
Members	***OUT***		***OUTS***		***(s, S)***	
	F1	***AUC***	***F1***	***AUC***	***F1***	***AUC***
R^{11}	0.9089	0.9201	0.8823	0.9287	0.9189	0.9288
R^{12}	0.8945	0.9111	0.9011	0.9341	0.9428	0.9494

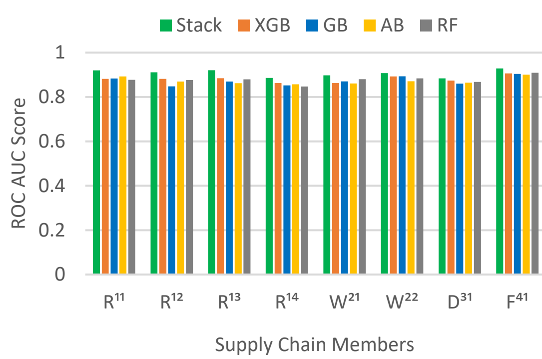
R^{13}	0.9132	0.9207	0.903	0.9371	0.9448	0.9468
R^{14}	0.8857	0.8862	0.8863	0.9055	0.9254	0.9337
W^{21}	0.8966	0.8977	0.846	0.8671	0.8829	0.8982
W^{22}	0.9019	0.9076	0.8413	0.8671	0.8749	0.8759
D^{31}	0.8827	0.8841	0.8829	0.8933	0.9448	0.9468
F^{41}	0.9285	0.9287	0.9119	0.9144	0.9539	0.9558

4.2 Graphical Results

Figure 4 represents of the performance of best five models for every supply chain member under OUT, OUT smoothing and (s, S) inventory policy, respectively.







(c) (s, S) inventory policy

Figure 4. Performance of best five ML models

4.3 Discussion

By adjusting hyperparameters, individual performance can be improved. Hyperparameters of any model changes with change in the dataset used for training the model. To achieve the best individual performance of all developed model, hyperparameters of each model has been adjusted separately for distinct inventory policies by using Random. Search CV. From the performance matrices, it can be noticed that for all the eight members of the divergent supply chain, the model developed with boosting ensemble technique performs better than other classifiers irrespective of the inventory policy they are following. Boosting Algorithms have a good AUC score and decent F1 Score, which is the combination of precision and recall of the machine learning classifiers. From the graphical representation of the performance of the best machine learning models for every supply chain member under distinct inventory policies, it can be noticed that the stacked ensemble model with XG Boost, Random Forest and Adaptive Boost as base models performs better than raw boosting algorithms for every member irrespective of the inventory policy followed by the members of the divergent supply chain.

Under the OUT-inventory policy, Factory has a comparatively high-performance measure than other supply chain members. Although, Random Forest with other boosting models performs better than other classifiers. For Distributor, Random Forest and XG Boost have higher AUC values after the stacked ensemble model. In the case of wholesalers, Gradient Boosting Model and Random Forest perform better. For retailers, XG Boost and ANN performs better than other classifiers. In contrast and SVC perform worst throughout the supply chain under the OUT-inventory policy. In the case of OUT smoothing inventory policy, the highest F1 Score can be observed at the Factory stage. For factory, XG Boost overperform compared toother classifiers. For the Distributor, CAT Boost and Random Forest perform better, whereas for Wholesalers and distributor XG Boost and Adaptive Boosting perform better than other supervised ML classifiers. In the case of (s, S) inventory policy, Factory has outstanding performance for Adaptive boosting, and Distributor has best AUC score for XG Boost. Whereas for Wholesalers and Retailers, XG Boost, and Adaptive Boosting have maximum AUC Score and F1- Score.

From the review of the performance assessment, it can be noticed that XG Boost, Gradient Boosting, Adaptive Boosting and Random Forest are the best classifiers. XG Boost is nothing but modified version of Gradient Boosting classifier. In order to improve the performance of ML classifiers, A meta learning based Stacked Ensembled Model (SEM) has been developed with XG Boost, Adaptive Boost and Random Forest as base classifiers and Logistic Regression as Final estimator, which performs better than other ensemble learning models. Table 9 provides the performance of the developed stacked ensemble model. It has the minimum AUC score of 0.8671 for the wholesaler under the OUTS inventory policy. Whereas maximum AUC score of 0.9558 is noticed at Factory under (s, S) inventory policy. AUC score in the range of 0.8671 to 0.9558 indicates that the stacked ensemble model has ahigh degree of predictive power. It can also be used for those practical cases in which demand distribution and inventory policy are unknown. However, the performance can be affected to some degree in accordance with the nature of the data.

After identifying the most reliable predictive classification model, it can be implemented in the real world. The stockout prediction model will help managers in predicting when stockouts will occur throughout the time. Using the model's predictions, managers may determine how much inventory they should acquire to avoid a stockout.

5. Conclusion

Inventory stockouts are costly to the organization and are very common in supply chains. Occurrence of stockout results in degradation of the overall supply chain performance. Poor inventory planning results in not only loss of revenue but also loss of market share. This situation can be overcome by proper inventory planning and control. With the advent of artificial intelligence and machine learning, supply chain managers are interested inosinate driven approach for making inventory-related decisions. This study considers a simple type of divergent supply chain with four-stage and eight members under different inventory-position-based inventory policies such as OUT, OUT Smoothing and (s, S). Python-based supply chain operation simulation is conducted for each inventory policy. The output of the simulation experiment reveals that (s, S) inventory policy has the highest stockout instances at each stage, followed by the OUT and OUT smoothing inventory policy. Data generated from supply chain inventory simulation is used for training and testing the machine learning classifiers.

The problem of data imbalance is solved by employing SMOTE sampling techniques, and it is found that algorithms used with sampling techniques perform better those without sampling techniques. Principal Component Analysis (PCA) is a technique that helps to eliminate the multicollinearity issue that arises while developing machine learning models. Tuning of the model's hyperparameters is required to get a stable and high-quality level of performance in the prediction process.

The primary focus of this research has been analysing various machine learning algorithms to predict stockouts. Considering this developed prediction models for each participant of a four-stage divergent supply chain consisting of eight members operating under three distinct inventory replenishment policies.

The assessment matrices show that the performance of the model developed with boosting classifiers is better than that of other classifiers for every supply chain member under each inventory policy. It has also been found that the combination of XG Boost, Ada Boost and Random Forest as a stacked ensemble model outperforms boosting algorithm and comes out as the best model for every supply chain member under all three inventory replenishing policies. A predictive classification model can be deployed for practical implementation once the best one has been identified. When the prediction model is used during order management, it will give every supply chain member the ability to take control measures. As a result, it will give rise to better operations and management of the supply chain.

Scope of future work includes deploying both simulation model and prediction model for better user experience. In this study, supervised machine learning models are investigated. In the extension of this work, deep learning algorithms can be investigated for stockout prediction, as they may perform better. The study's future scope also includes the estimation of stockout quantities in the event of stockout instance. When stockouts are foreseen, action can be taken to prevent such a situation by including predicted stockout quantities into the usual order quantity.

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